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Exploration on Environmental Causes of Coral Bleaching

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Abstract: In recent years, since global warming and human activities have contributed to massive coral bleaching events, it is significant to seek for the causations and predict the rate of coral bleaching to mitigate the influence and to decelerate bleachi,ng rate. The study focused on analyzing coral bleaching database from 1980 to 2020, revealing sea surface temperature anomaly (SSTA) and temperature cumulative thermal stress (TSA_DHW) are the major contributor of corals bleaching. In addition, climatic factors such as wind speed and cyclone frequency also conduce to coral bleaching. Resulted from principial component analysis (PCA), random forest regressor, dominant influencing factors are utilized in training multi-layer long short-term memory RNN (LSTM), support vector regression (SVR), and stacking regressor model, establishing models that predict coral bleaching percentage. Eventually, mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R2) are used to evaluate the accuracy of the model, revealing stacking regression model yielded the most accurate and steady predictions on coral bleaching percent comparing with other models.

Keywords: Deep Learning; Stacking Regressor Model; SVR; LSTM; Coral Bleaching Prediction

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1. Introduction

Coral reef dwells many marine organisms, encompassing complex 3D structures which enables biodiverse communities to form. According to research, although coral reef only occupies less than 0.1 percent of total ocean floor, it supported more than 25 percent of known marine organisms[1] and, thus, is known as “marine rainforest.” On the side of this, coral coexist with symbiont algae, such as zooxanthellae, which perform photosynthesis that synthesizes organic products, providing vital nutritional energy for corals and surrounding biosystem[2]. From 2015 to 2016, massive bleaching events occurred across tropics, which was the third global coral bleaching event that was recorded since 1980s, the first massive bleaching event[3]. China, from August 2020 to September, experienced unprecedented massive bleaching event in Hainan Island and Gulf of Tonkin (SCS), extending to China mainland and Hainan Island’s border reef. Field research revealed that, out from 74 investigated sites, 81.08% of sites experienced coral bleaching (with average bleaching percent being 51.14%)[4]. Commonly, coral can endure temperature ranging from 26°C to 29°C. When the temperature passes this range, high temperature will induce zooxanthellae produce deleterious reactive oxygen species(ROS) while photosynthesizing. ROS, toxic to coral polyps, will force coral to expel their symbiotic algae, loosing vital energy source and coloration (from pigments in the algae)[5]. This is why the phenomenon named as coral bleaching. Among the growth of CO2 concentration in atmosphere, the carbonic acid in ocean will increase, inducing the deduction of ocean pH. Such acidification will impact calcification of corals, making their structures become fragile, further lowering corals’ ability on enduring high temperature[6]. Since oral bleaching is not accidental from the global perspective, it is urgently needed for discussing quantitative factors that contribute to different regions’ bleaching events for proceeding further coral protection and recovery effort.

There are very few research that investigate different regions' environmental factors that lead to coral bleaching. Most of existing studies mainly focused on single region. Despite conventional statistical methods has been extensively utilized in analyzing environmental influencers for designated region: H. Kumagai used high resolution temperature thresholds and environmental models to predict coral bleaching but was limited to the specific region and its environmental variables [7]. Simon D.Donner utilized statistics to collect high resolution global coral bleaching database and discussed the influences of environmental factors that contribute to regional coral bleaching[8]. Similarly, Chuki Hongo et al. studied the spatiotemporal patterns of coral bleaching in different regions of Japan and used statistical methods to evaluate the impact of environmental variables on coral bleaching[9]. In the recent years, the developments of many deep learning algorithms, such as long short-term memory (LSTM)[10], support vector regression (SVR) [11], and stacked regression[12], have been widely used in image classification, natural language processing and other fields. For instance, Taoying Li et al. used the CNN-LSTM model to predict the concentration of PM2.5[13]; J. B. Heaton and N. G. Polson used the stacked regression model to solve financial forecasting and classification problems[14]; and H Zhong and J Wang used the vector field-based SVR that used building energy consumption prediction (ECP) to establish two energy consumption prediction models with high accuracy, strong generalization capability and robustness[15].

As the impact of climate change on coral reef ecosystems grows, it is necessary for us to use more innovative methods to solve the problems. This study, through analyzing collected data on seawater temperature, salinity environment, and etc. and forming prediction results with LSTM, SVR, and stacked regression models, systematically analyzed the key factors that affected coral bleaching, providing new scientific basis and methods for more accurately understanding and responding to coral bleaching. Specifically, this study will mainly yield the following results: (1) Utilize statistical analysis to determine the impact of various environmental factors on coral bleaching; and (2) Predict the percentage of coral bleaching one year later.

2. Methodology

Machine learning models have been widely used in data analysis and prediction. Common machine learning models include multi-layer long short-term memory RNN (LSTM), support vector regression (SVR), and stacking regressor model, in which LSTM can effectively deal with time related database, capturing long term reliability relationship, and especially fits on analyzing time relying environmental factors[16]. SVR, on the other hand, is better at treating nonlinear, multi-dimension, small database related regression problem[17]. Stacking regression model can combine the prediction result of LSTM and SVR, blending their advantages and rising the accuracy of prediction result[18]. Therefore, this paper will use these three models to analyze environmental factors that contribute to coral bleaching in these three sections.

2.1 Multi-Layer Long Short-Term Memory RNN (LSTM)

Multi-layer long short-term memory (LSTM) is a special type of recurrent neural networks (RNN)[19], specifically designed for dealing with time series. LSTM introduces a set of gating mechanisms (including input gate, forget gate and output gate) [20], which effectively avoids the gradient vanishing and gradient exploding problems when processing long sequence data[21]. The core of LSTM lies in the cell structure [22]. Each cell contains a "memory block" [23]. The forget gate of the memory block determines information that needs to be forgotten, the input gate determines which new information needs to be stored, and the output gate determines what information needs to be output to the next time step [24].

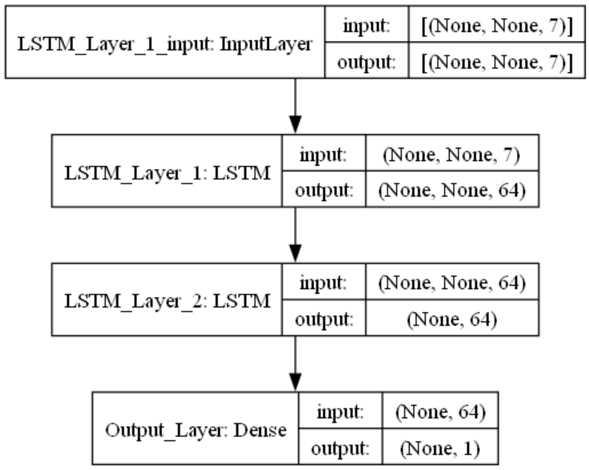

Figure 1: LSTM model structure

As shown in Figure 1, in this study, the input layer incepts a three-dimensional tensor [None,None,7] [25], where the batch size, time steps, and number of features are variables. The first layer processes the input sequence and transforms it into a 64-dimensional hidden state [26], with an output form of [None,None,64]. The second layer further processes this hidden state and returns the output of the last time step and generates [None,64]. Finally, the fully connected layers will present this output as a single regressor [27], predicting the percentage of coral bleaching, with the output [None,1].

2.2 Support Vector Regression (SVR)

Support vector regression (SVR) [28] is a supervised learning algorithm based on support vector machine (SVM) [29], which mainly used to deal with regression problems. Different from traditional linear regression, SVR transcribes data into a high-dimensional space [30] and finds the best regression hyperplane in the space[31], thereby improving the generalization ability of the model. The process embraces an introduction of the "ϵ-insensitive loss function" [32], which allows the model to not penalize prediction errors within a certain range, thereby improving the model's robustness to noise.

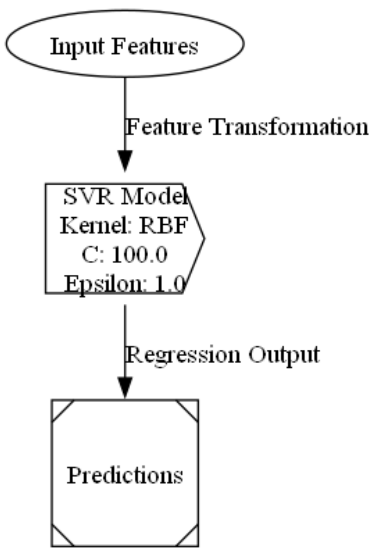

Figure 2: Workflow of Support Vector Regression (SVR)

First, as features are inputted, they are transformed into a high-dimensional space with the radial basis function (RBF) [33] , and the optimal regression hyperplane can be found in this space. As shown in Figure 2, this study uses RBF as the kernel function, sets the penalty parameter [34] C as 100.0, and the loss tolerance ϵ as 1.0, which enable the model to tolerate errors and reduce the risk of overfitting.

2.3 Stacked Regression

This study constructed a stacked regression model. The outputs of SVR and LSTM were inputted back to the stacked regression model for explaining the influencing factors of coral bleaching more comprehensive. The process is shown in Figure 3.

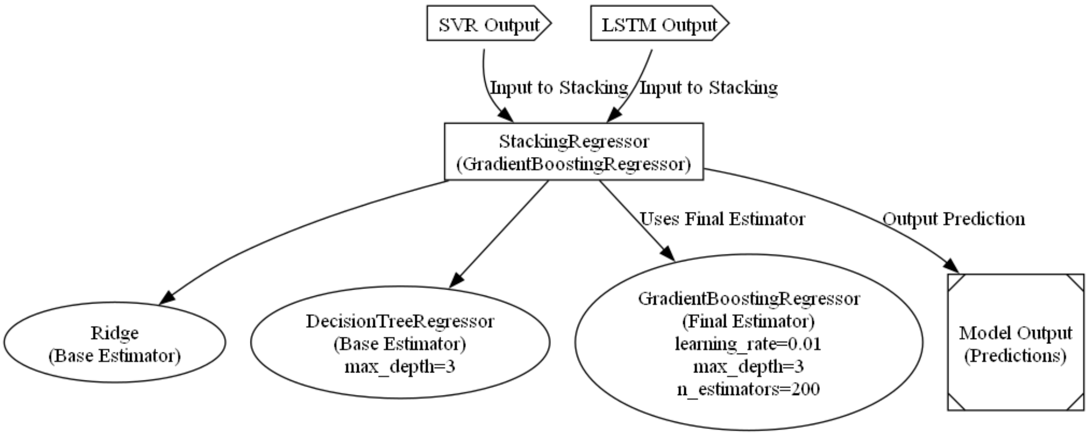

Figure 3: Simple architecture of stacked regression model

The SVR output and LSTM output in the figure are inputted back into the stacked regression model. The stacked regression model uses three base estimators [35]: ridge regression[36], decision tree regression (maximum depth 3) [37], and gradient boosting regression[38]. The final meta-learner is gradient boosting regression with a learning rate of 0.01, a maximum depth of 3, and 200 estimators. Finally, the stacked regression model combines the prediction results of these base models to generate the final prediction output.

3. Data Source and Preprocessing

Data source that this research used is collected by Robert van Woesik and Chelsey Kratochwill(https://springernature.figshare.com/articles/dataset/Global_Coral_Bleaching_Database/17076290?file=31573496). This article records global coral bleaching data from 1980 to 2020. The dataset contains 8973 records with multiple features, including sea surface temperature, sea surface temperature anomaly, wind speed, depth, turbidity, cyclone frequency, coral bleaching percentage, and etc. However, due to uncontrollable factors, there are some missing values in the data set. Therefore, in this article, we use the ‘isnull().sum()’ method in Python’s ‘pandas’ library to check each feature of the dataset and count the number of missing values in each category. For columns with 3 missing values, we fill them with the median of the column, including the depth column, which directly affects the living environment of corals (light and temperature). We delete the Quadrat_No column because it is an artificially endowed number and does not contribute coral bleaching.

Due to the complexity of these data, we plot the changing trends of the remaining features with histograms for further examinations, as shown in Figure 4.

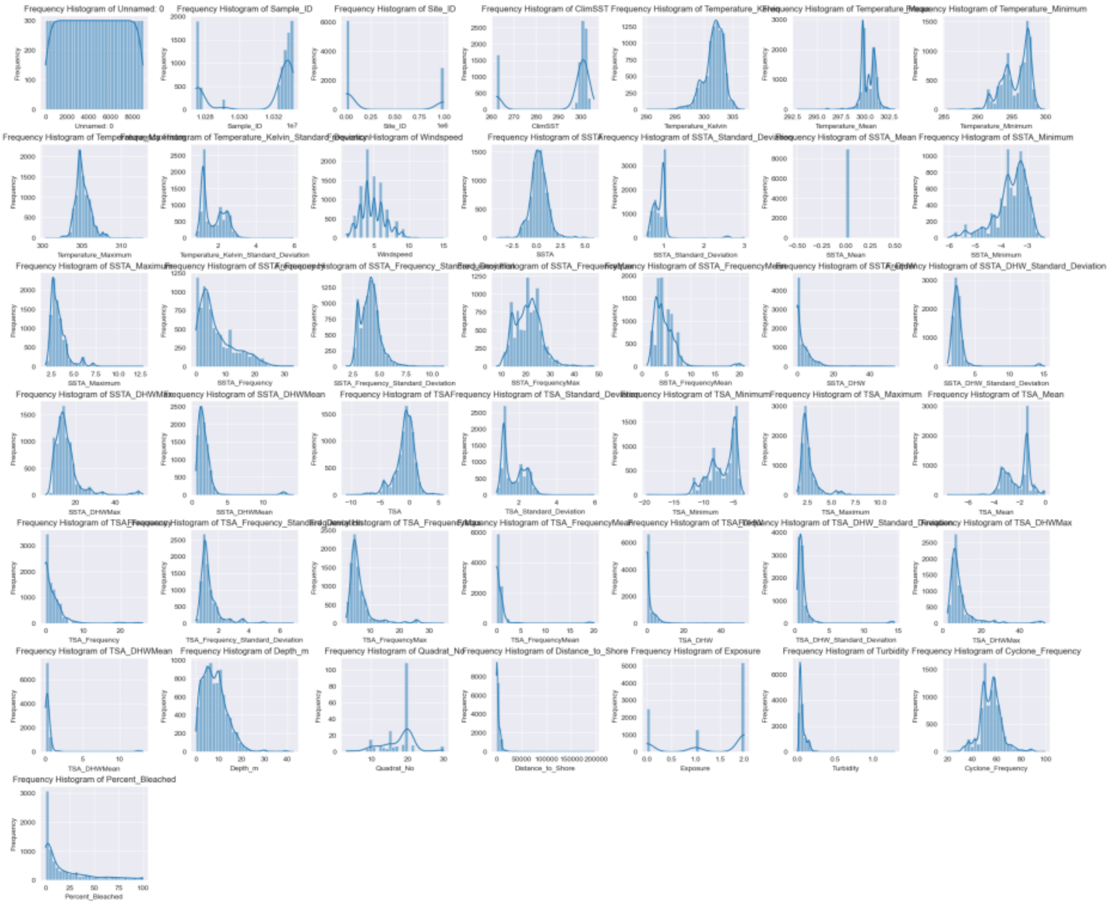

Figure 4: Histograms of main feature change trends

Table 1: Main characteristics analysis

	Unnamed: 0	Samphe ID	Site ID	ClimSST	Tembperature kekin	TemhperatureMean
count	8973.000000	8973000e+03	8973000e+03	8973.00000	8973.000000	8973.000000
mean	4487000000	1.031312e+07	3249599e+05	293.69843	301.760061	300.348378
std	2590.426316	2.341933e+04	4618183e+05	15.19937	1.721520	0.781719
min	1000000	1.027449e+07	2000000e+00	262.15000	290.100000	292.960000
25%	2244.000000	1.0276740e+07	6536000e+03	299.17000	300.940000	239.790000
50%	4487000000	1.032651e+07	1277800e+404	300.60000	301.980000	300.380000
75%	6730.000000	1.0329447e+07	9995430e+05	301.76000	302.975000	300.880000
max	8973000000	1.033170e+07	1000042e+06	305.89000	307.010000	303.080000

In the analysis of the dataset, there are of 8,973 sample records, which are sufficient and suitable for modeling. The average temperature data (Temperature_Kelvin) is 301.76 K, with small fluctuations. The average wind speed (Windspeed) is 4.79 m/s, but the difference is large, with the highest reaching 15 m/s.

The average value of coral bleaching (Percent_Bleached) is 20.56%, but it varies greatly, ranging from 0% to 100%. Most corals are distributed in shallow waters with an average depth of 8.32 meters, and some are far from the shore (up to 195 kilometers). The heat stress accumulation index (TSA_DHW) and cyclone frequency (Cyclone_Frequency) vary significantly in different regions and times.

In order to better determine the correlation between different features, the correlation coefficient is calculated, and the calculation formula is shown in (1). Also, in order to determine whether the correlation coefficient is significant and calculate the corresponding p-value, the t-test is used in this paper, and its formula is shown in (2).

$$r_{zy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{h}(x_i - \bar{x})^2 \sum_{i=1}^{h}(y_i - \bar{y})^2}} \tag{1}$$

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \tag{2}$$

The Pearson correlation coefficient (rxy) is a measure evaluating the strength of linear relationship between two variables x and y. In the formula, x_i and y_i represent the x and y values of the i^{th} sample, respectively; x and y are the means of x and y, respectively; and n is the total number of samples. This part of the calculation is done with the 'corr()' function in Pandas through analyzing correlation coefficients for the entire data frame, which yielded Figure 5.

Based on the distribution of t, we calculate the corresponding p-value. This p-value represents the probability of observing the current or more extreme results under the null hypothesis (assuming the two variables are unrelated). If the p value is less than 0.05, the correlation is considered significant. In heat map 6, only data with a significance level of $p < 0.05$ are displayed, which, in the other words, means that only statistically significant correlation coefficients are retained.

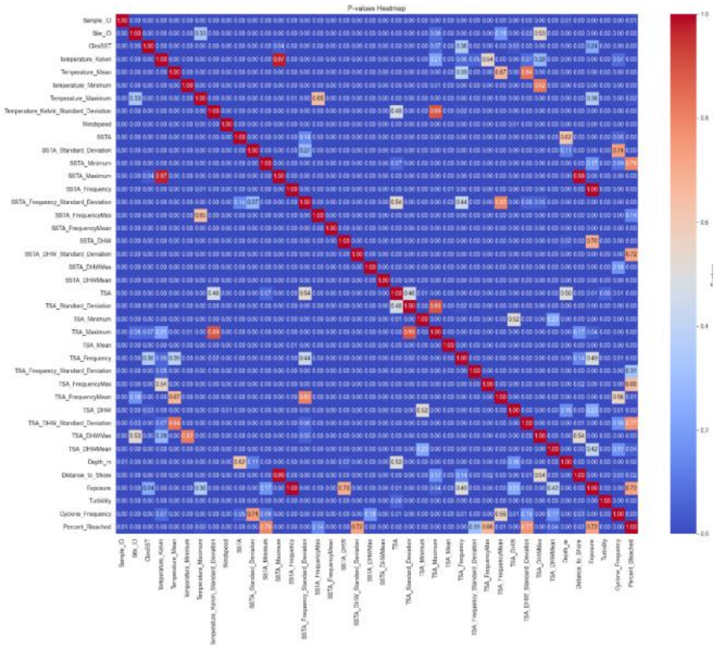

Figure 5: P value matrix

From the figure, it can be seen that features related to temperatures appear as dark red, indicating a high positive correlation between these variables. This makes sense since these variables are all essentially describing temperature characteristics, just expressed from different aspects. The temperature-related variables, such as Temperature_Kelvin, Temperature_Maximum, and Temperature_Mean, are highly positively correlated, reflecting the consistency of temperature characteristics. The SSTA variables were also strongly positively correlated with each other and were closely related to coral bleaching. Percent_Bleached is highly correlated with Temperature_Maximum and SSTA_Maximum, indicating that temperature extremes are the key factor in bleaching. Cyclone_Frequency and Turbidity are negatively correlated with temperature, indicating that temperature decreases when the number of these events increases. Depth_m is negatively correlated with temperature, indicating that the temperature decreases as the depth of water increases. Areas that are white or light, such as Exposure and Distance_to_Shore, indicate an absence of significant linear relationship.

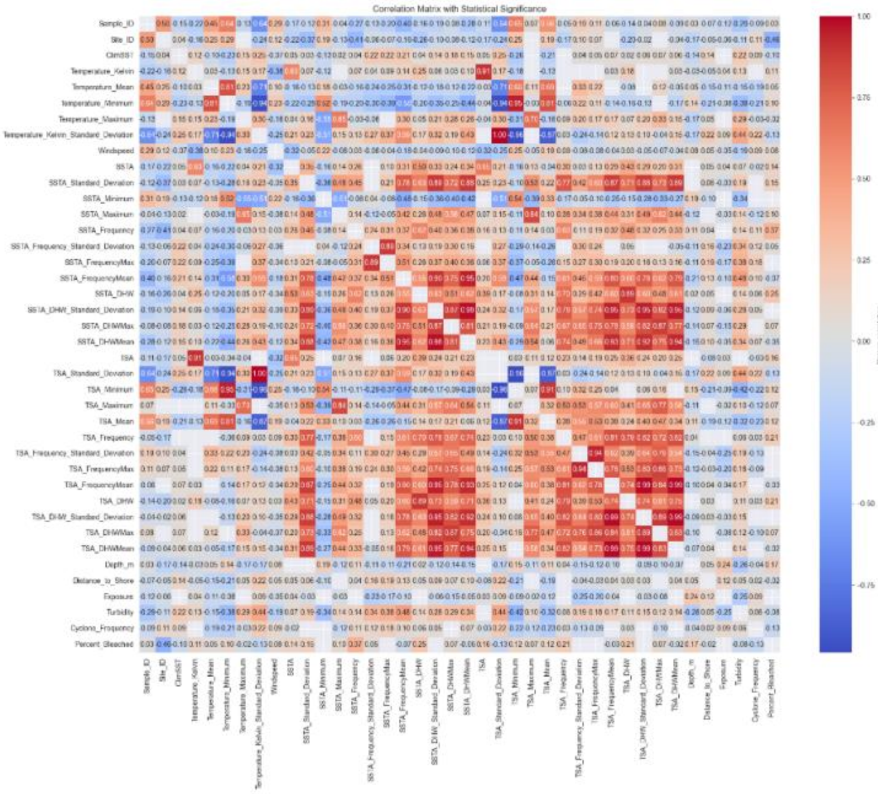

Figure 6: Correlation coefficient matrix

In the analysis, the correlation coefficient between the percentage of coral bleaching and the site number is -0.4557, showing a moderate negative correlation, with a P value of 0.0, which is statistically significant; the correlation coefficient between the minimum temperature and the temperature standard deviation is -0.9425, demonstating an extremely strong negative correlation, with a statistically significant P value that is close to 0; the correlation coefficient between the sea surface temperature anomaly and the cumulative heat of the sea surface temperature anomaly is 0.4306, revealing a moderate positive correlation. Thus, the relationships among coral bleaching percentage, site number, minimum temperature, temperature standard deviation, sea surface temperature anomaly and cumulative heat of sea surface temperature anomaly are statistically significant and have potential impacts on coral bleaching.

Then, random forest model is used access the importance of features. In analysis above, although the data set has many features, their correlations vary. In order to effectively identify the variables that have the greatest impact on the prediction of the target variable (in this case, the degree of coral bleaching), the random forest model is used to evaluate the importance of the features and screen out features that are relatively uninfluential on predicting coral bleaching.

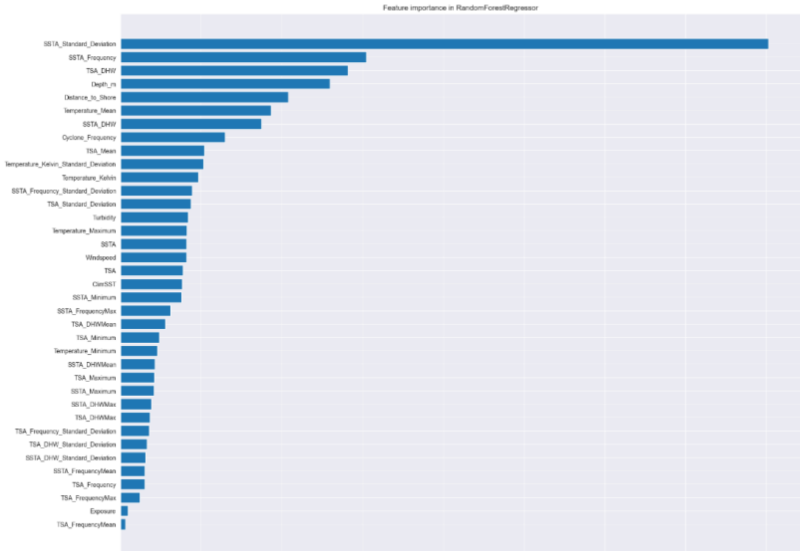

Figure 7 Importance of each feature evaluated by the random forest regression model for predicting coral bleaching percentage

In Figure 7, the graph ranked each feature in the order of their relative importance scores. The higher the importance of each feature, the greater the contribution of the feature is for predicting targeting variable. In the random forest model, variables that have the greatest impact on coral bleaching predictions include ocean temperature anomalies, accumulated thermal stress, and characteristics associated with geographic location. In addition, the cyclone frequency and water turbidity also have a certain impact on coral bleaching, whereas basic temperature variables and other secondary variables contribute less to the model's predictions. The high importance of SSTA and TSA features indicates that features related to persistent and transient changes in temperature are important components for understanding and predicting coral bleaching, because these indicators may capture the frequency and severity of temperature anomalies that may cause greater stress to corals than average temperature levels. Based on this analysis, the study finally selected the top 25% important features for subsequent research.

To reduce the complexity of the data set while retaining as much important information as possible, PCA is used to project the original high-dimensional data into a lower-dimensional space so that the data has maximum standard deviation in these new dimensions and retains as much original information as possible. The PCA processing process is described by formulas such as (3)-(7).

$$Z = \frac{X-\mu}{\sigma} \tag{3}$$

$$C = \frac{1}{n-1}\sum_{i=1}^{n}(Z_i - Z)(Z_i - Z)^T \tag{4}$$

$$CV = VA \tag{5}$$

$$Y = ZY_k \tag{6}$$

$$Y = XW \tag{7}$$

The standardized data Z is calculated by subtracting the mean μ from the original data X and dividing the result by the standard deviation σ. The eigenvalues and eigenvectors of the covariance matrix C are then solved, and the eigenvalue matrix Λ and the eigenvector matrix V represent the variance and direction of the features respectively. The principal components are sorted according to the size of the eigenvalues, and the top seven principal components with the highest cumulative variance contribution are selected. Then, the original matrix X is projected into the new space, reducing its dimensionality through transforming matrix W, and forms matrix Y, as shown in Table 2.

Table 2: PCA data processing results

The dataset is divided into a training set and a test set, where 80% of the data is used for training and 20% of the data is used for testing.

Index	PC1	PC2	PC3	PC4	PC5	PC6	PC7	Percent_Bleached
0	0.107432	1.489584	0.001452	0.396599	-0.052239	-0.084169	-0.376884	35.4
1	0.100917	1.460995	0.483127	0.120461	-0.124150	-0.190733	-0.442480	15.2
2	0.093580	1.480099	0.202134	0.240388	-0.134149	-0.158278	-0.511507	4.7
3	-0.024996	1.383182	1.561042	-0.170882	-0.583673	0.299311	0.017174	21.8
4	0.124252	1.459042	0.700633	-0.065842	-0.176240	-0.218078	-0.168926	19.6
5	0.087804	1.468117	0.813372	0.348458	-0.020293	-0.085766	-0.435121	28.0
6	-0.117440	1.569100	0.653226	-0.072068	-0.172095	-0.531354	0.100882	2.7
7	1.283731	1.552211	0.556068	-0.160851	-0.234115	0.977858	-0.904979	43.5
8	1.597371	1.766464	0.818607	-0.487926	-0.364509	2.015801	-0.305972	2.9
9	0.084727	1.578860	-0.247853	0.534993	0.064290	0.511303	-0.147491	19.7

4. Results and Discussion

In Python, SVR, SLTM, and stacked regression models are constructed in the structure shown in Figures 1, 2, and 3. Seven main features from 1980 to 2020 are used to predict the percentage of coral bleaching one year later, as shown below.

The SVR model uses cross-validation to optimize model parameters and prevent overfitting in the training process. In the training, the support vector regression (SVR) model uses five-fold cross-validations to select the optimal parameters combination. The final model is trained on the entire training set and evaluated on the testing set. MSE is used as a measure for the accuracy of the model's prediction.

In the training process of the SLTM model, the mean square error (MSE) is used as the loss functions and the Adam optimizer is used to update the parameters. To prevent overfitting, the early stopping and cross-validation mechanism are used to continuously optimize the model parameters in 500 rounds of training and to improve the generalization ability of the model.

The stacked regression model takes the output of the LSTM and SVR models as input and makes the final prediction using a gradient boosted tree model.

LSTM is suitable for analyzing the impact of time-related environmental factors (such as ocean temperature changes) on coral bleaching, and SVR is more capable of analyzing environmental factors impacting coral bleaching that are often complex and nonlinear. The stacked regression model, in turn, combines the prediction results of multiple basic models (such as LSTM and SVR) and generates a more powerful prediction model. As there are multiple models being used to predict the percentage of coral bleaching, the results of three models are compared in this section. Below are the true values and predicted values of these three models.

Figure 8 shows the accuracy of predicted values of the coral bleaching percentage of the three models through comparing with the actual values. Through comparing three models horizontally and vertically, it can be found that the accuracies of the SVR model and the LSTM model are lower than the accuracy of the stacked regression model.

Figure 8: Comparison of the actual values and predicted values of the three models

In order to evaluate the performance of these models, 10 samples are randomly selected from the testing set to predict the percentage of coral bleaching. Three indicators are used, namely, mean absolute error (MAE), root mean square error (RMSE), and determination coefficient (R2), as shown in formulas (8), (9), and (10). The indicators of prediction results from the corresponding models are shown in Tables 3, 4, and 5.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{9}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{10}$$

y_i is the actual value, whereas $\hat{y}_i$ is the prediction value.

Table 3 shows the mean absolute errors of the three models in predicting the percentage of coral bleaching. The average MAE of SVR is 348.9694, and the average MAE of LSTM is 281.5523, which is significantly lower than that of SVR, showing higher prediction accuracy. The stacked regression model has the lowest average MAE of 252.2430.

Table 3: MAE of experimental results

Samples	SVR	SLTM	Stacking Model
Average	348.9694	281.5523	252.2430

Table 4: RMSE of experimental results

Samples	SVR	SLTM	Stacking Model
Average	18.6807	16.7795	15.8822

Table 5: R2 of Experimental results

Samples	SVR	SLTM	Stacking Model
Average	0.4849	0.5844	0.6277

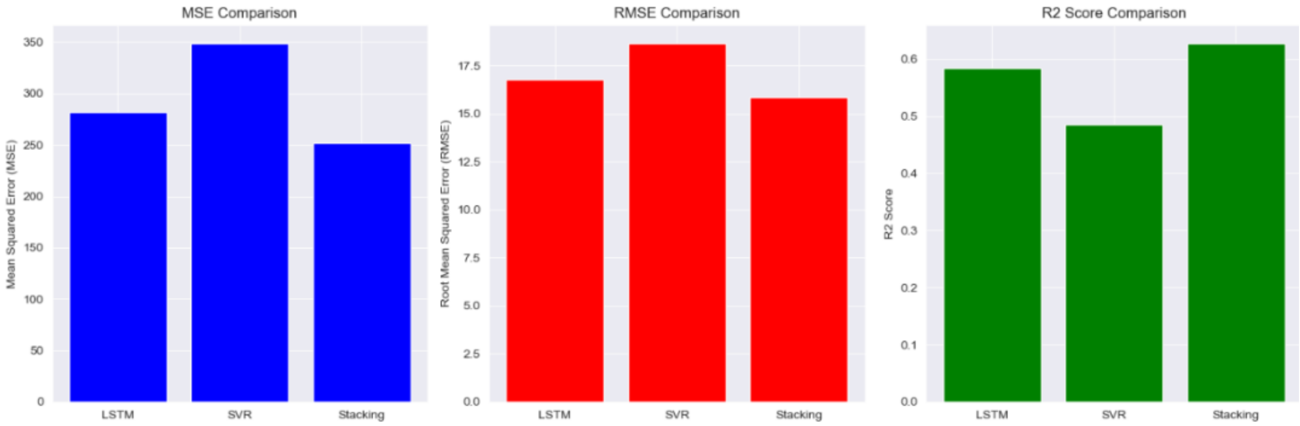

Figure 9: Histogram of MAE RMSE R2

It can also be seen from Tables 3 and 4 that the average RMSE of the stacked regression model is 15.8822, the lowest, and the average R2 is 0.6277, the highest. As shown in Figure 9, a graphic representation of the MAE, RMSE, R^2 of the three models, the accuracy and stability of the stacked regression model are higher than the other two models. In the experiment, an Apple MacBook with M2 chip, 2TB SSD, 16GB Unified Memory is used, taking 120 seconds to train SVR, 250 seconds to train LSTM, and 70 seconds to train the stacked regression model. Based on the above results, we can draw some conclusions:

(1) Random forest model is used to evaluate the importance of each feature in the dataset, When analyzing the factors that might contribute to coral bleaching. The experiment reveals that ocean temperature-related variables, especially sea surface temperature anomaly (SSTA) and temperature cumulative thermal stress (TSA_DHW), have the most significant impact on coral bleaching, and the extreme values and abnormal fluctuations of these factors are the main driving factors of coral bleaching. In addition, wind speed and cyclone frequency also have important impacts on coral bleaching. Higher wind speeds and cyclone activity frequency are associated with lower temperatures, thereby slowing the process of coral bleaching.

(2) In order to improve the training efficiency and prediction performance of the model, PCA (principal component analysis) is used to reduce the dimensionality of the data. After the reduction, only the top 25% of important features are retained, including key environmental factors such as ocean temperature, wind speed, and depth.

(3) The results show that the prediction ability of the stacked regression model is much higher than that of SVR and SLTM. By combining the output results of multiple models, the stacked regression model can predict more accurately on coral bleaching percentage, based on the impact of environmental factors.

In addition, I find that regardless of the sample size of the data set, the impact of feature selection on the model is very significant. As more numbers of features are used for model training and prediction of the percentage of coral bleaching, the training time of the model increase, whereas the prediction accuracy does not improve significantly. As shown in Table 4, when the top 25% of the most important features are selected for model training, the model error is minimized, and the training time is effectively controlled. This suggests that reasonable feature selection is crucial in improving the prediction accuracy of the model in this study.

5. Conclusion

This study analyzed coral reef bleaching data worldwide and proposed a deep learning model based on stacked regression to predict the percentage of coral reef bleaching. The model combines the advantages of LSTM (Long Short-Term Memory Network) and SVR (Support Vector Regression) and then improves the accuracy of coral bleaching prediction. The model combines the advantages of LSTM (Long Short-Term Memory Network) and SVR (Support Vector Regression), improving the accuracy of coral bleaching prediction. Features related to ocean temperature anomalies and climate events are selected as inputs, and the percentage of coral bleaching is used as output, since the coral bleaching process is closely related to changes in ocean temperature. The prediction process consists of the following steps: first normalize the dataset and then divide them into a training set (80% of the data) and a testing set (the remaining data). The random forest model is used to evaluate the importance of the features; principal component analysis (PCA) reduces the dimensionality; and finally, the data were input in the stacked regression model for training. The predicted value of the model is compared with the actual value, and the performance of the model is evaluated by three indicators: MAE, RMSE and R. The results show that the stacked regression mode performed better than the LSTM or SVR models.

In the course of the experiment, it is found that the ocean surface temperature anomaly (SSTA) and temperature accumulation heat stress (TSA_DHW) are the most significant factors contributing to coral bleaching. Extreme values and anomalous fluctuations in these factors are the main drivers of coral bleaching, in addition to climate events such as wind speed and cyclone frequency, which also have a significant impact on coral bleaching. Environmental characteristics such as depth and turbidity have a weak correlation with temperature.

In the experimental process, the stacked regression model performs well in terms of error by screening and optimizing the top 25% of the most important features, though the training time was long. With a training time of 19,800 seconds, the model achieves the lowest prediction error and the highest accuracy in all three models.

In future research, it is necessary to consider integrating more environment-related features to further improve the accuracy and applicability of the model in predicting coral bleaching. By introducing new data and features, the model will be optimized to better address the challenges facing coral reef ecosystems on a global scale.

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