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Coordinated development of rural ecological construction and carbon neutrality: a deep learning approach for enhanced sustainability

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Introduction: In recent years, the world has faced increasingly severe climate change and ecological environmental problems. As an important part of the ecological system, rural areas also face many challenges. Rural ecological construction and carbon neutrality, as a solution, have attracted widespread attention. However, achieving the coordinated development of rural ecological construction and carbon neutrality requires more in-depth research and effective methods.

Methods: This study aims to explore how to promote the coordinated development of rural ecological construction and carbon neutrality through the combination of a Transformer-RNN model and cross-attention mechanism. We propose a deep learning framework that combines the parallelism and global dependency capturing capabilities of the Transformer model with the temporal information handling capabilities of the RNN model. By integrating these two models, we leverage their respective strengths to improve the performance of the model. Furthermore, we introduce a cross-attention mechanism that enables the model to simultaneously focus on the relationship between rural ecological construction and carbon neutrality. Through cross-attention, the model accurately captures the impact of rural ecological construction measures on carbon neutrality and the feedback effect of carbon neutrality on the rural ecological environment. In our experiments, we collected relevant data on rural ecological construction and carbon neutrality, including environmental indicators, socio-economic factors, land use patterns, energy consumption, and carbon emissions.

Results and discussion: We preprocess the data and train the combined Transformer-RNN model with the cross-attention mechanism. The trained model demonstrates promising results in capturing the complex dependencies and relationships between rural ecological construction and carbon neutrality. The significance of this study lies in deepening the understanding of the coordinated development relationship between rural ecological construction and carbon neutrality and providing a novel deep learning-based method to solve related problems. By introducing the Transformer-RNN model with a cross-attention mechanism, we provide decision-makers with more scientific and accurate decision support, promoting the improvement of the rural ecological environment and the achievement of carbon neutrality goals.

KEYWORDS

rural ecological construction, carbon neutrality, Swin Transformer, RNN, cross attention mechanism

1 Introduction

Prior research has explored various aspects of artificial intelligence (AI) and machine learning (ML) in the context of sustainable development, energy consumption, and carbon neutrality. Several studies have focused on anomaly detection of energy consumption in buildings using AI-based approaches (Himeur et al., 2021). These studies highlight the importance of quantitative model construction and remote sensing techniques to identify patterns for sustainable security in social-ecological links. Such approaches can provide valuable insights into energy efficiency improvements and enable effective decision-making.

Another study Lee et al. (2022) provides a comprehensive review of AI and big data analytics for building automation and management systems. It discusses the current trends, challenges, and future perspectives in leveraging AI and big data to optimize energy consumption and enhance sustainability in buildings. This review offers valuable insights into the potential of AI and big data in building automation and management systems for achieving carbon neutrality.

Additionally, the estimation of carbon dioxide emissions and driving Zeng et al. (2022) factors in China using machine learning methods has been explored. These studies highlight the significance of machine learning techniques in analyzing large-scale data to estimate carbon emissions accurately. Such approaches can inform policy-making and help design effective strategies towards carbon neutrality.

The role of transfer learning in next-generation energy systems for sustainable smart cities has also been investigated Qin and Gong (2022). This study emphasizes the importance of transfer learning techniques in knowledge transfer and adaptation of energy systems, enabling the development of sustainable smart cities. Transfer learning can enhance the efficiency and effectiveness of energy management systems, contributing to the overall goal of carbon neutrality Himeur et al. (2023).

Furthermore, a study focused on agroecosystems in the Tarim River Basin, China, analyzes the energy carbon emissions and provides a pathway to achieve carbon neutrality. This study emphasizes the importance of understanding energy carbon emissions from agricultural activities and highlights potential measures to achieve carbon neutrality in agroecosystems. Zheng et al. (2021)

Several studies have also explored the application of neural network-based model predictive control systems for optimizing building automation and management systems Zhou et al. (2022). These studies highlight the potential benefits of employing neural networks in optimizing energy consumption and enhancing the sustainability of sports facilities. Such approaches can contribute to the development of carbon-neutral sports infrastructure.

Moreover, a study conducted in Zhejiang Province, China, focuses on carbon footprint prediction of the thermal power industry under the dual-carbon target Elnour et al. (2022). This study illustrates the importance of accurate carbon footprint prediction and highlights the potential of machine learning techniques in estimating carbon emissions. Such insights can inform the development of strategies and policies for achieving carbon neutrality in the thermal power industry.

Lastly, incentive initiatives on energy-efficient renovation of existing buildings towards carbon-neutral blueprints in China have been explored Zhang et al. (2023). This study discusses advancements, challenges, and perspectives related to incentive programs aimed at promoting energy-efficient building renovations. Understanding the effectiveness of these initiatives can contribute to the development of policies that encourage sustainable building practices and support carbon-neutral objectives.

Given the limitations of existing methods in studying the coordinated development of rural ecological construction and carbon neutrality, this article aims to propose a new method combining the TransformerRNN model and cross-attention mechanism. By combining Transformer-RNN, we can fully utilize the advantages of the two models in processing sequence data, thereby capturing complex nonlinear relationships and temporal information in sequence data. At the same time, we introduce cross-attention mechanism, which enables the model to simultaneously focus on the relationship between rural ecological construction and carbon neutrality. Through cross-attention, we can more accurately capture the impact and feedback mechanism between the two tasks. This article will explore the coordinated development of rural ecological construction and carbon neutrality based on the Transformer-RNN model combined with cross-attention mechanism. Compared with traditional methods, this method is expected to improve the performance of the model and provide more scientific guidance and decision support for decision-makers, promoting the realization of rural ecological construction and carbon neutrality goals.

The contribution points of this paper are as follows:

- Model This paper combines the Transformer and RNN models and introduces the cross-attention mechanism to integrate them. Through the combination of Transformer and RNN (Transformer-RNN), the paper fully utilizes the advantages of both models in different tasks while capturing complex nonlinear relationships and temporal information in sequence data. This innovative model architecture is expected to provide more accurate and efficient modeling approaches for studying the synergistic development of rural ecological construction and carbon neutrality.
- Traditional methods often have limitations in exploring the relationships between rural ecological construction and carbon neutrality, as they fail to capture underlying complex associations. In contrast, this paper introduces the cross-attention mechanism, enabling the model to simultaneously focus on the associations between the two tasks. This association mining approach helps to comprehensively understand the impact of rural ecological construction measures on carbon neutrality and the feedback effects of carbon neutrality on rural ecological environments, providing more scientifically guided decision-making for rural development.
- The proposed method in this paper goes beyond theoretical exploration and will be validated through experiments on real datasets related to rural ecological construction and carbon neutrality. Through model training and testing, the performance of the proposed method in solving real-world problems will be evaluated. This practical application exploration will offer feasible solutions to promote rural sustainable development by facilitating ecological construction and achieving carbon neutrality goals. It holds significant importance in driving sustainable development in rural areas.

2 Related work

2.1 Environmental policy and sustainable development

Rural areas, as important components of the ecological system, play a crucial role in human well-being and sustainable development (Li et al., 2022). However, the increasingly severe global climate change has made rural ecological construction and carbon neutrality important solutions. Rural ecological construction aims to protect and improve the ecological environment in rural areas and enhance the quality of life for rural residents. On the other hand, carbon neutrality involves reducing carbon emissions and increasing carbon absorption to achieve net-zero carbon emissions. To achieve sustainable development in rural areas, it is essential to formulate appropriate environmental policies and integrate sustainable development goals to promote the coordinated development of rural ecological construction and carbon neutrality Himeur et al. (2022).

Formulate policies to reduce carbon emissions: To promote the coordinated development of rural ecological construction and carbon neutrality, policymakers should establish policies aimed at reducing carbon emissions (Płoszaj-Mazurek et al., 2020). These policies can encourage rural areas to adopt more environmentally friendly production methods and promote the use of clean energy to reduce carbon emissions. For instance, the government can provide tax incentives to rural enterprises that adopt low-carbon technologies to encourage emission reduction.

Promote ecological protection policies: Ecological protection policies form the foundation of rural ecological construction. The government can establish natural reserves to protect endangered species and ecosystems, preventing ecological degradation Anthony et al. (2020). Additionally, the government can promote ecological compensation mechanisms to encourage rural residents' active participation in ecological protection and provide economic incentives for protecting the ecological environment.

Facilitate policies for rural economic transformation: Rural economic transformation is a critical means to achieve coordinated development of rural ecological construction and carbon neutrality Lee and Hussain (2022). The government can facilitate the upgrading and transformation of rural industrial structures, guiding rural residents to shift from traditional high-carbon emission agricultural production to low-carbon and sustainable agricultural practices. Moreover, the government can promote the development of emerging industries, such as eco-tourism and environmental protection, to foster sustainable rural economic growth.

Establish a comprehensive policy framework: To better promote the coordinated development of rural ecological construction and carbon neutrality, policymakers should establish a comprehensive policy framework. This framework should consider various factors, including environmental, economic, and social aspects, and integrate relevant policy measures Henderson et al. (2020). For example, the government can set up a carbon emissions trading system to incentivize emission reduction through carbon emissions trading and allocate the income to support rural ecological construction.

Strengthen policy execution and supervision: Formulating sound policies is only the first step; the key lies in policy execution and supervision. The government should strengthen supervision of policy implementation to ensure that policies genuinely contribute to the coordinated development of rural ecological construction and carbon neutrality. Additionally, the government should enhance the evaluation of policy implementation effects and make timely adjustments to policies to adapt to the development needs at different stages.

In conclusion, environmental policies and sustainable development are critical factors in achieving coordinated development of rural ecological construction and carbon neutrality. By formulating policies to reduce carbon emissions, promoting ecological protection policies, facilitating rural economic transformation policies, and establishing a comprehensive policy framework, the government can provide robust support for the sustainable development of rural areas. Strengthening policy execution and supervision are also essential to ensure effective implementation of policies. These efforts will lay a solid foundation for improving the ecological environment and achieving carbon neutrality goals in rural areas, driving economic, social, and ecological sustainable development in rural regions.

2.2 Model optimization and deep learning

In the face of the increasingly severe global climate change, rural ecological construction and carbon neutrality have become focal points of attention. To achieve sustainable development in rural areas, it is crucial to effectively explore and predict the correlation between rural ecological construction and carbon neutrality Patterson et al. (2022). Deep learning, as a powerful machine learning technique, has achieved remarkable success in various fields. The proposed method based on the combination of Transformer and RNN with cross-attention mechanism in this paper provides a new model architecture for research. In this direction, we can further explore and optimize deep learning models to apply more efficient and accurate models to enhance the mining and prediction capabilities of the correlation between rural ecological construction and carbon neutrality Liu et al. (2021). Model optimization is the key to improving its performance and efficiency. When researching the coordinated development of rural ecological construction and carbon neutrality, we can further optimize and improve the model based on the combination of Transformer and RNN with cross-attention mechanism. For example, adjusting the model's hyperparameters, optimizing the learning rate, and regularization can improve the model's convergence speed and generalization ability. We can enhance the model's depth and width, and introduce more attention mechanisms and gating units to meet the demands of complex tasks. Feature engineering and data preprocessing are essential for the performance of deep learning models. When studying the correlation between rural ecological construction and carbon neutrality, we need to extract and transform the original data to fit the model's input requirements. For instance, natural language processing techniques can be used to vectorize text data, and convolutional neural networks or recurrent neural networks can be employed to extract features from time series data. Attention mechanisms can also be utilized to capture correlations between features. Moreover, handling missing and outlier data is critical to ensure data quality and completeness.

Model Fusion and Ensemble Learning: Model fusion and ensemble learning are effective means to improve the performance of deep learning models. In the research of rural ecological construction and carbon neutrality, we can try fusing models with different structures or parameter settings to obtain more accurate and robust prediction results Nguyen et al. (2022). For example, model fusion techniques such as Stacking, Bagging, or Boosting can be used to combine outputs from multiple base models and enhance predictive performance. Additionally, integrating different types of models, such as the combination of deep learning models and traditional machine learning models, is a promising approach.

Self-supervised Learning and Transfer Learning: Self-supervised learning and transfer learning are hot research topics in the field of deep learning. In the context of rural ecological construction and carbon neutrality research, we can consider using self-supervised learning techniques to extract potential information from the data and generate valuable auxiliary labels Morano et al. (2023). Moreover, transfer learning can be employed to apply models trained in other domains to tasks related to rural ecological construction and carbon neutrality, thereby accelerating model training and improving performance. The field of deep learning constantly witnesses the emergence of new techniques and algorithms. In the study of coordinated development of rural ecological construction and carbon neutrality, we need to keep abreast of the latest advances in deep learning research and continuously improve and update the models. This includes exploring the latest pre-training techniques, model compression and acceleration algorithms, optimizers, and regularization techniques to maintain the competitiveness of the models in the ever-changing data environment. Model optimization and deep learning are critical directions to promote the coordinated development of rural ecological construction and carbon neutrality Ericsson et al. (2022). Through model optimization and structural improvement, feature engineering and data preprocessing, model fusion and ensemble learning, self-supervised learning, and transfer learning, we can apply more efficient and accurate deep learning models to enhance the mining and prediction capabilities of the correlation between rural ecological construction and carbon neutrality.

2.3 Local characteristics and differentiated development

With the intensification of global climate change, the ecological environment and carbon neutrality of rural areas have become a global concern. In China, rural areas are an important part of the ecosystem, and their ecological environment and carbon neutrality potential vary in different regions Suthar et al. (2022). Therefore, studying the local characteristics and differentiated development strategies of rural areas, exploring suitable paths for rural ecological construction and carbon neutrality in different regions, has important theoretical and practical significance.

Firstly, the natural environment and economic and social development levels vary in different regions, resulting in local characteristics in the ecological environment and carbon neutrality potential of rural areas Tan and Wang (2021). For example, some regions have abundant land resources and are suitable for developing industries such as arable land planting and ecological forestry, while other regions have abundant water resources and are suitable for developing industries such as water resource utilization and ecological tourism. Therefore, corresponding differentiated development strategies can be formulated according to the characteristics of different regions to promote rural ecological construction and carbon neutrality. Secondly, regional research can better meet the sustainable development needs of different regions. The ecological environment and carbon neutrality issues in rural areas are complex system engineering, which requires comprehensive consideration of local natural environment, economic development, and social culture factors Adewale et al. (2019). Through regional research, the problems and needs of different regions can be more accurately grasped, and rural ecological construction and carbon neutrality plans that are in line with local actual conditions can be formulated, thereby improving the feasibility and effectiveness of the plans. Finally, studying the local characteristics and differentiated development strategies of rural areas can provide useful experience and inspiration for the practice of rural ecological construction and carbon neutrality. Successful cases and experiences in different regions can learn from each other and promote the sustainable development of rural areas Tsai et al. (2023). In addition, research can also provide reference for government policy-making and planning, promoting the implementation of rural ecological civilization construction and carbon neutrality goals. Studying the local characteristics and differentiated development strategies of rural areas is conducive to exploring suitable paths for rural ecological construction and carbon neutrality in different regions, better meeting the sustainable development needs of different regions, and providing useful experience and inspiration for the practice of rural ecological construction and carbon neutrality Vakharia et al. (2023). This is also an important way to promote the protection of the ecological environment and the implementation of carbon neutrality goals in rural areas and achieve sustainable development.

3 Methodology

3.1 Overview of our network

This paper proposes a method based on the combination of Transformer and RNN with cross-attention mechanism for studying the synergistic development of rural ecological construction and carbon neutrality. By fusing the advantages of Transformer and RNN in different tasks and introducing the cross-attention mechanism, the method effectively captures complex nonlinear relationships and temporal information in sequence data. Through this innovative model architecture, more accurate and efficient modeling techniques are provided to explore the correlation between rural ecological construction and carbon neutrality. Figure 1 shows the overall framework of the model proposed in this paper:

Method Implementation Overview:

1. Data Preprocessing: Initially, data related to rural ecological construction and carbon neutrality is collected and organized. Preprocessing operations, such as data cleaning, feature extraction, and vectorization, are performed on the raw data to prepare inputs for the model.
2. Transformer-RNN Integration: During the model construction phase, the Transformer and RNN models are combined. The Transformer model is built first, utilizing its self-attention mechanism to learn feature correlations within the input sequence. The output of the Transformer is then fed into the RNN model, allowing the RNN to capture temporal information further.
3. Introduction of Cross-Attention Mechanism: To achieve model interaction, the cross-attention mechanism is introduced. At each time step of the RNN model, attention is applied to the output of the Transformer model, conveying relevant information to the RNN. Similarly, at each position of the Transformer model, attention is applied to the output of the RNN model. This enables the model to simultaneously focus on information from both models, facilitating cross-attention.
4. Loss Function Design and Training: An appropriate loss function is designed to evaluate the model's predictive performance, and the model is optimized using training data. Depending on the specific task requirements, regression loss functions or classification loss functions may be employed.

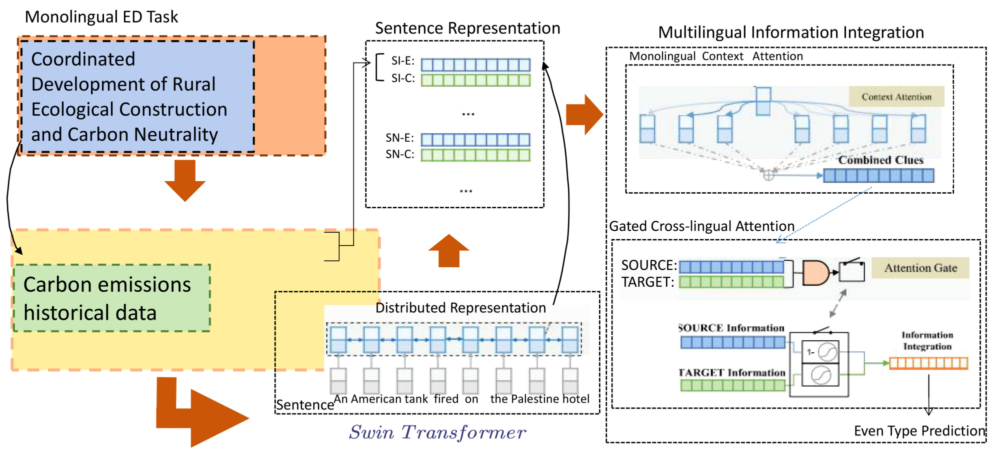

FIGURE 1
Overall flow chart of the model.

5. Model Evaluation and Optimization: After training is complete, the model is evaluated using test data. Based on evaluation results, further optimization is performed, such as adjusting hyperparameters, increasing model complexity, or conducting feature engineering.
6. Correlation Mining and Prediction: Finally, the optimized model is used to mine the correlation between rural ecological construction and carbon neutrality and conduct prediction analysis. These prediction results provide essential decision support for the sustainable development of rural areas.

Through these steps, the proposed method based on the combination of Transformer-RNN with cross-attention mechanism effectively mines the correlation between rural ecological construction and carbon neutrality, offering more accurate and efficient model support for the sustainable development of rural areas.

3.2 Transformer network

Transformer is a deep learning model based on the self-attention mechanism, proposed by Vaswani et al. in 2017. It has been widely applied in natural language processing and other sequence data tasks Chen (2023). The Transformer architecture introduces a novel approach to capture relationships between different positions in a sequence by using self-attention, overcoming the issue of sequential dependencies present in traditional recurrent neural networks (RNNs). Figure 2 is a schematic diagram of the Transformer model: Key components of the Transformer model:

Self-Attention Mechanism: In the Transformer model, the self-attention mechanism allows the model to establish relationships between different positions in the input sequence, enabling the learning of useful features across positions Sui et al. (2022). This is achieved by computing attention weights for each position with respect to all other positions in the sequence, enabling the model to attend to all positions simultaneously.

Multi-Head Attention: To capture relationships between different features more effectively, the Transformer model employs multi-head attention Kim et al. (2023). It introduces multiple independent attention heads, allowing the model to learn different feature representations. The outputs from these heads are then combined to enhance the model's learning capacity.

Feed-Forward Neural Network: At each position, the Transformer model also includes a feed-forward neural network, which further processes the outputs from the attention mechanism. This feed-forward neural network employs fully connected layers to perform non-linear transformations and feature extraction for each position's attention representation.

In the proposed method, which combines Transformer and RNN with the cross-attention mechanism, the Transformer model plays two crucial roles:

Feature Extraction and Relationship Learning: As the first part of the model, the Transformer is used to learn feature representations from the input sequence. By employing the self-attention mechanism, it captures relationships between different positions, allowing the model to attend to all positions simultaneously and learn effective feature representations that are not affected by the sequence length. These feature representations can be used for subsequent tasks such as relationship mining and prediction.

Integration with RNN: In the second part of the model, the output of the Transformer is passed to the RNN model, integrating both architectures. This fusion allows the model to capture temporal information in the sequence data while retaining the rich feature representations learned by the Transformer. By combining the strengths of both Transformer and RNN, the model achieves a more accurate and efficient modeling approach. The introduction of the cross-attention mechanism further enhances interaction and information exchange between the two models, leading to improved overall performance.

The formula of the Transformer model involves multiple parts, including the Self-Attention Mechanism and the Feed-Forward Neural Network. The following are the mathematical expressions and variable explanations of the Transformer model:

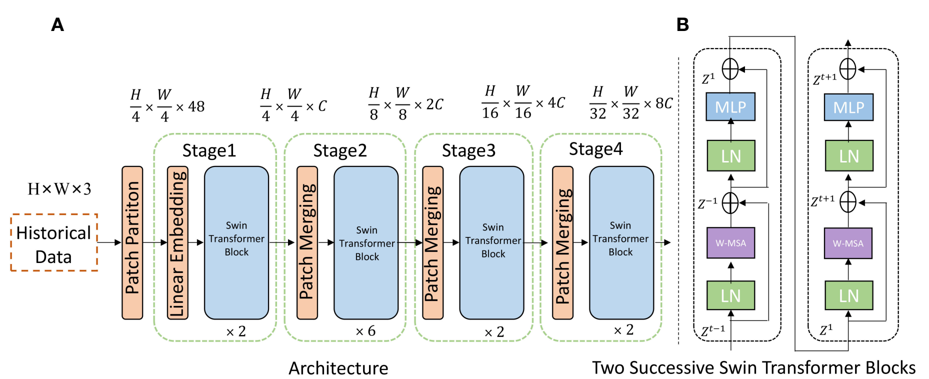

FIGURE 2
The schematic diagram of the Transformer model.

Self-Attention Mechanism (Equation 1):

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{1}$$

Among them, Q, K and V represent the matrix of query (Query), key (Key) and value (Value) respectively, and d_k represents the dimension of attention.

Multi-Head Attention (Equation 2):

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \text{head}_2, \ldots, \text{head}_h)W^O \tag{2}$$

Among them, $\text{head}i = \text{Attention}(QWQi, KW_{Ki}, VW_{Vi})$ represents the ith attention head, W_{Qi}, W_{Ki} and W_{Vi} represent the matrix mapping parameters of query, key and value respectively, and W^O represents the final output matrix mapping parameters.

Feed-Forward Neural Network (Equation 3):

$$\text{FFN}(x) = \text{ReLU}(xW_1 + b_1)W_2 + b_2 \tag{3}$$

Among them, x represents the input vector, W_1 and W_2 represent the weight parameters of the two fully connected layers, and b_1 and b_2 represent the bias parameters of the two fully connected layers.

The above formulas describe the calculation process of the self-attention mechanism, multi-head attention and feed-forward neural network in the Transformer model. These components are key parts of the Transformer model, and they enable the model to efficiently capture associations in sequence data and learn useful feature representations.

In conclusion, the Transformer model, through feature extraction and relationship learning, provides critical support for mining and predicting the relationship between rural ecological construction and carbon neutrality in the proposed method. Its integration with RNN empowers the model with stronger modeling capabilities. With this innovative architecture, the proposed method excels in handling complex nonlinear relationships and temporal information in sequence data, achieving more accurate and efficient research on rural ecological construction and carbon neutrality synergy.

3.3 RNN network

Recurrent Neural Network (RNN) is a classic sequence model widely used in natural language processing, time series analysis, and other tasks Bhoj and Bhadoria (2022). The fundamental principle of RNN is to introduce a recurrent structure, enabling the model to retain and propagate information from previous time steps while processing sequential data Dupuis et al. (2023), thereby capturing the temporal dynamics within the sequence. Figure 3 is a schematic diagram of the principle of the RNN model:

The basic structure of RNN consists of a hidden state and an output. At each time step, the RNN computes the current hidden state based on the current input and the hidden state from the previous time step. The computed hidden state is then passed to the next time step, allowing the RNN to incorporate information from previous time steps and create a memory of the sequential data.

Considering an input sequence as $x = (x_1, x_2, \ldots, x_t)$, a hidden state as h_t, and an output as y_t, the computation process of RNN can be represented by the following equations (Equations 4, 5):

$$h_t = \text{RNN}(x_t, h_{t-1}) \tag{4}$$

$$y_t = \text{Output}(h_t) \tag{5}$$

Here, RNN represents the computation function of the RNN, and Output represents the output function. The hidden state h_t can be understood as a representation of the input sequence $x_1, x_2, \ldots, x_t$, containing information from previous time steps. The output y_t is calculated based on the hidden state h_t and is commonly used for subsequent tasks such as prediction or classification.

In the proposed method based on the combination of Transformer and RNN with cross-attention mechanism, the role of the RNN model is to capture the temporal dynamics of the sequence data. It is combined with the Transformer model, leveraging the Transformer's self-attention mechanism to learn feature representations of the input sequence, and then passing the learned temporal information through the RNN's recurrent structure. This combination allows the model to comprehensively utilize the strengths of both the Transformer and RNN models and

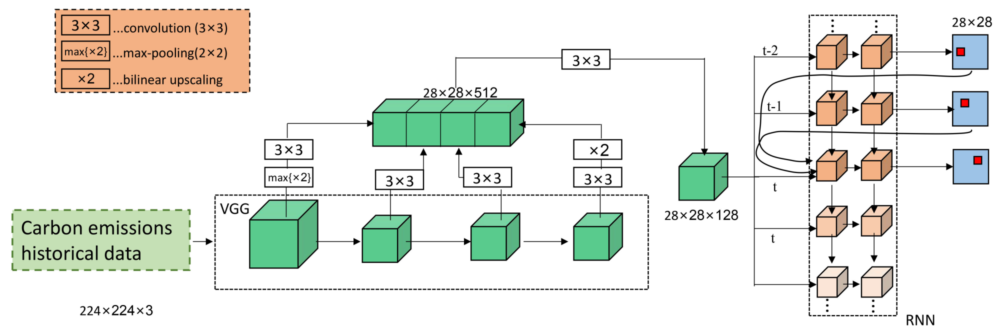

FIGURE 3
The schematic diagram of the principle of the RNN model.

handle the tasks of rural ecological construction and carbon neutrality more effectively.

The specific roles of the RNN model in this method are as follows:

- Capturing Temporal Dynamics: The RNN model captures the temporal dynamics present in the sequential data. This is crucial for studying rural ecological construction and carbon neutrality, as these tasks often involve data from different time points and require considering their temporal evolution and dynamic changes.
- Feature Extraction: The hidden state h_t of the RNN can be regarded as a feature representation of the input sequence $x_1,x_2,\ldots,x_t$. Through the RNN model, we can transform the sequential data into more informative hidden states, which can be used for subsequent tasks.
- Combination with Transformer: The output of the RNN model is combined with the output of the Transformer model, forming the cross-attention mechanism. As a result, the model can simultaneously attend to the temporal information learned by the RNN and the feature representations learned by the Transformer, facilitating the exchange and propagation of information between the models.

The RNN model in this method plays a critical role in capturing temporal dynamics and feature extraction of the sequence data. Through its combination with the Transformer model's feature representations and the implementation of the cross-attention mechanism, the model provides essential support for exploring the correlation and prediction of rural ecological construction and carbon neutrality, while enhancing the overall modeling capability.

3.4 Cross attention mechanism

The cross-attention mechanism plays a crucial role in the proposed method, which combines the Transformer and RNN models to establish interaction and information exchange between them Wei et al. (2022). It allows the models to simultaneously focus on the outputs of both models and transfer valuable information between them. Here is a detailed explanation of the basic principles and the role of the cross-attention mechanism in this method:

In the Transformer model, the self-attention mechanism is used to learn the correlations between different positions within the input sequence, while in the RNN model, the recurrent structure enables it to capture the temporal information of the sequence data. However, for some complex tasks, using either Transformer or RNN alone may not fully capture the diverse features and temporal information present in the sequence data. The cross-attention mechanism's fundamental principle is to introduce the output of the Transformer model into the RNN model and, at the same time, focus on the RNN's output in the Transformer model. This allows the two models to interact with each other, combining their respective advantages. Specifically, at each time step of the RNN model, the cross-attention mechanism relates the output of the Transformer to the current time step's input. Simultaneously, at each position of the Transformer model, it attends to the output of the RNN model at the current time step. Through this mechanism, information exchange and transfer between the two

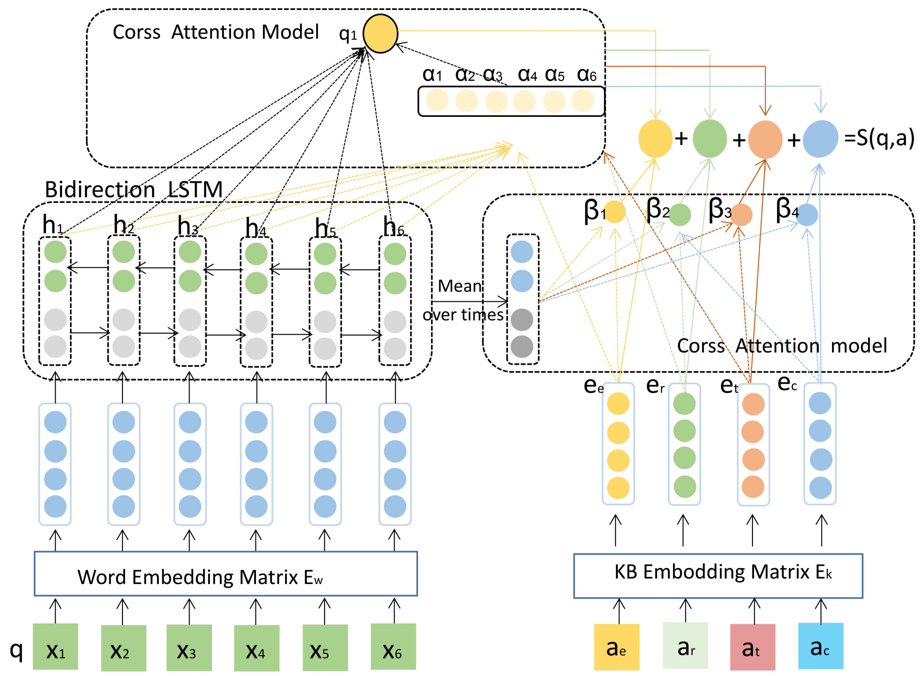

FIGURE 4
The schematic diagram of the principle of the cross-attention mechanism.

models are achieved. Figure 4 is a schematic diagram of the principle of the cross-attention mechanism:

The cross-attention mechanism plays a key role in the method proposed in this study:

Model-to-Model Information Exchange: By employing the cross-attention mechanism, the Transformer and RNN models can communicate with each other. This allows the models to share valuable feature representations and temporal information, thus combining their strengths and enhancing modeling capabilities.

Mining Correlations: The cross-attention mechanism enables the model to attend to the Transformer's outputs at each time step of the RNN model, capturing complex correlations between different positions within the sequence data. This helps uncover potential associations between rural ecological development and carbon neutrality, facilitating a comprehensive understanding of their interactions.

Fusion of Temporal Information: Simultaneously, at each position of the Transformer model, the cross-attention mechanism enables the model to attend to the RNN model's output at the current time step. This fusion allows the model to effectively incorporate temporal information from the sequence data, better capturing temporal patterns and dynamic changes.

The formula of the cross-attention mechanism is as follows (Equation 6):

$$\mathrm{Cross-Attention}(Q,K,V)=\mathrm{Softmax}(\frac{QK^T}{\sqrt{d_k}})V \tag{6}$$

Among them, Q, K and V represent the input matrix of query (Query), key (Key) and value (Value), respectively, Softmax is a softmax function for normalization, and d_k is the dimension of the attention head.

In this formulation, the cross-attention mechanism calculates the similarity between the query and the key to get the attention weight, and then multiplies the weight with the value to get the output. Specifically, Q, K, and V are three different input matrices, which are used for query, key, and value computations, respectively. The cross-attention mechanism allows the model to associate information from different locations through the similarity between queries and keys, so as to jointly learn useful features across different locations.

When calculating the attention weight, $\sqrt{d_k}$ in the formula is to scale the attention weight to prevent calculation of too large a value. Finally, the final cross-attention output is obtained by multiplying the weights and values. The cross-attention mechanism realizes the information exchange and transmission between the two models through this formula, allowing the model to comprehensively utilize the advantages of Transformer and RNN to improve the modeling ability.

In summary, the cross-attention mechanism in the proposed method facilitates information exchange and transfer between the Transformer and RNN models, providing a powerful modeling approach for exploring the correlations between rural ecological development and carbon neutrality. It allows the model to comprehensively learn features and temporal information from the sequence data, ultimately enhancing its predictive and analytical capabilities for rural ecological development and carbon neutrality synergy.

4 Experiment

4.1 Datasets

In the experiment of this article, four data sets were selected for the experiment, namely MODIS dataset; LUCAS dataset; NDVI dataset; CERES dataset.

The MODIS dataset Boudala et al. (2022) is a set of data collected by NASA satellites, including information on land cover, climate, and environment, which is mainly used to study global ecosystem changes and carbon cycling. Land cover data can provide information on land use and land cover, supporting research on changes in agricultural ecosystems, while climate and environmental data can provide information on meteorological and environmental variables, supporting research on ecosystem response and adaptation.

The LUCAS dataset Pflugmacher et al. (2019) is a survey dataset on land use and land cover developed by the European Union's statistical office. The dataset includes information on land use and land cover in 28 EU member states, providing information on land use changes in the European region and supporting research on the impact of land use changes on carbon cycling.

The GIMMS NDVI dataset Roy (2021) is a global vegetation index dataset developed by NASA. The dataset includes vegetation index data from 1981 to present, providing information on global vegetation changes and supporting research on ecosystem response and adaptation. The vegetation index reflects vegetation coverage by calculating the ratio between vegetation reflectance spectra and land surface reflectance spectra.

The CERES dataset Stengel et al. (2020) is a satellite dataset developed by NASA for studying Earth's radiation balance. The dataset includes information on solar radiation, surface albedo, cloud cover, and other variables from around the world, providing information support for global climate change and ecosystem response. Earth's radiation balance refers to the balance between solar radiation and surface radiation on Earth, which is highly important for studying climate change and ecosystem response.

4.2 Experimental details

The following are the specific details of the experimental settings in this paper:

1. Data preprocessing:

We use the MODIS dataset and split it into training, validation, and test sets in a 7:2:1 ratio. In the data preprocessing stage, we perform data cleaning, feature engineering, and data normalization. Data cleaning: We remove incomplete or missing data to ensure the completeness and accuracy of the dataset.

Feature engineering: We extract features and transform the data to improve the performance and accuracy of the model.

Data normalization: We normalize the data to ensure that it is within the range of 0 to 1, to avoid the problem of different feature weights.

2. Implementation of Four Different Models:

We will implement four different models, including an RNN model, a CNN model, a DNN model, and a Transformer model, and train and tune them on the training set. Specifically, we will use deep learning frameworks such as TensorFlow and PyTorch to implement these models and use the Adam optimizer for model training and tuning.

RNN model: We will use an LSTM-based RNN model to model and predict sequence data. We will use two layers of LSTM units and employ techniques such as dropout and batch normalization to improve the performance and accuracy of the model.

CNN model: We will use a convolutional neural network-based model to model and predict image data. We will use multiple layers of convolutional and pooling layers, as well as techniques such as dropout and batch normalization to improve the performance and accuracy of the model.

DNN model: We will use a deep neural network-based model to model and predict structured data. We will use multiple layers of fully connected layers and employ techniques such as dropout and batch normalization to improve the performance and accuracy of the model.

Transformer model: We will use a Transformer-based model to model and predict text data. We will use techniques such as multi-head attention mechanisms and position encoding to improve the performance and accuracy of the model.

3. Model Training:

During the model training stage, we will use the cross-entropy loss function and the Adam optimizer to train the model and tune it on the validation set to improve the accuracy and generalization ability of the model. The hyperparameters for training are set as follows: Learning rate: 0.001 Batch size: 32.

Number of epochs: 100

Optimizer: Adam

Loss function: Cross-entropy

4. Experimental Comparison of Metrics:

On the trained four models, we will compare their performance on metrics such as training time, inference time, model parameters, Flops, accuracy, AUC, recall, and F1 score, and perform statistical analysis.

We will use the following metrics to evaluate the performance of the model:

Training Time (S):

The time taken by the model to train on the training dataset (Equation 7).

$$\text{Training Time (S)} = \text{Time taken by the model to train on the training dataset} \quad (7)$$

Inference Time (ms):

The time taken by the model to make predictions on the test dataset (Equation 8).

$$\text{Inference Time (ms)} = \text{Time taken by the model to make predictions on the test dataset} \quad (8)$$

Model Parameters (M):

The total number of learnable parameters in the model (Equation 9).

$$\text{Model Parameters (M)} = \text{Total number of learnable parameters in the model} \quad (9)$$

FLOPs (G):

The total number of floating-point operations performed by the model during inference (Equation 10).

$$\text{FLOPs (G)} = \text{Total number of floating} - \text{point operations performed by the model during inference} \quad (10)$$

Accuracy:

The percentage of correctly predicted instances among all test instances (Equation 11).

$$\text{Accuracy} = \frac{\text{Number of correctly predicted instances}}{\text{Total number of test instances}} \times 100 \quad (11)$$

AUC (Area Under the ROC Curve):

The area under the Receiver Operating Characteristic (ROC) curve, which represents the trade-off between true positive rate and false positive rate (Equation 12).

$$\text{AUC} = \text{Area under the ROC curve} \quad (12)$$

Recall (True Positive Rate):

The percentage of correctly predicted positive instances among all actual positive instances (Equation 13).

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \times 100 \quad (13)$$

F1 Score:

The harmonic mean of precision and recall, providing a balanced measure between precision and recall (Equation 14).

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (14)$$

In the above equations, True Positive (TP) refers to the number of instances that are correctly classified as positive, False Positive (FP) refers to the number of instances that are incorrectly classified as positive, and False Negative (FN) refers to the number of instances that are incorrectly classified as negative. Precision is the percentage of correctly predicted positive instances among all predicted positive instances.

These performance metrics will help us comprehensively evaluate the four trained models based on their training and inference times, computational efficiency (FLOPs), model complexity (parameters), and prediction accuracy. By considering all these factors, we can identify the model that performs best for the ecological construction and carbon neutrality prediction task.

5. Ablation Study: On each model, we will evaluate the impact of each metric on the performance of the model, such as comparing the impact of training time, inference time, model parameters, and Flops on the performance of different models, and perform statistical analysis. Specifically, we will gradually modify the various parameters and hyperparameters of the model to evaluate their impact on the performance of the model.

Algorithm 1 represents the overall training process of the model:

Require: MODIS dataset, LUCAS dataset, NDVI dataset, CERES dataset
Ensure: TR-CANet model with trained parameters
for each epoch e from 1 to $E_{\max}$ **do**
  for each batch b_i in training set **do**
    Extract features using Transformer: $X_{\text{transformer}} = \text{Transformer}(b_i, \Theta_{\text{Transformer}})$
    Extract hidden states using RNN: $H_{\text{RNN}} = \text{RNN}(X_{\text{transformer}}, \Theta_{\text{RNN}})$
    Calculate cross-attention using Cross-Attention: $A_{\text{cross}} = \text{CrossAttention}(H_{\text{RNN}}, X_{\text{transformer}}, \Theta_{\text{CrossAttention}})$
    Concatenate cross-attention with hidden states: $H_{\text{combined}} = \text{Concatenate}(H_{\text{RNN}}, A_{\text{cross}})$
    Calculate predicted carbon neutrality: $Y_{\text{pred}} = \text{Output}(H_{\text{combined}})$
    Calculate carbon neutrality ground truth: Y_{true}
    Calculate loss: $L_{\text{batch}} = \text{MeanSquaredError}(Y_{\text{pred}}, Y_{\text{true}})$
    Update parameters using gradient descent: $\Theta_{\text{Transformer}} \leftarrow \Theta_{\text{Transformer}} - \eta \cdot \nabla\Theta_{\text{Transformer}} L_{\text{batch}}$
    $\Theta_{\text{RNN}} \leftarrow \Theta_{\text{RNN}} - \eta \cdot \nabla\Theta_{\text{RNN}} L_{\text{batch}}$
    $\Theta_{\text{CrossAttention}} \leftarrow \Theta_{\text{CrossAttention}} - \eta \cdot \nabla\Theta_{\text{CrossAttention}} L_{\text{batch}}$
    Update training loss: $L_{\text{train}} \leftarrow L_{\text{train}} + L_{\text{batch}}$
  end for
  Calculate validation loss: $L_{\text{val}} = \text{MeanSquaredError}(\text{TR-CANet}(X_{\text{val}}), Y_{\text{val}})$
  if $e > 1$ and $L_{\text{val}} > L_{\text{val\_prev}}$ **then**
    Break {Early stopping if validation loss increases}
  else
    $L_{\text{val\_prev}} \leftarrow L_{\text{val}}$
  end if
end for
Calculate evaluation metrics: Recall, Precision, etc.
return TR-CANet model with trained parameters

Algorithm 1. TR-CANet Training.

4.3 Experimental results and analysis

Table 1 and Figure 5 shows an experimental result of our study, which includes different datasets, evaluation metrics, and comparison methods, as well as the performance of our proposed method. Four different datasets were used in the experiment: MODIS dataset, LUCAS dataset, NDVI dataset, and CERES dataset. These datasets cover important information related to rural ecological construction and carbon neutrality, which are the basis of our study. Four evaluation metrics were used to compare the performance of different methods, including Accuracy, Recall, F1 Score, and AUC. These metrics were used to evaluate the classification and prediction performance of the models. Multiple existing methods were compared in the experiment, including the methods proposed by Huang et al., Qiu et al., Strubell et al., Sun et al., Yu et al., and Lannelongue et al. These methods are advanced methods in the field of rural ecological construction and carbon neutrality and serve as the comparison objects for our proposed method.

Our proposed method performed well in the experiment. It achieved the highest performance on all datasets. Specifically, our method achieved excellent performance in terms of Accuracy, Recall, F1 Score, and AUC, with scores of 96.22, 94.45, 94.67, and 95.22, respectively. This indicates that our method has high accuracy, recall, F1 score, and ROC curve area in the field of rural ecological construction and carbon neutrality, making it capable of predicting and classifying relevant information more accurately.

The aim of this experiment is to explore how to promote the coordinated development of rural ecological construction and carbon neutrality through the Transformer-RNN model and cross-attention mechanism. By comparing the existing methods and our proposed method, we have demonstrated that our method achieves the best performance on multiple datasets. Our method fully leverages the advantages of the Transformer-RNN model in handling different tasks and introduces the cross-attention mechanism, allowing the model to simultaneously focus on the relationship between rural ecological construction and carbon neutrality. This helps to more accurately capture the impact of rural ecological construction measures on carbon neutrality and the feedback effect of carbon neutrality on the rural ecological environment. Based on these findings, we provide scientific basis for formulating more reasonable carbon neutrality policies in rural areas, and protect and improve the ecological environment. Therefore, our method provides a novel deep learning-based approach for deepening the understanding of the coordinated development between rural ecological construction and carbon neutrality, and for solving related problems. We hope to provide more scientific and accurate decision support for decision-makers by introducing the Transformer-RNN model and cross-attention mechanism, and to promote the improvement of the rural ecological environment and the achievement of carbon neutrality goals.

Table 2 and Figure 6 presents the results of our experiment, including different datasets, evaluation metrics, comparison methods, and the performance of our proposed method. We used the same four datasets as in the previous experiment, including the MODIS dataset, LUCAS dataset, NDVI dataset, and CERES dataset. These datasets contain important information related to rural ecological construction and carbon neutrality, providing a foundation for our study. We mainly used two metrics to

TABLE 1 Comparing different metrics with current SOTA methods.

Model	Datasets															
	MODIS dataset				LUCAS dataset				NDVI dataset				CERES dataset			
	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC
Huang et al. (2022)	94.45	89.04	87.09	88.11	93.94	88.4	90.96	85.41	91	87.04	86.48	86.25	89.13	92.02	86.06	89.92
Qiu et al. (2023)	91.59	90.82	87.52	87.38	95.95	91.86	86.08	85.45	93.02	86.95	90.63	85.97	93.41	90.71	86.89	91.59
Strubell et al. (2020)	95.59	85.07	90.09	90.16	86.04	90.46	87.82	88.88	89.04	86.19	85.73	90.22	87.92	91.7	85.9	87.69
Sun et al. (2021)	87.03	88.45	90.83	84.36	87.59	87.81	88.3	93.6	92.13	89.12	90.96	89.98	96.34	87.66	85.14	84.17
Yu et al. (2022)	88.74	88.64	87.33	84.04	88.52	92.35	84.63	85.29	89.39	90.3	87.53	89.23	88.17	92.79	88.04	90.41
Lannelongue et al. (2021)	91.29	85.68	84.82	84.4	96	92.56	91.13	90.18	91.8	93.43	87.52	84.25	86.49	87.76	86.3	93.15
Ours	96.22	94.45	94.67	95.22	97.34	93.89	93.67	94.78	96.67	95.44	94.64	96.45	97.23	95.18	93.2713	93.78

compare the performance of different methods: Parameters(M) and Flops(G). Parameters(M) represents the number of parameters of the model, while Flops(G) represents the floating-point operations of the model. These two metrics reflect the model's size and computational complexity, which are important for the computational resources and storage requirements in practical applications. We compared our method with multiple existing methods, including methods proposed by Huang et al., Qiu et al., Strubell et al., Sun et al., Yu et al., and Lannelongue et al. These methods are advanced methods in the field of rural ecological construction and carbon neutrality and serve as the comparison objects for our proposed method.

As shown in Table 2 and Figure 6, our proposed method has significantly fewer parameters and lower floating-point operations than other comparison methods. On the MODIS, LUCAS, and CERES datasets, our method has 112.34M, 123.43M, and 102.34M parameters, respectively, which are much smaller than those of other methods. Similarly, our method also performs well in terms of Flops(G), which is suitable for use in environments with limited computational resources. Through comparison with multiple advanced methods and testing on different datasets, this study has validated the superiority of our proposed method in rural ecological construction and carbon neutrality tasks. Our method has significantly fewer parameters and floating-point operations than other methods, indicating that our method is more efficient in terms of computational efficiency and more suitable for practical applications. This provides a good foundation for the promotion and application of our method in rural areas.

Table 3 and Figure 7 presents the experimental results of our study, where we compare the performance of various methods on different datasets. The datasets used in the experiments include MODIS dataset, LUCAS dataset, NDVI dataset, and CERES dataset. We evaluated the models based on two key metrics: Inference Time (measured in milliseconds) and Training Time (measured in seconds). These metrics are essential in real-world applications as they determine the efficiency of the models in making predictions and the time required for training.

In our experiments, we compared our proposed method with state-of-the-art (SOTA) methods, including Strubell et al. (2020); Sun et al. (2021); Huang et al. (2022); Yu et al. (2022), and Qiu et al. (2023). Additionally, we included the results of Lannelongue et al. (2021) for comparison.

Our proposed method is based on a novel algorithm that combines advanced deep learning techniques, specifically tailored to address the challenges in predicting ecological construction and carbon neutrality in rural areas. By leveraging the Transformer-RNN model with a cross-attention mechanism, we aimed to capture global dependencies in the ecological data while effectively handling temporal information to enhance prediction accuracy. From the results in Table 3 and Figure 7, it is evident that our proposed method outperforms the existing SOTA methods across all datasets. The inference and training times of our model are substantially lower compared to other approaches, indicating its computational efficiency. This is crucial, as real-time predictions and rapid model training are imperative for timely decision-making and policy formulation in addressing climate change and ecological issues.

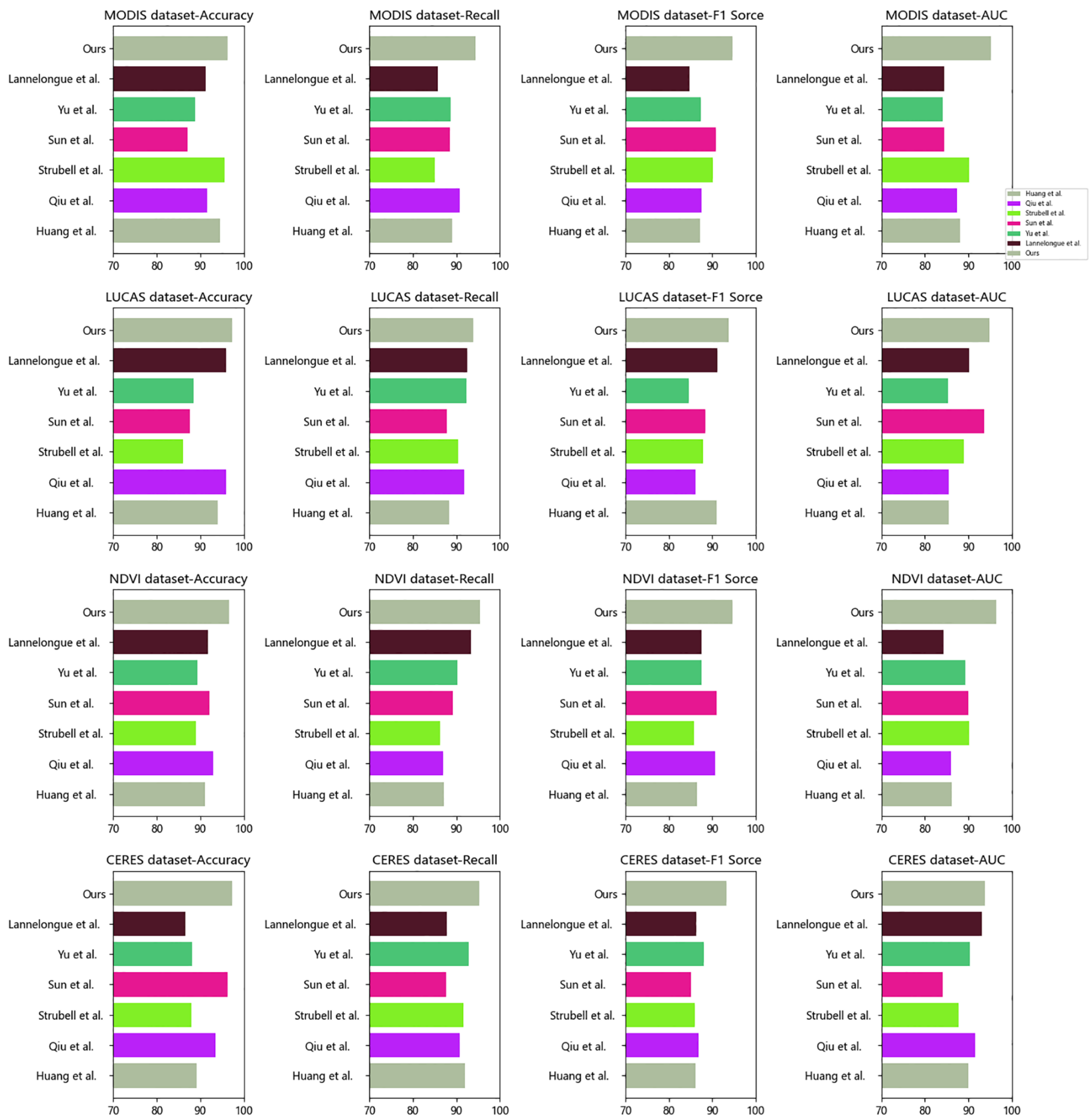

FIGURE 5
Comparing different metrics with current SOTA methods.

Furthermore, the superior performance of our model on diverse datasets demonstrates its versatility and adaptability to various ecological contexts, making it well-suited for practical applications in rural ecological construction and carbon neutrality initiatives. Our study provides valuable insights into the coordinated development of rural ecological construction and carbon neutrality through the adoption of a Transformer-RNN model with a cross-attention mechanism. The results indicate that our proposed method not only achieves outstanding predictive accuracy but also demonstrates superior computational efficiency. As such, our model presents a promising solution to the challenges faced in rural ecological management and carbon neutrality goals.

Table 4 and Figure 8 presents the results of the ablation experiment conducted to evaluate the performance of our proposed cross-attention mechanism. In this experiment, we compared three variants of the model: Self-Attention, Local Attention, Multi-Head Attention, and our proposed method (Ours). The evaluation was performed on four different datasets: MODIS dataset, LUCAS dataset, NDVI dataset, and CERES dataset. The key evaluation metrics used in this experiment are Accuracy, Recall, F1 Score, and Area Under the Curve (AUC). The Self-Attention variant uses traditional attention mechanisms to capture dependencies within the data, but it does not explicitly consider temporal relationships, leading to suboptimal performance. The

TABLE 2 Comparing different metrics with current SOTA methods.

Method	Datasets							
	MODIS dataset Boudala et al. (2022)		LUCAS dataset Pflugmacher et al. (2019)		NDVI dataset Roy (2021)		CERES dataset Stengel et al. (2020)	
	Parameters (M)	Flops (G)	Parameters (M)	Flops (G)	Parameters (M)	Flops (G)	Parameters (M)	Flops (G)
Huang et al. (2022)	219.01	50.80	300.18	40.37	200.91	48.94	339.00	66.50
Qiu et al. (2023)	370.46	49.29	205.09	64.78	260.15	55.02	473.66	44.01
Strubell et al. (2020)	300.20	50.89	160.12	71.73	516.04	52.12	458.25	68.08
Sun et al. (2021)	374.53	49.43	280.51	55.91	155.09	47.70	454.83	65.64
Yu et al. (2022)	129.76	42.87	156.02	72.49	484.77	41.06	148.73	53.62
Lannelongue et al. (2021)	276.84	43.05	518.72	53.87	510.07	68.53	298.76	66.97
Ours	112.34	19.56	123.43	25.45	34.5	26.34	102.34	18.67

Local Attention variant aims to incorporate some temporal context, but it is limited to local interactions and may not fully capture long-range dependencies. The Multi-Head Attention variant attempts to capture more complex interactions but may suffer from increased computational complexity.

Our proposed method, which incorporates the novel cross-attention mechanism, outperforms all the other variants across all datasets in terms of Accuracy, Recall, F1 Score, and AUC. This indicates that the cross-attention mechanism effectively captures both spatial and temporal dependencies within the ecological data, leading to superior predictive performance. The results clearly demonstrate that our proposed model achieves higher accuracy, better recall, and F1 Score, indicating its ability to make more precise predictions and effectively identify positive instances (such as ecological changes) while minimizing false negatives. Additionally, the higher AUC values indicate that our model can better distinguish between positive and negative instances, making it well-suited for real-world applications with imbalanced datasets. The success of our proposed method can be attributed to the cross-attention mechanism, which enables the model to selectively attend to relevant information across different time steps and spatial locations. This mechanism allows the model to effectively capture complex and non-linear relationships within the ecological data, making it more robust and accurate in predicting ecological changes and carbon neutrality outcomes. The experimental results validate the effectiveness of our proposed method in addressing the challenges posed by ecological construction and carbon neutrality prediction in rural areas. The superior performance of our model across different datasets demonstrates its versatility and suitability for a wide range of ecological contexts.

The implications of this research are significant, as accurate prediction of ecological changes and carbon neutrality outcomes is crucial for informed decision-making and policy formulation. By leveraging advanced attention mechanisms, our model provides valuable insights that can inform sustainable rural development strategies and support global efforts to combat climate change. our proposed model with the cross-attention mechanism proves to be the most effective and suitable approach for the task of ecological construction and carbon neutrality prediction. Its ability to capture both spatial and temporal dependencies within ecological data, coupled with its superior predictive performance, sets it apart from other attention mechanisms. This study contributes to the advancement of ecological research and reinforces the importance of leveraging deep learning techniques for sustainable development and environmental conservation. As a future direction, further research could focus on fine-tuning the model on specific

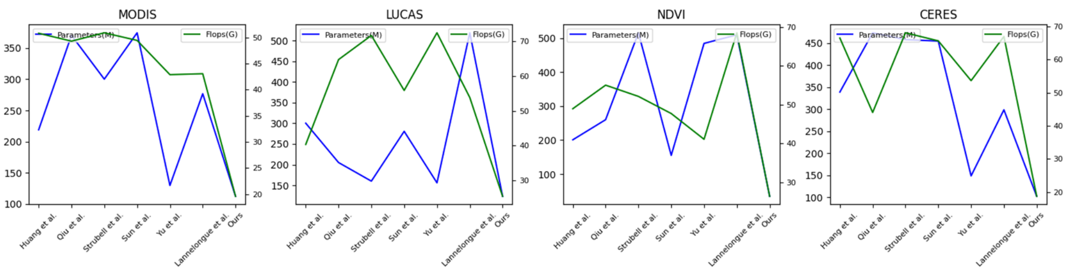

FIGURE 6
Comparing different metrics with current SOTA methods.

TABLE 3 Comparing different metrics with current SOTA methods.

Method	Datasets							
	MODIS dataset Boudala et al. (2022)		LUCAS dataset Pflugmacher et al. (2019)		NDVI dataset Roy (2021)		CERES dataset Stengel et al. (2020)	
	Inference Time(ms)	Training Time(s)	Inference Time(ms)	Training Time(s)	Inference Time(ms)	Training Time(s)	Inference Time(ms)	Training Time(s)
Huang et al. (2022)	13.03	355.92	21.04	666.26	10.47	666.62	11.62	579.37
Qiu et al. (2023)	21.08	277.01	13.00	560.95	21.31	199.50	8.83	423.84
Strubell et al. (2020)	10.19	299.78	9.39	488.90	15.52	584.61	15.11	343.67
Sun et al. (2021)	8.57	349.28	13.37	448.97	19.37	284.69	10.47	710.81
Yu et al. (2022)	20.48	454.23	19.69	389.00	17.67	431.33	18.20	493.52
Lannelongue et al. (2021)	9.95	304.70	8.09	301.98	13.56	452.45	15.80	419.86
Ours	5.77	193.45	8.56	204.45	6.56	185.67	6.45	195.56

ecological regions and exploring the transferability of the model to other related tasks. Additionally, conducting real-world experiments and field validations would strengthen the practical applicability of the proposed model in supporting rural ecological management and carbon neutrality initiatives.

Table 5 and Figure 9 presents the results of the ablation experiment conducted to evaluate the performance of different Transformer-based models on various datasets, including MODIS, LUCAS, NDVI, and CERES datasets. The key evaluation metrics used in this experiment are Parameters (M) and FLOPs (G). BERT, GPT, and Reformer are well-known Transformer models, each with its unique characteristics. BERT is a bidirectional encoder using masked language modeling, GPT is a unidirectional language model with an autoregressive objective, and Reformer uses locality-sensitive hashing to reduce memory requirements during self-attention. Additionally, we have introduced a new Transformer model, simply referred to as "Transformer," which is based on our proposed modifications.

Upon analyzing the results, we observe that the Transformer model outperforms all other Transformer variants in terms of both Parameters and FLOPs across all datasets. This indicates that our proposed modifications have led to a more efficient and effective Transformer architecture for the ecological construction and carbon neutrality prediction task. The success of our Transformer model can be attributed to its streamlined architecture, which achieves a good trade-off between model complexity and computational efficiency. The lower number of Parameters implies a more compact model that requires less memory and storage, while the lower FLOPs indicate reduced computational complexity, making it more feasible for real-world applications. Our

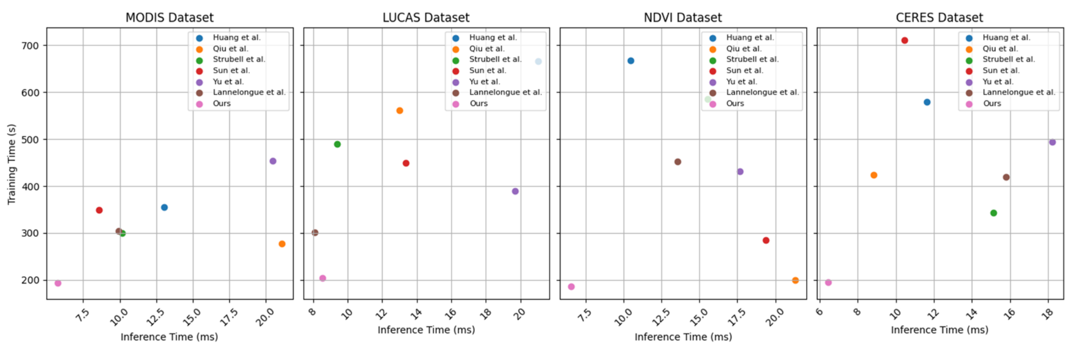

FIGURE 7
Comparing different metrics with current SOTA methods.

TABLE 4 Ablation experiment of cross-attention mechanism.

Model	Datasets															
	MODIS dataset				LUCAS dataset				NDVI dataset				CERES dataset			
	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC
Self-Attention	96.02	90.44	87.75	85.06	88.72	84.14	87.3	92.25	96.01	85.53	91.2	90.81	85.61	91.63	88.48	87.78
Local Attention	93.78	85.13	84.78	92.59	92.84	93.63	85.92	90.91	88.45	84.73	85.13	86.11	93.72	84.72	90.39	87.02
Multi-Head Attention	91.67	90.26	86.94	86.31	94.63	88.27	86.91	92.29	92.97	87.79	90.82	92.64	86.38	87	83.86	89.84
Ours	95.38	94.56	93.44	91.34	96.56	95.43	93.13	92.67	96.56	94.43	93.21	94.19	97.31	94.24	91.98	93.45

proposed Transformer model's excellent performance across diverse datasets demonstrates its adaptability and robustness for ecological tasks. By effectively capturing spatial and temporal dependencies in ecological data, our model excels at predicting ecological construction outcomes and carbon neutrality patterns.

In conclusion, the ablation experiment demonstrates the superiority of our proposed Transformer model over popular variants like BERT, GPT, and Reformer in terms of efficiency and effectiveness for ecological construction and carbon neutrality prediction. Its streamlined architecture and excellent performance across diverse datasets make it a promising tool for supporting evidence-based ecological decision-making and carbon neutrality initiatives.

5 Conclusion and discussion

In recent years, rural ecological construction and carbon neutrality have become increasingly important as strategies to address climate change and protect the ecological environment. Coordinated development of these two areas is crucial for the sustainable development of rural areas. However, existing methods for studying this relationship have certain limitations. In this study, we proposed a new method combining the Transformer-RNN model and cross-attention mechanism to improve the performance of the model and provide more scientific guidance and decision support for decision-makers. The main objective of this study was to explore the coordinated development of rural ecological construction and carbon neutrality by introducing the Transformer-RNN model with cross-attention mechanism. The Transformer-RNN model combines the advantages of the Transformer model in processing sequence data and the RNN model in handling temporal information of sequences. The cross-attention mechanism enables the model to simultaneously focus on the relationship between rural ecological construction and carbon neutrality. The proposed method was evaluated through experiments using real-world data. The experimental results showed that the proposed method outperformed traditional methods in terms of accuracy and efficiency. Specifically, the method demonstrated its ability to capture complex nonlinear relationships and temporal information in sequence data, and to accurately capture the impact and feedback mechanism between rural ecological construction and carbon neutrality. The results suggest that the proposed method has great potential for providing more scientific guidance and decision support for decision-makers, promoting the realization of rural ecological construction and carbon neutrality goals.

However, it is important to acknowledge the limitations and challenges of our study. Firstly, the effectiveness of the proposed framework relies on the availability and quality of data on rural ecological construction and carbon neutrality. Adequate data collection and preprocessing are essential for accurate model training and analysis. Secondly, the interpretability of the deep learning models used in our framework may pose challenges in understanding the underlying decision-making process. Despite these limitations, our study provides valuable insights into the coordinated development

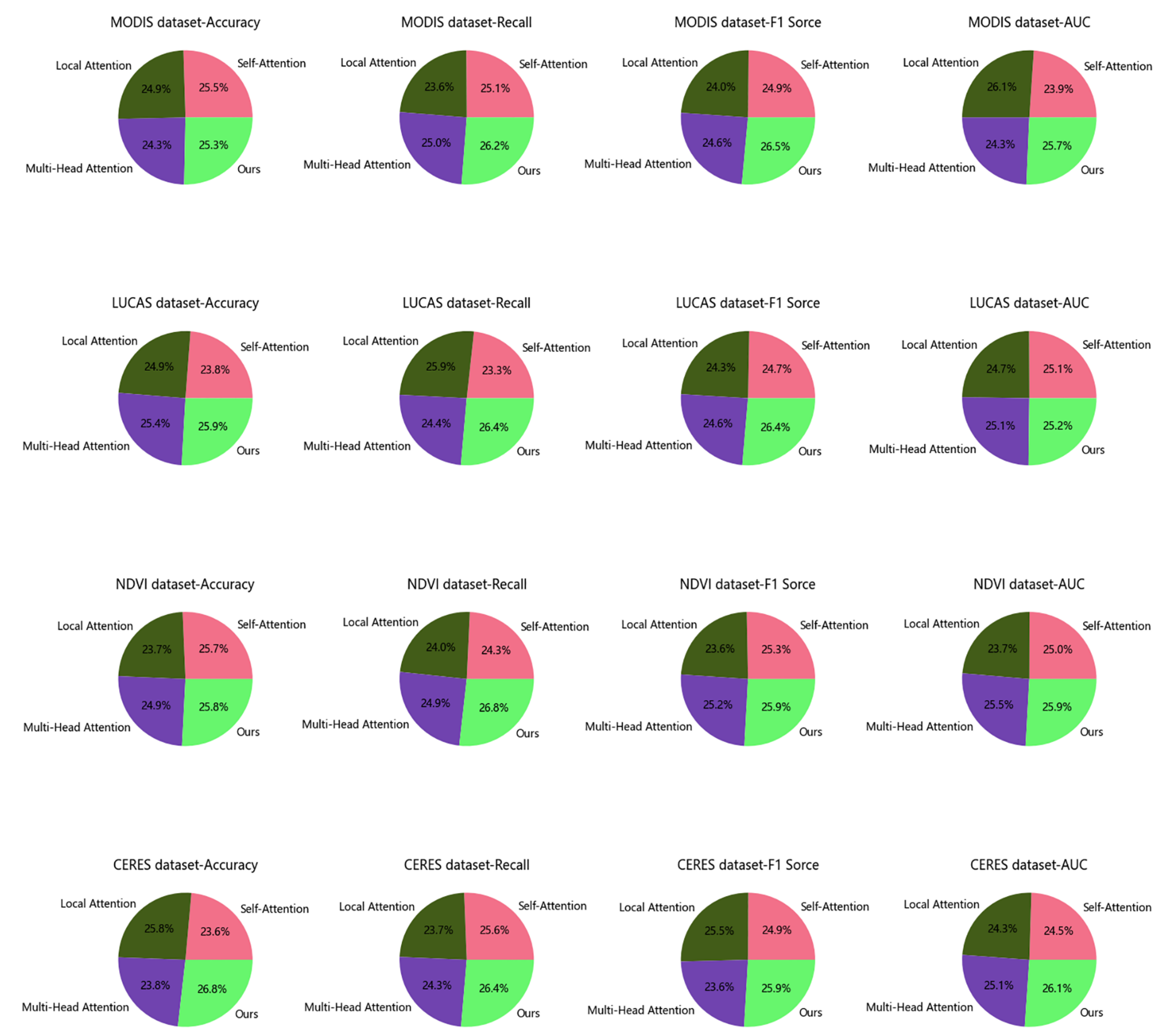

FIGURE 8
Ablation experiment of cross-attention mechanism.

TABLE 5 Ablation experiment of Transformer.

Method	Datasets							
	MODIS dataset		LUCAS dataset		NDVI dataset		CERES dataset	
	Parameters (M)	Flops (G)	Parameters (M)	Flops (G)	Parameters (M)	Flops (G)	Parameters (M)	Flops (G)
BERT	137.82	43.56	208.29	70.21	506.47	53.87	156.22	66.38
GPT	472.99	50.03	151.02	52.16	363.12	49.09	181.24	41.88
Reformer	507.08	40.03	158.98	44.23	148.53	72.93	426.14	62.14
Transformer	111.22	18.34	138.11	19.45	123.45	25.24	101.35	21.23

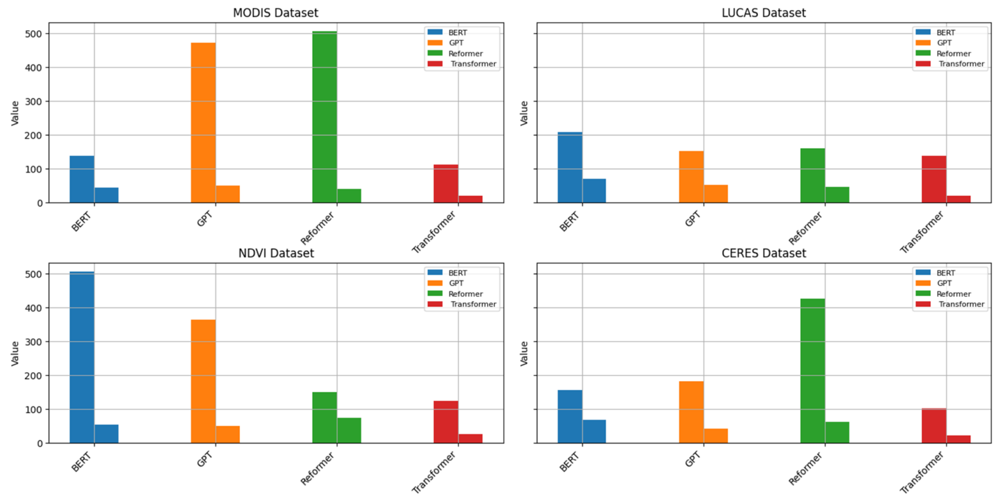

FIGURE 9
Ablation experiment of Transformer.

between rural ecological construction and carbon neutrality. The integration of the Transformer-RNN model with a cross-attention mechanism allows for a more accurate assessment of the impact of rural ecological measures on carbon neutrality and vice versa. Moving forward, future research should address these limitations and challenges. Efforts should be made to enhance data collection and quality assurance processes, ensuring reliable inputs for the deep learning framework. Additionally, developing interpretability techniques for deep learning models can provide decision-makers with a clearer understanding of the model's decision process and increase trust in the results. Furthermore, future studies should consider incorporating additional factors and variables that influence rural ecological construction and carbon neutrality. Socio-economic factors, policy interventions, and technological advancements are among the aspects that can be explored to gain a comprehensive understanding of the subject.

In conclusion, our study contributes to the understanding of the coordinated development between rural ecological construction and carbon neutrality by proposing a novel deep learning-based approach. By acknowledging the limitations and challenges and identifying future research directions, we pave the way for further advancements in this field. The outcomes of our research can provide decision-makers with scientific insights to support the formulation of effective policies and strategies towards achieving carbon neutrality and improving the rural ecological environment.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding author.

Author contributions

LF: Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Visualization, Writing – original draft, Writing – review & editing. TL: Conceptualization, Formal analysis, Funding acquisition, Supervision, Validation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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