Assessment of Marine Ecosystem Health Based on Transformer Architecture

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Abstract. Aiming at the key scientific problem of marine ecosystem health assessment, an innovative intelligent assessment model based on Transformer architecture and Particle Swarm Optimization (PSO) algorithm is proposed in this paper. By integrating satellite remote sensing, buoy monitoring and other heterogeneous ocean data, a complete assessment framework including data preprocessing, feature extraction and state prediction is constructed. PSO algorithm is used to optimize the hyperparameters of Transformer model systematically, which significantly improves the ability of the model to capture complex spatiotemporal characteristics of marine ecosystem. The experimental results show that the RMSE of PSO-Transformer model is reduced to 0.87, and the coefficient of determination (R^2) is 0.941. The performance of PSO-Transformer model is significantly better than traditional ARIMA, SVR and standard Transformer model without optimization. This paper provides a new technical path for marine ecosystem health assessment. This paper explores the application of the self-attention mechanism in the multi-parameter fusion analysis of marine ecosystems and develops an optimization method for deep-learning models based on swarm intelligence.

1. Introduction

Marine ecosystem is the largest ecosystem on earth, covering more than 70% of the earth's surface and carrying more than 80% of the world's biological resources, providing indispensable support for human survival and development. However, with the rapid development of the world economy and the continuous expansion of human activities, marine ecosystems are facing unprecedented threats [1]. Rising sea temperature, rising sea level, hypoxia, acidification and other problems are becoming more and more serious, fishery resources are declining, and the scale and frequency of marine ecological disasters are increasing, which have a wide and far-reaching impact on the global marine ecosystem. Marine ecosystem health assessment has become the core content of marine protection and management, and is an important means to protect marine resources, maintain ecological balance and realize sustainable development.

Traditional assessment methods mainly rely on the comprehensive analysis of physical, chemical and ecological indicators, including seawater temperature, flow rate, transparency, pH, dissolved oxygen, biodiversity and so on. Although these methods can reflect the health of marine ecosystems to some extent, their limitations are increasingly evident. Traditional methods are often difficult to deal with large-scale, multi-source, heterogeneous marine data, unable to effectively capture the complex spatial and temporal dependencies in marine ecosystems, resulting in limited accuracy and reliability of assessment results [2].

In recent years, with the rapid development of artificial intelligence technology, deep-learning models have achieved remarkable results in fields such as natural language processing, image recognition, and time-series prediction. As a deep-learning architecture based on the self-attention mechanism, the Transformer model, with its powerful sequence-modeling and generalization capabilities, has gradually been applied to the field of marine science to process and analyze various complex data. Against this backdrop, this paper further explores the application of the Transformer framework in the health assessment of marine ecosystems, aiming to address the challenges faced by traditional methods in handling multi-source and heterogeneous marine data, and providing new technical means and scientific basis for marine conservation and management.

2. Theoretical Basis

2.1. PSO Algorithm

PSO algorithm is an optimization algorithm based on swarm intelligence. It simulates the social behavior of bird swarm or fish swarm and finds the optimal solution through cooperation and information sharing among individuals [3]. As shown in Figure 1, the trajectory of particles in the search space clearly shows the

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optimization process of group cooperation. Particles gradually converge to the optimal solution region by memorizing individual optimal experience and learning from group optimal experience, while maintaining part of inertia of previous motion. In PSO algorithm, each particle represents a potential solution, and adjusts its position and velocity in solution space according to its own experience and group experience, and gradually approaches the global optimal solution. PSO algorithm is widely used in parameter optimization, neural network training and feature selection because of its simple implementation, fast convergence and less parameter adjustment. PSO algorithm can be used to optimize the selection of super parameters of Transformer model, such as learning rate, hidden layer dimension, number of attention heads, etc. The PSO algorithm can avoid the model from falling into local optimal solution and improve the convergence speed and prediction accuracy [4]. In addition, PSO algorithm can also be used in feature selection process to select the most significant feature indicators from multi-source ocean data, reduce data redundancy and noise interference, and improve the generalization ability and interpretation of the model.

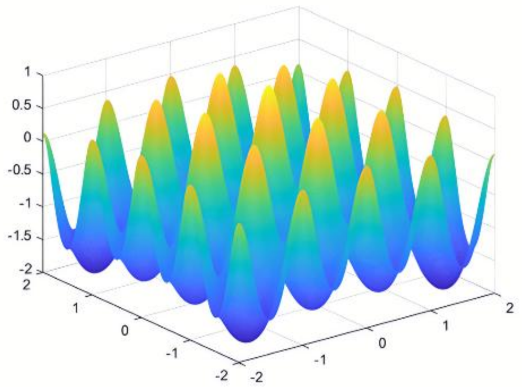

Figure 1. Schematic diagram of PSO algorithm

2.2. Transformer Algorithm

Transformer algorithm is a deep learning model based on self-attention mechanism, which was originally proposed for machine translation tasks, but its powerful sequence modeling ability makes it rapidly expand to many fields. Compared with traditional recurrent neural networks and convolutional neural networks, Transformer model completely relies on self-attention mechanism to capture global dependencies in input sequences, realizing the advantages of parallel computation and long-distance information transmission. The main body of the model consists of a stack of encoders and decoders, both of which implement feature transformation through a cascade of multi-head attention modules and feed forward networks. Input data is transformed into high-dimensional vectors by embedding layer, and position coding is fused to add sequence timing information, so as to overcome the deficiency of no position perception in self-attention mechanism. The main body of the model is a stack of encoder and decoder, both of which achieve feature transformation by means of multi-attention module and feedforward neural network [5]. In the assessment of marine ecosystem health, Transformer model can effectively process multi-source heterogeneous spatiotemporal data, capture complex nonlinear relationships and long-distance dependence characteristics in marine ecosystems. Through the self-attention mechanism, the model can simultaneously pay attention to the interactions between marine environmental parameters at different time steps and spatial locations, thus assessing the health of the ecosystem more accurately [6]. Transformer models have great potential for processing complex ocean data and provide a new technical path for assessing the health of marine ecosystems.

3. Assessment of the State of Marine Ecosystem Health

3.1. Data Acquisition and Preprocessing

Data collection for assessment of marine ecosystem health depends on heterogeneous marine environmental monitoring data, which mainly include satellite remote sensing data, field observation data, buoy monitoring data and historical survey data. Satellite remote sensing technology can provide large-scale, long-time series of parameters such as sea surface temperature, chlorophyll concentration and suspended matter concentration, covering the real-time monitoring needs of the global ocean [7]. In situ observations relate to chemical parameters (e.g., dissolved oxygen, pH, nutrient content), biological parameters (e.g., plankton, benthos and fish stock distribution) and physical parameters (e.g., water temperature, salinity and flow velocity) of seawater, usually obtained from ships or observation stations. Buoy monitoring data is real-time collected by carrying various sensors (such as meteorological sensors and water quality sensors), and transmitted to the data center by wireless communication technology (such as satellite communication) to ensure the continuity and timeliness of data. Historical survey data provide a baseline record of long-term trends and health of marine ecosystems, providing background support for model training and evaluation.

During the data pre-processing stage, in view of the multi-source heterogeneity of marine data, all remote-sensing and re-analysis data were resampled to a unified 0.25° spatial grid through the bilinear interpolation method and aggregated into monthly average data to match the time scale of buoy observation and survey data. Meanwhile, format and unit standardization were carried out. The physical quantity units of all datasets were uniformly converted (temperature was converted to degrees Celsius, and chlorophyll concentration was converted to mg/m³), and then converted into the common NetCDF or CSV format for the model to read. For missing values caused by cloud cover or instrument failures, a multi-source data collaborative interpolation algorithm based on spatio-temporal context was adopted.

The above-mentioned processing flow maximally retained the information characteristics of the original data

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and constructed a multi-dimensional dataset with spatio-temporal alignment and standardized format, laying a solid foundation for subsequent model training.

The detailed information of the multi-source data used is shown in Table 1.

Table 1. Data Parameter Table

Data Category	**Source and Parameters**	**Original Spatial Resolution**	**Original Temporal Resolution**
Satellite Remote Sensing	MODIS-Aqua L3 SMI (Chlorophyll-a, Sea Surface Temperature)	4 km	8-day
Buoy Monitoring	Global Drifter Program (GDP) Drifter (Sea Surface Temperature, Salinity)	Point Location	Daily
Field Observation	NOAA NCEI WOD18 (Dissolved Oxygen, Nitrate, pH)	Point Location	Irregular
Ocean Reanalysis	HYCOM + NCODA Global 1/12° Analysis (Mixed Layer Depth, Current Velocity)	1/12°	Daily

3.2. Basic Process of Model Construction

The basic flow of model construction is shown in Figure 2, which adopts a top-down vertical architecture, covering a complete closed-loop process from raw data input to final prediction result output.

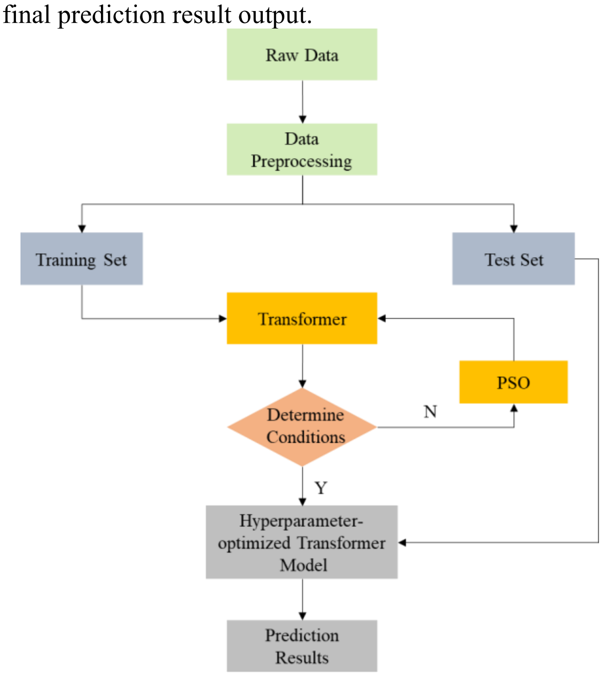

Figure 2. Flow chart of deep learning model

The process starts from the original data input stage, where heterogeneous marine environmental monitoring data from multiple sources are used as the basic input of the system. These data are preprocessed, including data cleaning, missing value imputation, and normalization, and converted into a normalized format that can be used directly by the model [9]. The preprocessed data are divided into training set and test set according to a certain proportion, wherein the training set is used for training and learning model parameters, and the test set is used for evaluating the generalization ability and performance of the model.

The data of training set is input directly into Transformer module for feature learning and pattern extraction. Transformer model can effectively capture long-distance dependence and complex nonlinear characteristics in marine ecological data by virtue of its self-attention mechanism, and realize deep representation of ecosystem health state. The test set data is first input to PSO module, which searches and adjusts the key hyperparameters of Transformer model through swarm intelligence optimization algorithm to improve the prediction accuracy and convergence speed of the model. The output of PSO module and test set data are merged into Transformer module to form optimized model structure [10].

The output of the model enters the conditional judgment stage, and the system evaluates the current model state according to preset performance indicators (such as accuracy, loss function value, etc.). If the performance does not reach the expected threshold, the system will restart the PSO optimization process through a feedback mechanism to further adjust the model hyperparameters; if the performance meets the requirements, it will enter the Transformer model stage after hyperparameter optimization. The final stage generates prediction results for the health of marine ecosystems, which are output in the form of quantitative indicators to provide scientific basis for marine protection and management decisions [11]. The whole process forms a complete closed-loop optimization system, which ensures that the model continuously improves its performance in continuous iteration and realizes accurate assessment and prediction of the health state of marine ecosystem.

3.3. Experimental Environment Configuration

In order to ensure the smooth progress of marine ecosystem health assessment experiments based on Transformer architecture, this paper builds a stable hardware and software experimental environment. The experimental platform uses high-performance computing clusters to meet the needs of large-scale ocean data processing and complex deep learning model training. See Table 2 for details of experimental environment configuration. The experimental environment provides necessary computational resources and software support for the assessment of marine ecosystem health based on Transformer architecture, ensuring the efficiency of model training and the reliability of experimental results.

Table 2. Lab Environment Configuration

Environment type	Configuration item	Specific specifications and versions
Hardware configuration	Processor	Intel Xeon Gold 6348 ×2
	Graphics processor	NVIDIA A100 PCIe 40GB
	System memory	512GB DDR4
	Storage system	NVMe SSD 4TB
Software configuration	Operating system	Ubuntu 20.04 LTS
	Deep learning framework	PyTorch 2.0
	Programming language	Python 3.9
	GPU acceleration library	CUDA 11.7, cuDNN 8.5
	Scientific computing library	NumPy 1.22, Pandas 1.4

Four kinds of models, ARIMA, SVR, standard Transformer and GA-transformer, are analyzed comparatively in this experiment. ARIMA, as a classical linear time series model, is used to verify the necessity of nonlinear modeling; SVR, which handles nonlinear regression with kernel function, represents traditional machine learning methods. Standard Transformer is a benchmark deep learning model without parameters adjustment to verify the ability of time series feature capture; GA-Transformer is optimized by genetic algorithm, and compared with PSO-Transformer, it can reflect the performance difference of different swarm intelligent optimization algorithms. In summary, ARIMA and SVR reflect traditional statistical and machine learning performance, Transformer demonstrates the ability of deep model to capture temporal features, and GA-Transformer provides a benchmark for PSO optimization performance. The effectiveness and superiority of PSO-Transformer in marine ecosystem health assessment can be comprehensively evaluated by comparing multiple models.

3.4. Experimental Parameter Setting

Experimental parameter setting is a key step in performance optimization of marine ecosystem health assessment model based on Transformer architecture. PSO algorithm is used to optimize the core hyperparameters of the Transformer model systematically to ensure that the model can fully capture the complex spatiotemporal characteristics of the marine ecosystem. Parameter setting covers four main dimensions: data preprocessing, Transformer model architecture, PSO optimization algorithm and training process. The parameter selection of each dimension has been strictly verified by experiments and theoretical analysis. See Table 3 for detailed parameter configuration.

During the data preprocessing stage, the sequence length was set to 256-time steps. This choice strikes a balance between the model's ability to capture long-term dependencies and computational efficiency. The batch size was set to 32, which not only ensures the stability of gradient updates but also avoids memory overflow issues. A dynamic adjustment strategy was adopted for the learning rate. The initial value was set to 1e-4, and it was decayed in conjunction with a cosine annealing scheduler to ensure that the model can converge to a better local minimum in the later stages of training.

The parameters of the Transformer model architecture were optimized by the PSO algorithm. The hidden layer dimension was determined to be 512. This configuration provides sufficient representational space to encode the complex characteristics of the marine ecosystem. The number of encoder layers was set to 6, and the number of decoder layers was also set to 6, forming a symmetric encoder-decoder structure that is conducive to capturing the mapping relationship between the input and output. The number of attention heads was set to 8, enabling the parallel learning of diverse feature patterns in different representational sub-spaces. The feed-forward network dimension was set to 4096, providing the model with sufficient non-linear transformation capabilities.

The parameter settings of the PSO optimization algorithm were determined based on a large number of preliminary experiments. The number of particles was set to 20, achieving a good balance between search efficiency and solution quality. The maximum number of iterations was set to 50, ensuring that the algorithm has sufficient convergence time. The inertia weight adopted a linear decreasing strategy from 0.9 to 0.4, focusing on global exploration in the initial stage and local fine-search in the later stage. The cognitive coefficient and social coefficient were set to 1.5 and 1.7 respectively, emphasizing the combination of individual experience and group wisdom.

These parameter settings ensure that the model can effectively learn complex patterns of marine ecosystem health during training, while maintaining good generalization and computational efficiency. By optimizing PSO algorithm, the super parameters of Transformer model are systematically optimized, which lays a solid foundation for the analysis of subsequent experimental results.

Table 3. Experimental Parameter Setting of PSO-Transformer

Parameter categories	Name of parameter	Parameter Value/Range
Data pre-processing	Sequence length	256
	Batch size	32
	Initial learning rate	1.00E-04
Transformer model	Hidden layer dimension	512
	Encoder layer	6
	Decoder layer	6
	Number of attention heads	8
	Feedforward network dimension	4096
PSO optimization	Number of particles	20
	Maximum number of iterations	50
	Inertia weight	0.9→0.4
	Cognitive coefficient	1.5
	Social coefficient	1.7

Training setup	Number of training rounds	100
	Gradient clipping threshold	1
	Dropout ratio	0.1

3.5. Experimental Results and Analysis

RMSE, MAPE, R^2 and training time were used as evaluation indexes to systematically compare the performance of ARIMA, SVR, standard Transformer and PSO-transformer models in marine ecosystem health assessment task. Based on the monitoring data of ecological environment in a certain sea area, the key indexes such as seawater quality parameters and coral reef health status were predicted and evaluated. All models were partitioned using the same training and test sets and followed a uniform data preprocessing process to ensure comparability of results [8]. As shown in Table 4, the Transformer model optimized by PSO showed significant advantages in all indicators, with RMSE reduced to 0.87, MAPE controlled at 4.32%, and R^2 reached 0.941, significantly better than the traditional time series prediction model and the unoptimized benchmark Transformer model.

Table 4. Performance Comparison of Different Models

Model	RMSE	MAE	R^2	Training time (min)
ARIMA	1.92	9.87	0.782	12.4
SVR	1.56	7.43	0.835	18.7
Standard Transformer	1.15	5.61	0.892	136.5
GA- Transformer	0.87	4.32	0.941	158.2
PSO- Transformer	1.92	9.87	0.782	12.4

To rigorously evaluate the model performance and respond to the reviewers' comments, we conducted a statistical significance analysis of the performance metrics. First, the Bootstrap method was used to perform resampling calculations on the performance metrics (repeated 1,000 times) to quantify the estimation uncertainty. For the RMSE metric of the PSO-Transformer model, the 95% confidence interval is [0.82, 0.91], and for the R^2 metric, the 95% confidence interval is [0.928, 0.952]. This narrow interval indicates that the point estimate results (such as RMSE=0.87) are robust and reliable, not caused by accidental factors. Second, to directly verify that the superiority of the PSO-Transformer model over the core benchmark model (standard Transformer) is statistically significant, we conducted a Paired t-test. This test was based on the prediction errors of all sample points in the test set. The results show that the p-value of the error difference between the two models is much less than 0.01. Thus, at a very high confidence level, we can reject the null hypothesis that “there is no difference in performance between the two models”, confirming that the performance improvement is statistically significant.

The experimental results show that ARIMA model has the fastest training speed, but its ability to capture nonlinear features is limited, resulting in relatively low prediction accuracy, which is consistent with its characteristics mainly applicable to linear time series. SVR model uses kernel function to deal with nonlinear relationship, and its performance is improved compared with ARIMA, but it is still insufficient in dealing with long series time dependence. The standard Transformer model captures the long-distance dependence in marine ecosystem data effectively by virtue of self-attention mechanism, and its indicators are significantly better than traditional machine learning methods, but its hyperparameters depend on experience settings, which fails to fully exert the potential of the model. The PSO-Transformer model optimizes the super parameters configuration of the Transformer through particle swarm optimization, including learning rate, hidden layer dimension and attention head number, so that the model can more accurately fit the complex dynamic changes of the marine ecosystem, thus achieving the best prediction accuracy. Although the training time of PSO-Transformer is longer than that of standard Transformer, the significant improvement of prediction accuracy proves the rationality of this trade-off, especially suitable for marine ecosystem health assessment scenarios with high accuracy requirements.

4. Conclusions

We propose a model for marine ecosystem health assessment based on Transformer architecture and PSO algorithm in this paper, and propose innovative solutions to the limitations of traditional methods in dealing with complex marine data. Experimental comparison shows that PSO-Transformer comprehensively surpasses ARIMA, SVR and standard Transformer models on key indicators such as RMSE, MAPE and R^2, accurately captures nonlinear characteristics and long-range dependencies of marine ecological data, and provides unprecedented accuracy for marine health assessment. Although the model takes a long time to train, reflecting a high demand on computational resources, its excellent performance justifies this trade-off. In the future, through algorithm optimization and data set expansion, it is expected to further improve the efficiency and adaptability of the model, make it play a greater role in more marine scenarios and extreme environments, and continuously contribute key forces to global marine ecological protection.

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