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Research on Multi-Parameter Prediction of Rabbit Housing Environment Based on Transformer

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ABSTRACT

The rabbit breeding industry exhibits vast economic potential and growth opportunities. Nevertheless, the ineffective prediction of environmental conditions in rabbit houses often leads to the spread of infectious diseases, causing illness and death among rabbits. This paper presents a multi-parameter predictive model for environmental conditions such as temperature, humidity, illumination, CO2 concentration, NH3 concentration, and dust conditions in rabbit houses. The model adeptly distinguishes between day and night forecasts, thereby improving the adaptive adjustment of environmental data trends. Importantly, the model encapsulates multi-parameter environmental forecasting to heighten precision, given the high degree of interrelation among parameters. The model's performance is assessed through RMSE, MAE, and MAPE metrics, yielding values of 0.018, 0.031, and 6.31% respectively in predicting rabbit house environmental factors. Experimentally juxtaposed with Bert, Seq2seq, and conventional transformer models, the method demonstrates superior performance.

KEYWORDS

Attention Mechanism, Multi-Parameter, Prediction, Rabbit House Environment, Time Series

INTRODUCTION

The expansion and optimization of the livestock industry provide significant prospects for agricultural development, poverty reduction, food security, and human nutrition (Hernandez-Patlan et al., 2023). The rabbit industry is a significant contributor to economic development due to factors such as brief breeding cycles, minimal start-up capital, and easy entry (Bolster & Wireless News, 2023). The demand for animal products is continuously increasing in many countries (Cullere et al., 2018). However, as people's understanding of the connection between diet and health has deepened, food safety and public health have become important areas of concern (Pavan et al., 2022). Rabbit meat, known for its high

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protein content, low fat, and low cholesterol, has gained popularity among the public, in recent years (Dalle Zotte & Szendrő, 2011). Consequently, there is a higher demand for rabbit meat that meets the standards of hygiene, health, and safety. However, the environmental conditions profoundly affect the physiological functions, health status, and feed conversion rates of livestock, including rabbits (Agea et al., 2019). Rabbits, in particular, are highly sensitive to environmental changes, necessitating stable conditions for optimal growth and development (Shawna et al., 2023). Parameters such as temperature, humidity, light, carbon dioxide, and ammonia concentrations, along with dust levels, are critical in rabbit housing. Research indicates that low humidity can incur respiratory diseases in rabbits, while high humidity could expedite the spread of infectious diseases (Li et al., 2023). Lower temperatures may reduce food intake, impair reproductive capabilities, and increase susceptibility to diseases such as rabbit fever, whereas high temperatures may induce heatstroke in rabbits, leading to infections that could affect reproduction or even cause death. Moreover, the quality of environmental air notably impacts the health of rabbits. Rabbit waste and urine, combined with polluted bedding straw, generate harmful gases such as ammonia and carbon dioxide (Xia et al., 2022). The accumulation of these gases along with dust can elevate the likelihood of disease outbreak among rabbits. Thus, fluctuations in environmental parameters pose substantial problems in rabbit housing, impacting health, growth, and survival rates. Therefore, accurate control of environmental parameters in rabbit houses is crucial for healthy breeding, intensive farming, and large-scale rabbit production. Predicting the changing trends and impacts of these environmental parameters is a necessary step towards achieving accurate environmental regulation.

Traditional regulation techniques for the rabbit-house environment have relied on the accumulation of experience and manual monitoring. However, the complexity and uncertainty of environmental parameters make this method limited. Problems include significant errors in manual monitoring, high costs, and difficulties managing large data volumes, yielding inaccurate environmental parameter predictions. Changes in environmental parameters significantly impact the growth and health status of rabbits. Addressing the monitoring needs of rabbit-house environments, Chandra et al. (2023) suggested a livestock environmental management system for measuring CO_2 concentration in barns, enabling remote control of barn environments. Xinrui et al. (2023) developed an approach to modulate total atmospheric ammonia emissions concerning space and time by updating high-resolution crop maps and animal housing location databases. They created an agricultural ammonia emission model, enabling better control decisions for indoor farmhouse environments. Shin et al. (2023) proposed an optimal mechanical ventilation system for outdoor air cooling based on weather forecast data. They tackled barn interior environmental quality and thermal insulation issues– thereby optimizing ventilation control strategies to ensure uniform air distribution and enhance barn indoor environment quality. However, the time-lag characteristics of changes in various environmental factors in rabbit houses pose challenges. If a rabbit house's environmental parameter predictions are not effective or timely, inability to control the environment changes may lead to rabbit illnesses or deaths, thus impeding the development of the rabbit industry.

Artificial intelligence has made great strides, and machine learning algorithms are now applied prevalently in environmental prediction. Recurrent neural networks (RNNs) are frequently used algorithms that can identify correlations within sequence data. However, RNNs face challenges in the prediction of long-sequence environmental data due to issues related to gradient explosion and vanishing gradients. To overcome these shortcomings, Hochreiter and Schmidhuber (1997) proposed the long short-term memory (LSTM) network, which adds gate units to RNNs, effectively circumventing long-term dependency problems and enhancing modeling capacity for sequence data. However, when the sequence length increases, it limits the LSTM network's memory capacity, affecting its predictive efficacy. Researchers have recently applied the transformer model, a deep learning architecture specifically designed for sequence modeling, to environmental prediction. Compared to the LSTM, the transformer excels at handling long-sequence data and can autonomously learn the relevance of environmental data through a self-attention mechanism, thereby capturing key features better and improving prediction accuracy. However, most research primarily focuses on single variable time series prediction, whereas in practical environmental variables the interplay of multiple factors is often evident. Constructing a multivariable prediction model using the correlation between various environmental variables can enhance the overall prediction accuracy (Wan et al., 2019).

Given this, the authors' study takes the challenge of predicting environmental parameters in rabbit hutches and introduces a multiparameter prediction model based on the transformer. This model allows to accurately forecast environmental information within a certain future period for rabbit hutches. This provides a reference for adjusting existing environmental factors in rabbit hutches, consequently altering the future environment of the hutch to effectively improve raising rabbits' yield and quality, reduce breeding costs, ensure healthy growth of rabbits, and achieve intelligent precision breeding.

The primary contributions of this study are as follows:

1. Traditional time-series prediction models often operate under the assumption of uniform time distribution, overlooking the variances in environmental characteristics between day and night. This study presents a novel model, based on the transformer architecture, adept at adaptively distinguishing between day and night settings to better forecast the changing environmental data trends.
2. Conventional methods for environmental prediction solely account for individual parameter changes without considering their mutual influence and interaction. By analyzing the Pearson correlation coefficient of each environmental parameter, this study indicates a strong coupling amongst them. Hence, multiparameter environmental prediction can boost accuracy and reliability of results.
3. The development of a multiparameter prediction model for rabbit hutch environments, using transformer technology, can significantly enhance prediction precision and accuracy of environmental parameters, thus improving breeding efficiency and fostering sustainable development. This research contributes innovative concepts and practical strategies for intelligence-based information, environmental sustainability, and quality standardization in rabbit farming.

The remaining sections of this paper are organized as follows: The second section provides the literature review, the third and fourth sections detail the authors' methods and experiments, respectively, and the fifth section provides the conclusion.

LITERATURE REVIEW

The predictive modeling of rabbit house environments can be informed by extensive time-series data from past observances. Initially, research in this regard was predominantly vested in statistical methodologies such as autoregressive models (Hinich, 2012) and exponential smoothing models (Karunarathne & Chung, 2020), which were limited in their capacity to articulate linear relationships among modeled features, thus inhibiting prediction accuracy. However, the evolution of artificial intelligence technology has propelled the growth of nonlinear relationship modeling, and, consequently, time-series prediction techniques rooted in deep learning have gained considerable recognition. Tong et al. (2013) adopted five turbulence models, namely Shear Shear Stress Transport Model, Renormalization Group Model, Reynolds Stress Model, Shear Stress Transport with Wall Functions Model, K-epsilon Two-equation Model with Shear Stress Transport, to forecast the concentration of ammonia in pig houses. The findings validated the Random Number Generator Model model as the most compatible with measured data. Karunarathne et al. (2020) recommended a process region division-centric model to predict the concentration of ammonia in cow houses. Mitkov et al. (2023) built self-regression integral sliding average LSTM RNN models to prognosticate indoor environmental parameters, thereby generating a reference for standardization of environmental factor parameters.

Wang et al. (2022) cultivated an LSTM network prediction model informed by deep learning techniques, and incorporated historical and actual sensor-monitored impact data. Consequently, they realized accurate temperature change predictions at a success rate of 93% and above. Similarly, Cen et al. (2023) proposed a method to predict CO_2 mass concentration based on an Random Forest-Particle Swarm Optimization-LSTM model, where the LSTM model was trained by parameters optimized via the particle swarm optimization algorithm. This methodology achieved accurate prediction of CO_2 parameter dynamics in sheep houses at a root mean square error (RMSE) of 75.422ng.m−3 and a mean absolute error (MAE) of 51.839μg.m-3. Although these models can decipher the internal dynamics of environmental parameters, they solely concentrate on single-parameter predictions. Boudhan et al. (2019) explored the comparative dynamics and internal mechanisms of dust under both dry and humid conditions, and inferred a correlation between humidity and dust. Yang et al. (2023) utilized random forest algorithms and coupled coordination degree models to study the impact mechanisms of multicoupling systems, thereby establishing a basis for verifying correlations among weather-related factors. Rad et al. (2022) also evaluated the direct interplay between air pollution and environmental parameters via machine learning methodologies, and examined temperature, humidity, light intensity, dust concentration, and some gas changes. In so doing, they unveiled the law of mutual influence and interaction among disparate environmental parameters. Practical predictive applications also evidence coupling relationships among environmental parameters in livestock houses. As such, future multiparameter predictions may prove more utilitarian than isolated parameter prediction data, because they would ideally engender continuous sequences.

As a result, many researchers have engaged in profound exploration of multiparameter association sequence prediction methodologies with the aim of accurately predicting livestock house environmental parameters. Guo et al. (2023) suggested an adaptive global-local graph structure learning and gate control cyclic unit combination model. This model can disintegrate the matrix of multivariate time series into global and local components to captivate the shared information among variables. It uses global-local prediction techniques to echo the nonlinear dependency relationship in variable time series, thereby better actualizing time series prediction. Bolton et al. (2023) employed a multivariable LSTM fully convolutional network to ascertain the predictive capacity of the ADS-B classification model by altering the dimension of training data and input features. They found the method prduced superior predictive effects. Prioritizing the need for environmental regulation within rabbit houses, Ji et al. (2023) coalesced several rabbit house environmental parameters and established a multivariate multistep prediction model for rabbit house environment variables using the Seasonal-Trend decomposition procedure based on Loess algorithm. The model enables multistep predictions for temperature, humidity, and carbon dioxide concentration within rabbit houses, thus ensuring precise environmental control.

Despite their utility, these models often suffer from slow convergence speeds and instability. Vaswani et al. (2017) introduced a simplistic network architecture, Transformer, in light of the adoption and rapid development of deep learning algorithms. This architecture, which rejects recursion and convolution entirely, utilizes an attention mechanism that connects encoders and decoders via the self-attention mechanism. The experiments demonstrated that this model expedited training time by improving parallelism (Nguyen et al., 2023; Ye et al., 2023).

The efficacy of the transformer model in forecasting time series has been remarkable, but its application within environmental monitoring fields is rather limited due to variances in research objects, environmental parameter processing algorithms, and time cycle dilemmas. Therefore, the accuracy of predictions and the utilization of global features by transformer models can be enhanced. In response, the authors propose a multiparameter prediction method for rabbit house environments founded on transformers. The integration of attention mechanisms into the model allows to concentrate on global information and interaction among multiple variables more closely, leading to more precise capture of data characteristics and dynamic changes. Therefore, the authors' approach enhances the accuracy and adaptability of predictions for the environment within rabbit houses.

METHODOLOGY

In this study, the authors scrutinized the environmental data from rabbit barns and proposed an adaptive multiparameter time-series prediction model predicated on the transformer model. This model can accurately foresee changes in the rabbit barn environment, thereby enabling intelligent breeding practices.

As Figure 1 shows, the transformer model adopts a structure that comprises encoder and decoder mechanisms. Each layer of the encoder integrates a multihead attention layer and a feed-forward pass layer. Considering the significant difference in environmental climate between summer and winter, which has varying degrees of impact on the physical condition of animals (Rödel et al., 2023), the authors analyzed the dataset of changes in rabbit hutch environment parameters during the summer and winter periods. This dataset records the changes in rabbit hutch environment parameters over time (Equation1):

$$N = \left\{ \left(x_1^{t_1}, y_1^{t_1}\right), \left(x_2^{t_2}, y_2^{t_2}\right), \left(x_3^{t_3}, y_3^{t_3}\right) \cdots \left(x_i^{t_n}, y_i^{t_n}\right) \mid x_i^{t_n} \in \left(0,1,2,3,4,5,6\right), y_i^{t_n} \in R^d \right\} \tag{1}$$

In this context, N denotes the dataset, x signifies the total feature labels in the sample, and there are six feature vectors representing *i* samples. The term *y* alludes to the predicted sample labels and *n* represents the temporal sample features at time *t*. Thus, the data input for the environment in the rabbit house at time *t* manifests as Equation 2 shows:

$$x^t = \left\{ x_1^t, x_2^t, x_3^t, x_4^t, x_5^t, x_6^t \mid x_i^t \in R^{d_x} \right\} \tag{2}$$

The predicted output that corresponds to the data from the rabbit hutch environment is as follows:

$$y^t = \left\{ y_1^t, y_2^t, y_3^t, y_4^t, y_5^t, y_6^t \mid y_i^t \in R^{d_y} \right\} \tag{3}$$

Following the training processes applied to this dataset, the model can accurately predict changes in the environment of the rabbit housing.

As Figure 1 shows, the transformer model adopts an encoder-decoder architecture. Each layer of the encoder structure contains a multihead attention layer and a feedforward connection layer. The multihead attention layer divides the input sequence into multiple different subsequences and calculates multiple attention vectors for each subsequence. These vectors are finally spliced together, undergo linear transformation, and obtain a richer and more detailed feature representation matrix Query, Key, Value. In the rabbit barn environment data, the softmax function establishes connections between any two environmental variables at any point in time. This serves to determine the degree of relevance between the feature variables at the current moment and the time feature variables across different segments. It effectively preserves long-distance information.Then, each Value vector is multiplied by the softmax function to maintain attention to the current rabbit barn environment, while concurrently helping the model to reduce attention to irrelevant variables in the barn's environment over time. This approach enhances the model's efficiency and the accuracy of its outputs. This formula is shown in Equation 4:

$$Attention\left(Q, K, V\right) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

Following the training of the model on this dataset, it was able to accurately predict changes in the environment of rabbit houses. The multihead attention layer deploys multiple independent “heads” to concentrate on distinct pieces of information, thereby extracting more comprehensive features and augmenting the model’s performance and stability.

Owing to the differences in training data length between encoders and decoders, decoders are typically trained using the maximal length of data as the computational unit. They rely solely on preceding data to influence current data without consulting subsequent data for reference (Roy & Bhaduri, 2023). Hence, a masked multihead attention layer is added subsequent to the multihead attention layer and feed-forward connection layer on the decoder. It is necessary to cover up the data after the current position, limit the attention process of specific positions, so as to ensure that the model can obtain correct context information and improve the expressiveness and generalization ability of the model. To avert issues of vanishing gradients and exploding gradients during model training, and to increase model robustness along with model convergence, residual connections and layer normalization are added after every sublayer.

The transformer model enables time series forecasting by documenting the environmental observations of a rabbit barn in chronological order, which illustrates changes in the rabbit barn environment (Wang et al., 2023). The Pearson correlation coefficient is a statistical measure that describes the strength of linear correlation between two variables, ranging between -1 and 1. Larger absolute values indicate a stronger linear correlation between the two variables. In this study, the authors calculated the Pearson correlation coefficient for daily rabbit hutch environmental data using Equation, attaining the correlation between distinct parameters:

$$r = \frac{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)\left(y_i - \overline{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2}\sqrt{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2}} \tag{5}$$

In Equation, r symbolizes the Pearson correlation coefficient, x and y represent the corresponding data points of the two variables, and n portrays the number of data points.

The calculation of Pearson’s correlation coefficient of rabbit hutch environmental variables evidences a positive correlation between temperature and these environmental parameters: Carbon dioxide, ammonia concentration, light intensity, and dust concentration. The algorithm flow is reflected in the pseudocode in Table 1. The coefficients are 0.216, 0.7, 0.541, and 0.732, respectively.

Figure 1. Transformer model structure diagram

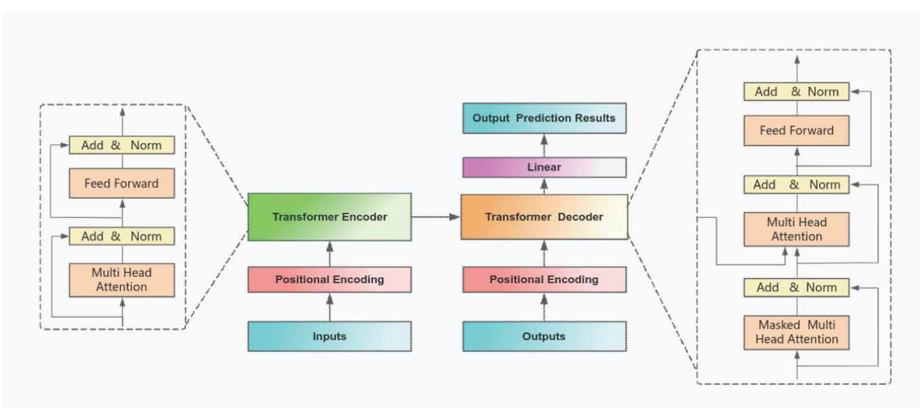


Table 1. Pseudocode for Pearson correlation coefficient: Algorithm of rabbit house environment parameters

Algorithm 1 **Calculation of Pearson Correlation Coefficient of Environmental Parameters of Rabbit House**
Input: Temperature data T, humidity data H, CO_2 concentration data C, ammonia concentration data A, dust concentration data D. 1. Define a function to calculate the Pearson correlation coefficient (x, y) a. Input: x and y are two lists representing two sets of data. b. Calculate the mean of x and y. c. Calculate the standard deviation of x and y. d. Calculate the covariance of x and y. e. Calculate the Pearson correlation coefficient = covariance /(standard deviation of x * standard deviation of y). f. Return the Pearson correlation coefficient. 2. Define a function to calculate the Pearson correlation coefficient matrix (data). a. Input: Data is a two-dimensional list representing multiple sets of data, each set of data contains six parameters. b. Initialize a 6x6 zero matrix to store the Pearson correlation coefficients c. **for** each pair of data sets in the input data **do** d. **return** the Pearson correlation coefficient matrix e. **end for** f. Read rabbit hutch environmental parameter data. g. Call the function to calculate the Pearson correlation coefficient matrix (data). 3. Output: The Pearson correlation coefficient matrix.

However, the authors found a negative correlation between temperature and humidity, represented by a coefficient of -0.631. This implies that, when the temperature drops, the carbon dioxide, ammonia concentration, light intensity, and dust concentration will also decrease, while the humidity in the rabbit hutch will rise (Jie et al., 2023).This suggests an intimate relationship between various rabbit hutch parameters; therefore, predictions based on single parameters are unlikely to accurately depict these complex inter dependencies. In contrast, the use of multiple parameters can predict the trend of change in the rabbit hutch environment more accurately, offering a crucial reference for ensuring the growth and well-being of the rabbits.

The inherent design of the transformer model does not facilitate the learning of temporal dependencies. Hence, to incorporate temporal information into the sequence, the authors introduced absolute position information for the acquisition time by appending position encoding to the input. Upon evaluating the dataset, the authors discovered substantial variance in the rabbit barn environmental information on a minute-to-minute and hourly basis. Therefore, in this study, the authors express the timestamp as two distinct elements, namely hour and minute.. Both elements are decomposed into sine and cosine components to accurately capture the sequential information of the ongoing time step. This strategy yields precise positional encoding for the self-attention module, thereby realistically reflecting time characteristics. As Equations 6 and 7 indicate, the vector PE signifies the positional encoding of the sine and cosine functions congruent to time, while *i* denotes the dimensionality of the vector, and "pos" is suggestive of the token's position in the time series. Each token's positional information is captured through a vector of length d_model:

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right) \tag{6}$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right) \tag{7}$$

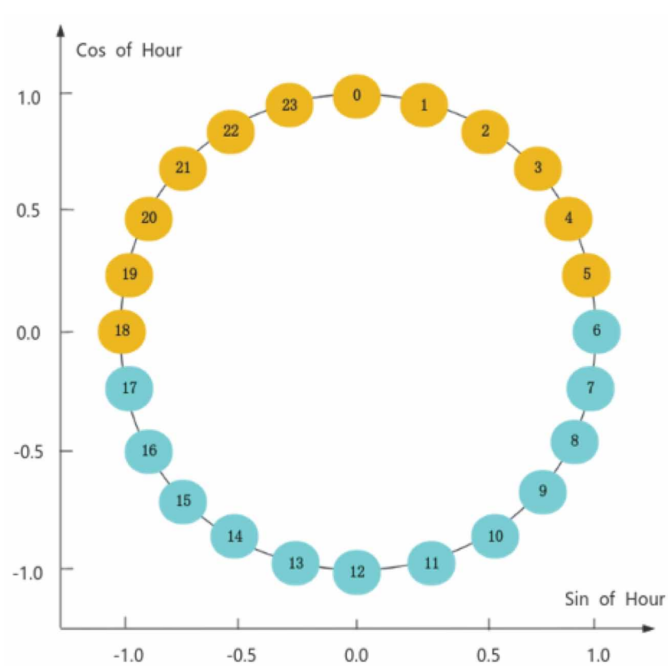
The authors' analysis considered inherent diurnal variations, specifically differing properties between day and night. The authors incorporated an adaptive module that introduced a time-based switching mechanism. This dynamically translated the boundary point separating day and night into a critical threshold. Guided by this threshold, data variables are bifurcated into two distinct feature sets for processing. These are instrumental in facilitating information interaction between transformer models, enabling the derivation of more accurate prediction outcomes.

In Figure 2, each hour serves as a temporal datapoint, with sine and cosine values forming the abscissa and ordinate, respectively. This method locates the positional encoding at diverse moments, crafting a circular time axis that operates on a 24-hour cycle. Accordingly, various moments are designated as either day or night using the set threshold. Daytime is represented by blue markers with a threshold set at 06:00, while nighttime is marked yellow with a threshold set for 18:00, signaling the shift from day to night. Employing this threshold delineates day and night periods again, accurately mapping the temporal feature. It enables the network to precisely comprehend timing information and effectively manage long-term dependencies. In the final step, the authors integrated the six-dimensional time positional encoding with the original dataset's six variables. This results in a 12-dimensional feature set, substantially enhancing the accuracy of time series forecasting models.

The authors employed the preprocessed data to train the transformer model, with the algorithmic workflow in Figure 4. They designated the dimensions of input and output as 32×36×12 and 32×12×12 correspondingly, where 32 signifies the batch size, 36 and 12 stand for the temporal steps; the latter 12 denotes the dimension after positional encoding. In other words, each instance consists of 12 features, utilizing the preceding 36-point data to forecast the subsequent 12-point data. To minimize variance among features and bolster data comparability, the authors standardized the data to yield dimensions of 32×36×512 and 32×12×512 for the input and decoder training, implying that each position's vector representation is 512-dimensional.

In the encoder phase, the authors computed the attention distribution by deploying a multihead self-attention layer to encode the variable-length input sequence. Applying a mask prohibited the

Figure 2. Time-series positional encoding



visibility of preceding information and transferred this limit to the decoder. This ensured that the decoder solely perceived the available historical data, averting any future information during training and hence enhancing the model's prediction accuracy. Subsequently, the authors implemented channel-adaptive scaling on each vector's dimension, deduced the relationship amongst feature pairs using two linear layers, and included ReLU activation functions for an improved network nonlinear representational capability. Figure 3 shows the processing procedure. Additionally, to avoid overfitting, the authors incorporated dropout procedures to sporadically render some neurons inactive, compelling the model to learn varied feature depictions and achieve better generalization during training.

In the decoder phase, constructed on top of the encoder, the authors introduced an additional masked multihead self-attention layer. The utilization of an upper triangular matrix for zero-filling repressed the information beyond the current position, thus fulfilling the decoding objective. By calculating the attention distribution of each point in the target sequence in relation to all positions, it acquired the existing context information. Employing a masking procedure to direct the attention distribution and weighting, ensured the decoded sequence mirrored the input sequence. Finally, the authors outputted a 32×12×512-dimension tensor from the decoder and mapped the 512-dimensional feature vector to a 12-dimensional vector through a Linear layer. This allowed the model's output to be directly compared and calculated with the target value, attaining the prediction objective.

EXPERIMENTS

Dataset

The authors collected the data for this experiment from a rabbit farming base located in Zhangjiakou City, Hebei Province. The environmental parameter measurement took place from December 3rd, 2022, to November 2nd, 2023, spanning a total of 47 days. The measurement period was divided into two seasons, namely, summer and winter. The researchers measured environmental parameters such as temperature, humidity, light intensity, NH_3 concentration, CO_2 concentration, and PM2.5 concentration. To ensure the continuity and accuracy of the data, they took measurements every minute. In total, the authors collected 63,130 data points, including 18,490 continuous data points generated during the summer and 44,640 data points generated during the winter. Table 2 presents the variation data of environmental parameters at different stages of a day in winter and summer. The equipment employed for data collection was provided by Zhangjiakou City, Hebei Province

Figure 3. Attention mechanism flowchart

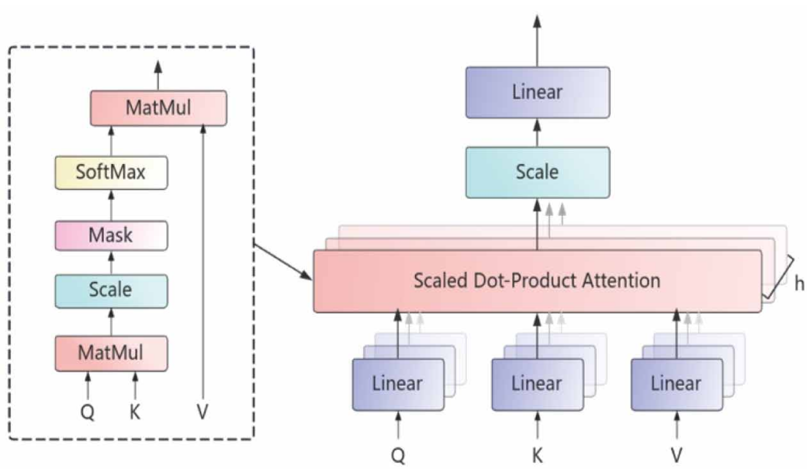


Figure 4. Transformer algorithm flowchart

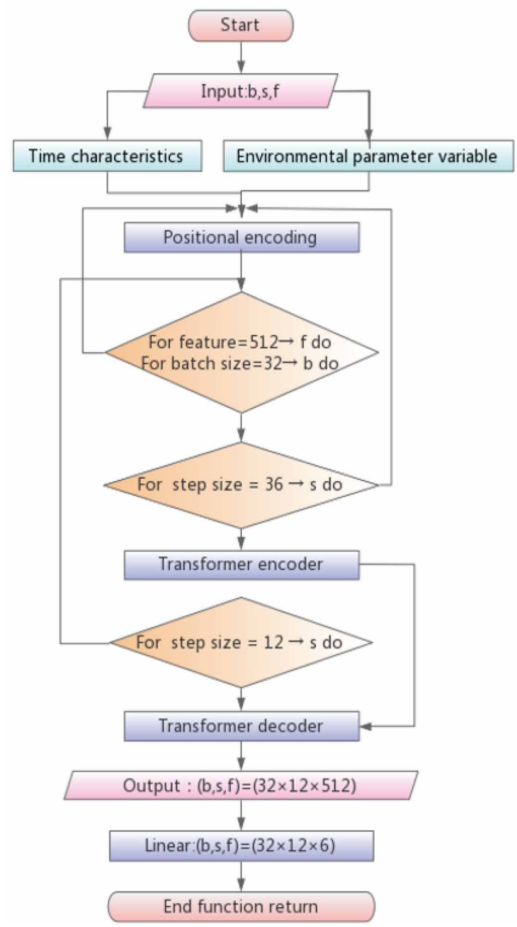


Table 2. Sample display of the author's original dataset

Sensor_id	Reindexed_id	Timestamp	Temperature	Humidity	CO_2	NH_3	Lumination	$PH_{2.5}$
1	1	2023-07-31 03:44:43+00:00	22.2	75.1	511	3	0	1
1	1	2023-07-31 12:04:16+00:00	25.5	73.9	1010	8	301	4
1	1	2023-07-31 18:34:21+00:00	24.5	79.6	546	4	7	5
1	1	2023-07-31 23:37:02+00:00	23.7	79.1	482	5	0	7
2	2	2022-11-28 03:40:46+00:00	20.9	63.4	472	2	0	3
2	2	2022-11-28 12:29:34+00:00	23.1	61.3	795	11	123	5
2	2	2022-11-28 18:38:17+00:00	22.9	63.3	589	7	2	4
2	2	2022-11-28 23:38:44+00:00	21.8	60.8	513	5	0	9

Smart Agriculture Co., Ltd. The sensor_id represents the unique sensor number used to differentiate the sensors. The Reindexed_id is a reassigned number for the sensor facilitating streamlined data processing and integration. The parameter Timestamp indicates the data collection time, while the additional six datasets represent environmental parameters of the rabbit house including temperature, humidity, CO_2 concentration, NH_3 concentration, light intensity, and $PH_{2.5}$ concentration. The authors divided the data, based on time sequence, into a training set and a test set at a proportion of 7:3. They used the training set to develop a multiparameter prediction model for the rabbit house environment, and the test set to assess the model's performance. Additionally, they used the test set to evaluate the model's ability to generalize.

Experimental Settings

To verify the feasibility and effectiveness of the model in practical applications, in this study the authors used real farm data for training and testing, comparing the predictive accuracy and performance of the model in different complex environments. The aim was to provide scientific reference and guidance for environmental monitoring and control solutions in the agricultural farming industry, further improving the intelligent level of rabbit shed environment monitoring and control, and achieving precise, efficient, and sustainable farming practices.

Bert, Seq2seq, and transformer are the most common time series prediction models that have been widely applied in real-life scenarios, and many scholars have verified their predictive abilities with good results (Chen et al., 2022; Huang et al., 2023; Rosmaliati et al., 2023; Takeshi et al., 2022; Yang et al., 2022; Zhang et al., 2024). The Bert model is capable of capturing contextual information, but it has a large computational load. The Seq2seq model is suitable for sequence-to-sequence tasks, but it suffers from information loss and generation bias. Traditional transformer models have self-attention and parallel computation capabilities, but they incur significant computational and memory overhead when dealing with long sequences. Therefore, conducting comparative experiments with these three models is crucial for evaluating the effectiveness of the improved transformer model the authors proposed in this paper in terms of handling time series and improving prediction accuracy. Under the same operating environment and hyperparameters, taking the input of rabbit shed environmental parameters as independent variables and the output of predicted environmental parameter values as dependent variables, conducting comparative experiments with Bert, Seq2seq, and transformer models can provide a more comprehensive, objective, and scientific evaluation of the performance of these models in predicting multiple parameters of the rabbit shed environment. This will facilitate mutual learning and optimization among different models and promote the development and improvement of related technologies.

The computational resources the authors employed included an Intel(R) Core(R) CPU E5-2690 v3 @ 2.60GHz processor, 32GB memory, NVIDIA GeForce RTX 3060 graphics card, and a Win10 operating system. The authors built the prediction model architecture using Python 3.10 and TensorFlow 2.8.1 framework. To ensure optimal performance, avoid overfitting, and ensure consistent learning across models, the authors applied the Adam optimizer, set weight decay to 0.003, and ensured the learning rate was uniform. Each iteration comprised of 36 training samples, and the researchers performed a total of 30 iterations.

To impartially gauge the efficacy of each model, the authors employed RMSE, MAE, and MAPE as evaluation metrics for predicting rabbit housing environment parameters. Equations 8 to 10 detail the computation formulas for these metrics:

$$S_{RMSE} = \sqrt{\frac{1}{n}\sum_{i-1}^{n}\left(y_{pred}\left(i\right) - y\left(i\right)^{2}\right)} \tag{8}$$

$$S_{MAE} = \frac{1}{n}\sum_{i-1}^{n}\left|y_{pred}\left(i\right) - y\left(i\right)\right| \quad (9)$$

$$S_{MAPE} = \frac{1}{n}\sum_{i-1}^{n}\left|\frac{y_{pred}\left(i\right) - y\left(i\right)}{y\left(i\right)}\right| \times 100\% \quad (10)$$

Here, $y(i)$ denotes the observed value of the rabbit housing environment at the ith instance, $y_{pred(i)}$ signifies the corresponding predicted value, and n stands for the length of the sequence used for verification. The variables S_{RMSE}, S_{MAE}, and S_{MAPE} correspond to the values of RMSE, MAE, and MAPE, respectively (Zhou et al., 2023).

Experimental Comparison Results

To verify their proposed predictive model's efficacy, the authors executed experiments and juxtaposed it against Bert, Seq2seq, and traditional transformer models. Furthermore, they analyzed and evaluated each model's results. Figures 5—10 portray the comparative analysis, while Table 3 illustrates the error analysis.

Figures 5—10 present the prediction results of environmental parameters within a rabbit hutch against Bert, Seq2seq, and traditional transformer models. Furthermore, the authors analyzed and evaluated the performanceIn addition, the author analyzed and evaluated the performance of the model from the four different models. The Seq2seq model and Bert model both utilize autoregressive models, which, due to the limitations in their input and output layer structures, are capable only of single-parameter prediction. The improved model based on transformer proposed in this paper is used for multiparameter prediction, while the authors compared the single-parameter prediction using Seq2seq and Bert models, respectively. Observations from Figures 5 through 10 reveal that, in both the Bert model and the Seq2seq model, the predicted values for humidity, illumination, ammonia concentration, and dust concentration in the rabbit hutch environment significantly deviate from the actual values. In contrast, the authors' multiparameter prediction method notably aligns more closely with the actual environmental variables. This finding corroborates the efficacy of the authors' approach,

Figure 5. Comparison results of temperature model prediction in rabbit hutch

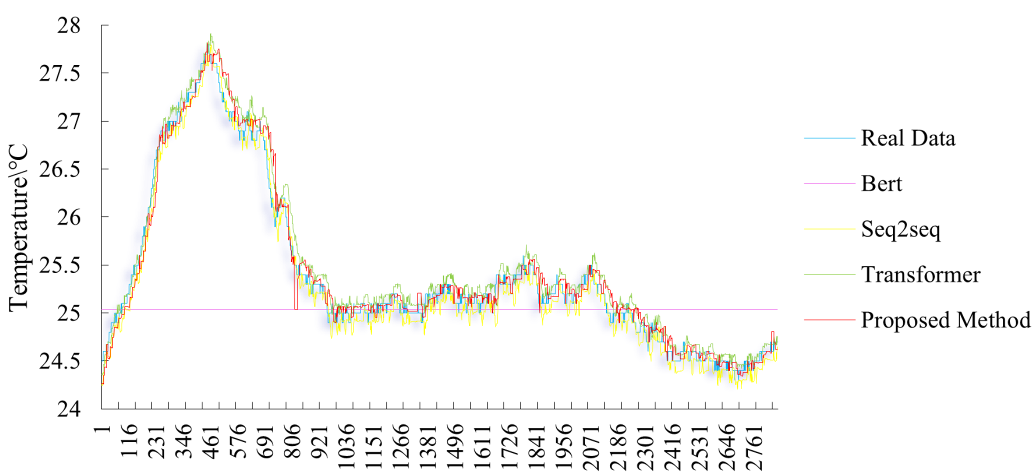


Figure 6. Comparative results of rabbit house humidity model prediction

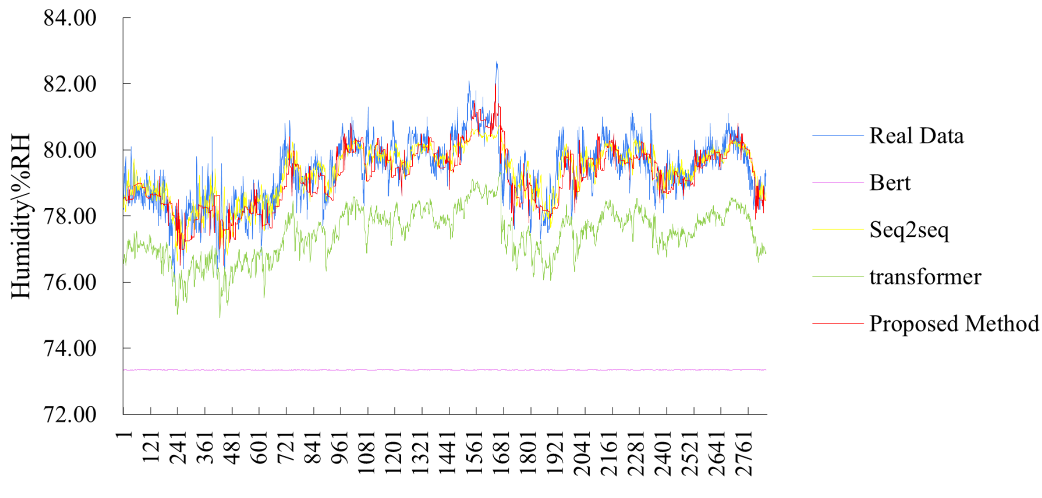


Figure 7. Comparison of predicted CO_2 concentration in the rabbit house model

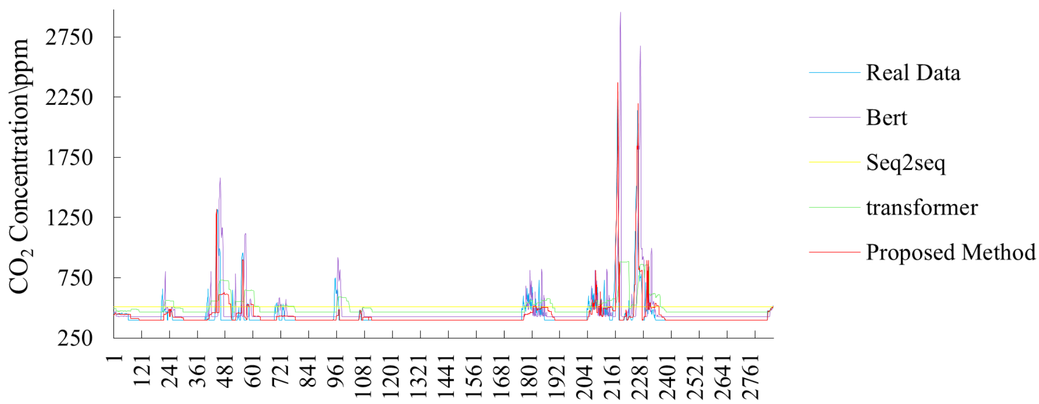


Figure 8. Comparative results of predictions for ammonia concentration in the rabbit house model

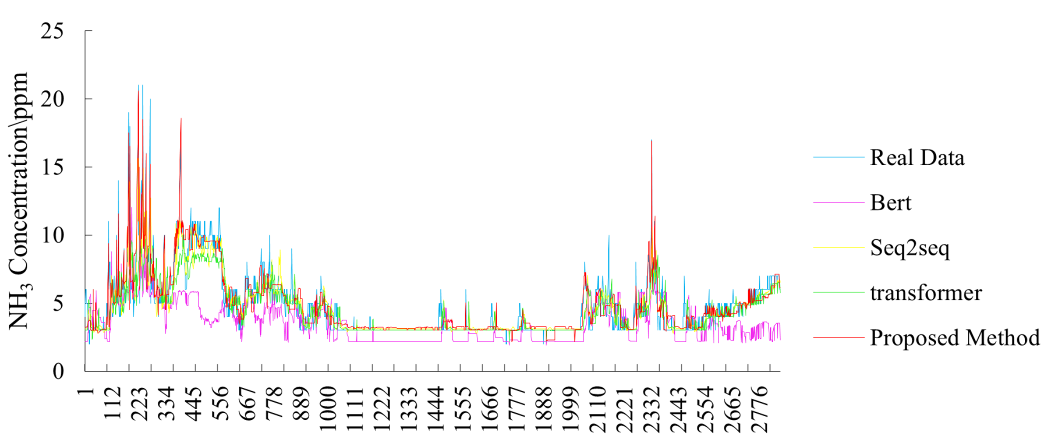


Figure 9. Comparison result diagram of rabbit house lumination model prediction

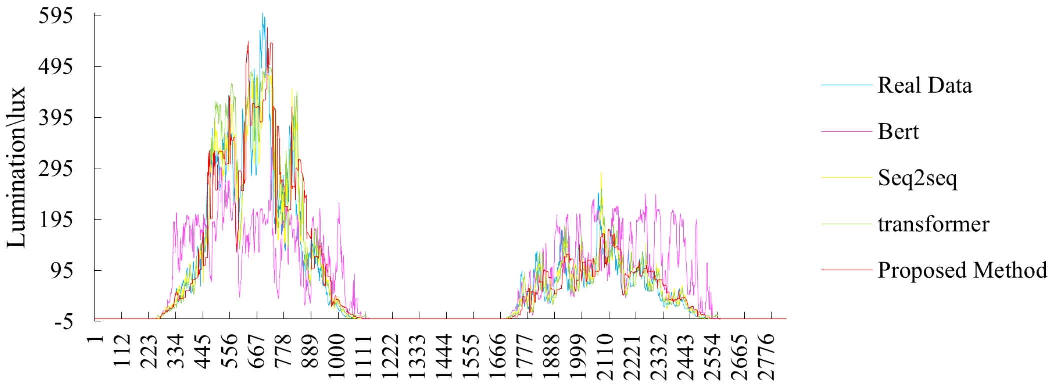
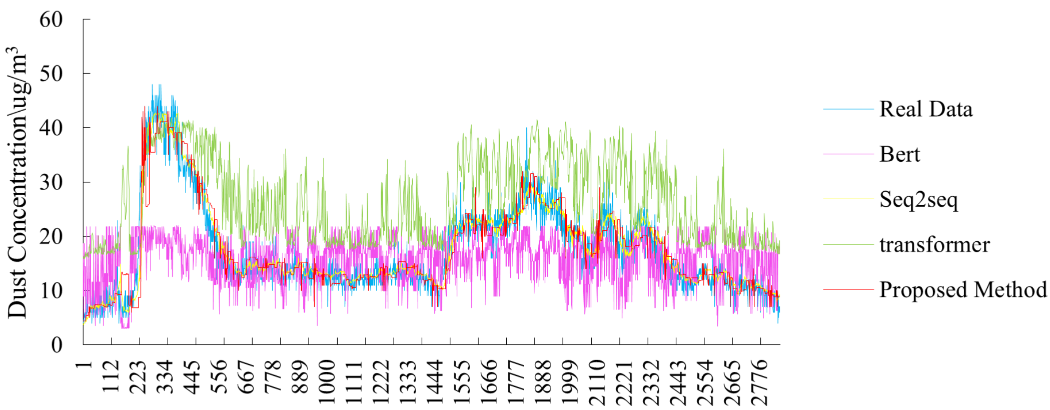


Figure 10. Comparison of prediction results for dust concentration model in rabbit house



which determines the interrelations among environmental variables using the Pearson correlation coefficient. By incorporating multivariable parameters into the model training, the authors' method effectively distills the interdependencies among temperature, carbon dioxide concentration, and other parameters. Consequently, this enhances the predictive accuracy for humidity, illumination, ammonia concentration, and dust concentration in rabbit hutches.

The comparison between Figures 6 and 7 evidences that the predictive models of Seq2seq, transformer, and the authors' successfully predict the concentrations of carbon dioxide and humidity parameters. However, the authors' method outperforms others in Figure 6, particularly in detecting minute fluctuations. For humidity prediction, the three evaluation indicators RMSE, MAE, and MAPE reached 0.391, 0.462, and 0.136, respectively. Figures 9 and 10 illustrate that, although the authors' method exhibits noticeable variance in predicting abrupt fluctuations, it accurately captures the overall trends. This side-by-side comparison implicitly validates the effectiveness of the authors' method in predicting multiple parameters in a rabbit hutch environment, thereby enhancing the model's generalization capabilities. This suggests that the authors' approach is not only adept at capturing fine-scale variations, but also maintains robustness in forecasting overarching environmental trends, a crucial aspect in enhancing predictive accuracy in complex ecological settings.

Traditional transformer models often have no special consideration for the processing of temporal features, which easily leads to the decline of model performance. In contrast, the authors' proposed

Table 3. Comparison of model evaluation indicators

Variables	Indicators	Bert	Seq2seq	Transformer	Proposed Method
Temperature	RMSE	0.438086	0.022997	0.070954	0.017527
	MAE	0.598104302	0.107615205	0.118355407	0.09849082
	MAPE	1.780837398	0.154199187	0.38954065	0.301317073
Humidity	RMSE	5.561041	0.468088	1.680472	0.390732076
	MAE	5.973731894	0.470315054	1.865782966	0.462746513
	MAPE	6.926741117	0.631811224	2.01257868	0.136234566
CO_2	RMSE	18.934814	62.17453	24.304443	4.199433214
	MAE	74.06714749	114.7846252	103.9707092	30.0870848
	MAPE	6.112644201	11.63556455	3.435925383	0.707745768
NH_3	RMSE	3.244447	1.748586	2.653348	1.700463847
	MAE	1.62113329	0.723504383	0.83002705	0.561178581
	MAPE	81.0893	24.57846667	56.77513333	24.01759983
Lumination	RMSE	0.210842	0.0603	0.121041	0.406934184
	MAE	47.95649298	19.867477	21.83033904	20.22131271
	MAPE	47.37919903	9.9400056	28.88793	1.723361157
$PH_{2.5}$ concentration	RMSE	2.119222	5.007615	6.984184	4.636380129
	MAE	6.386824989	2.084472672	9.313546711	2.138534671
	MAPE	185.6917667	16.20401667	168.1180333	10.99390986

improvement method adopts the adaptive circadian feature processing method, which can adjust the model processing method according to the data characteristics of different time periods, and improves the accuracy and reliability of prediction. In contrast experiments, as time progresses, as Figure 5 shows, there is a noticeable decline in the predictive accuracy of the transformer model. In contrast, the authors' proposed enhanced adaptive diurnal feature processing method significantly stabilizes the predictive values across various time segments. As Table 3 indicates, in comparison to the diminishing accuracy of the transformer model, the authors' study employs an adaptive approach to diurnal feature processing. This is achieved by integrating a temporal dimension into the input feature vector, consequently enhancing the precision of temperature forecasting. The three evaluation metrics (i.e., RMSE, MAE, and MAPE) exhibited reductions of 0.053, 0.02, and 0.088, respectively. This substantiates that incorporating diurnal features allows for a more nuanced representation of temporal segment variations, enabling the model to deliver more accurate predictions, especially in scenarios with significant diurnal variations. Additionally, the authors' methodology not only maintains temperature forecasting accuracy, but also effectively reduces the most temperature-correlated humidity assessment indices: RMSE, MAE, and MAPE by 68.1%, 61.1%, and 85.4%, respectively. This further corroborates the efficacy of the enhanced adaptive diurnal feature processing method the authors proposed in this study, demonstrating its capability to improve prediction stability and adaptability in complex meteorological forecasting scenarios with substantial diurnal temperature variations.

The analysis of Figures 7 and 8 highlights that, although the Bert model adeptly predicts carbon dioxide and ammonia concentrations, the authors' predictive model exhibits superior performance. It reduced carbon dioxide concentration indicators RMSE, MAE, and MAPE by 0.932, 0.738, and 0.939, respectively, and it reduces ammonia concentration indicators by 0.027, 0.224, and 0.023, respectively.

In conclusion, the authors' predictive model consistently achieves greater compatibility in predicting the rabbit hutch environment compared to traditional single-variable prediction methods, such as the transformer model, and demonstrates improved accuracy over other models. Evaluation indicators RMSE, MAE, and MAPE have also been lowered, affirming the multiparameter predictive model based on the transformer performs better in predicting the rabbit hutch environment.

CONCLUSION

This paper introduced an adaptive multiparameter time series prediction model for rabbit shelter environments, leveraging the transformer. The authors employed the Pearson correlation coefficient to ascertain the linear correlation amidst the environmental parameters of the rabbit shelter, underlining the coupling among various environmental factors. In order to boost the model's predictive capability, the authors proposed a parallel prediction approach for multiple environmental parameters. Bearing in mind the substantial disparities between the day and night environments within the rabbit shelter, the authors incorporated a segmented positional encoding method to accurately pinpoint time features in the transformer's time-series prediction model, thus yielding superior prediction outcomes. Subsequently, the researchers utilized the trained model for multiparameter predictions within the rabbit shelter environment. Results denote that the transformer-based model possesses significant precision, with an MAE amounting to a mere 3.1%. The model, when juxtaposed with other existing research outcomes in comparative experiments, exhibits commendable promise and applicability. It could provide effective reinforcement and guidance for multiparameter prediction regulation within rabbit shelter environments.

The method the authors proposed in this paper can be widely applied to various prediction problems, such as sales forecasting, stock price prediction, market demand forecasting, environmental monitoring and early warning, and traffic flow prediction. By considering multiple parameters and different temporal distributions, it can predict future trends and changes more accurately, enabling wiser decision-making. Additionally, this method can also be applied in the medical field to predict in advance the risk of diseases that patients may develop by considering their personal characteristics, environmental factors, and time factors, and take corresponding preventive measures. It can also monitor the trend of disease transmission and take timely measures to control the spread of epidemics. Therefore, the method proposed in this paper has a wide range of application potential and can provide more accurate and reliable support for practical decision-making.

Future endeavors could delve further into optimization methods for the transformer model within rabbit shelter environment prediction regulation, such as integrating additional algorithms and refining regulation strategies, to augment the model's stability and robustness within real-world environments.

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CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest to report regarding this study.

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