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Research on Enterprise Digital Agility Based on Machine Learning:
An Evaluation of Green Financial Technology

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ABSTRACT

To help enterprises quickly adapt to the environment of green finance, a technology innovation performance prediction method based on machine learning is proposed to improve digital convenience. Firstly, by analyzing scientific and technological innovation, the authors design four characteristics: the number of theses, the quantity and quality of projects, the level of technology transformation, and the value of commercialization. Then, according to the above features, a feature processing method based on improved attention mechanism is proposed to deeply explore the internal relationship between the four features. Finally, a performance evaluation method is used based on the temporal convolution network (TCN) that can predict the performance of scientific and technological innovation by inputting enhanced features. The experiment demonstrates that the proposed method can reach 0.846, 0.869, and 0.851 in terms of the precision, recall, and H value, respectively, which can help enterprises predict the performance and improve the electronic convenience of enterprises.

KEYWORDS

digital management, green finance, improved attention, scientific and technological innovation

INTRODUCTION

Research on Enterprise Digital Agility Based on Machine Learning: An Evaluation of Green Financial Technology

Amidst the advancements in green finance, the competition in the realm of science and technology is escalating with intensity. How to quickly gain advantages in the competitive market has become an issue in the management of the Science and Technology Innovation (STI) industry (Li et al., 2020; Umar & Safi, 2023). As the most intuitive method to evaluate the degree of development, performance appraisal is the key to assessing the scientific and technological innovation in green finance, and this has the power to promote its development.

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Scientific and technological innovation stands as the sole pathway towards the development of green finance. Regular and quantitative evaluation of the performance of scientific and technological innovation can enhance both efficiency and compliance (Chen et al., 2023; Wang et al., 2021). Through the novel technologies, regulators can more quickly and accurately obtain and process a large amount of STI data and improve the efficiency and precision of regulatory work. At the same time, assessing sci-tech innovation can also support regulators in implementing more effective green finance policies and regulations for the sustainable development of the financial market. In addition, through the establishment of environmental data platforms, risk assessment models, and early warning systems, potential environmental and climate risks can be detected and responded to early, reducing the vulnerability and protecting the interests of financial institutions and investors (Ge et al., 2022). It is a complex task to assess the scientific and technological innovation capability of green finance, so there are many difficulties. First of all, scientific and technological innovation involves a wide range of fields and different types of technologies, each of which has its own unique characteristics and evaluation criteria. Therefore, the assessment of S&T innovation capability is often subjective and diverse (Wang et al., 2022). Secondly, scientific and technological innovation is a long-term process, and its results and impacts often need to be revealed over a relatively long time scale. Due to the uncertainty and evolution of technology, it is necessary to consider the future potential and development direction to assess scientific and technological innovation capability, which increases the uncertainty and difficulty of assessment. However, innovation activities often contain many unstructured and implicit factors, which are difficult to be quantified and measured (Ibrahim et al., 2022; Liu & Wang, 2023). Therefore, data acquisition and quantification are important challenges when assessing the performance of STI. Finally, due to the rapid evolution and reform of green finance, the methods for assessing the performance of STI need to suit the rapidly updated technology, and it is difficult to use a single method to evaluate the performance.

The development of machine learning provides a novel research approach for evaluating the performance of scientific and technological innovation in green finance. Based on the above difficulties (Aggarwal & Thakur, 2013), many scholars have studied it. According to different needs, different indicators are set to assess scientific and technological innovation (Curzi et al., 2019). First, key performance indicators (KPIs) are set to evaluate the performance of individuals or organizations in the field of STI. KPIs can be quantitative and measurable indicators that are used to assess the degree to which performance targets are being achieved. Second, by setting clear goals and standards, KPIs facilitate the evaluation of employees' performance in effectively carrying out their work tasks and accomplishing their goals. Employees set the goals together with management and regularly track and evaluate the achievement of the goals. Thirdly, the assessment of individuals or organizations' contributions and achievements at work centers on the results and outcomes they accomplish (Ali et al., 2019). The evaluation process places emphasis on appraising the tangible impact of employees on organizational goals and value creation. Fourthly, the evaluation of an individual or organization's performance entails observing their behavior, working methods, and exhibited skills and attitudes within their job role. This approach concentrates on assessing behaviors and working styles to discern their influence on technological innovation (Memon et al., 2019). By employing these four performance measures, the evaluation of STI performance in the context of green finance can be approached quantitatively (Al-Jedaia & Mehrez, 2020). In the realm of machine learning, researchers can utilize regression models, classification models, time series models, and association analysis mining models to address this task. For example, when the regression model is used to continuously predict scientific and technological innovation in green finance through historical data, the innovation capability can be directly quantified as the research output, the patent applications, the innovation partnerships, and other entities. When the classification model is used, the STI of individuals or organizations can be directly classified and finally quantified to different levels of innovation capability. These methods and indicators can be selected and combined according to the specific context and objectives of STI to evaluate all aspects of STI. However, there are many problems with these methods. Existing scientific and technological innovation performance assessment methods rely only on a single model for simulation, which cannot fully reflect the achievements of scientific and technological innovation (Liu et al., 2021).

To address this issue, the authors study the performance evaluation method of green fintech innovation based on machine learning. The main research contributions are as follows:

1. According to the characteristics of green finance, the authors quantify and extract different features, which can represent the performance of STI, and propose a feature processing method based on an improved attention mechanism.
2. According to the above features, the authors propose a performance evaluation method based on the temporal convolution network (TCN) to fully highlight the key points in the features and conduct performance evaluation.
3. In the experiment, the authors' method outperforms the performance of many excellent models and can accurately evaluate the performance of STI in green finance.

RELATED WORKS

Indeed, performance appraisal encompasses both retrospective and prospective perspectives. The past orientation involves a fair assessment of employees' or organizations' past accomplishments using historical data as a basis, and commensurate compensation is awarded accordingly. Future-oriented refers to finding out the relationship between performance and various influencing factors according to the excavated assessment results and finding out the methods to improve performance accordingly.

The application of performance evaluation methods has been very extensive and mature, and scholars from various countries have conducted corresponding studies on the performance evaluation in various industries. Decramer et al. (2012) took the performance of employees in universities and educational institutions in low-income countries as the research object, studied the relevant institutional elements of employees and their units, and obtained the important factors affecting the performance evaluation. Yu et al. (2014) employed the Defell to obtain the evaluation index system of university education. Jauhar et al. (2017) utilized DEA to compute the relative efficiency of Indian higher education institutions and measured the relative productivity for different departments according to teaching and research, which not only considered the environmental factors, but also improved the calculation speed. Abdellatif and Asma (2019) designed a knowledge management system. In view of the impact of knowledge management on performance, they proposed the KMS theory, conducted a survey on universities, and used regression analysis to calculate the weight of indicators. Zeng et al. (2020) used adaptive ability to test the factor structure of self-reported adaptive measurement and performance-based tasks, but a multi-feature method is needed to further evaluate the validity of the adaptive measurement structure. Milkhatun et al. (2020) conducted a performance assessment on the lecture quality of college teachers' performance and used the K-Medoids algorithm to conduct cluster analysis to mine the factors affecting the classroom quality of teachers. Nojavan et al. (2021) evaluated the performance of educational units by the fuzzy analytic hierarchy process. Firstly, the fuzzy Servqual questionnaire was used to collect students' expectations and suggestions for educational units, and the fuzzy analytic hierarchy process and fuzzy Topsis were used to calculate the index weight and service quality ranking, respectively.

Considering that performance appraisal often contains a large number of subjective judgments, many researchers have begun to use some objective methods to evaluate and assess the performance. Kirimi and Moturi (2016) employed a data mining algorithm to extract insights into employees' work performance, enabling the evaluation and prediction of their performance levels. This analysis validated that employees' performance is indeed influenced by factors such as educational background, major, marital status, and other pertinent variables. Siahaan (2021) used skills, attitude, responsibility, absence, and other aspects as evaluation indicators of contract employees and used machine learning methods to evaluate their performance. Joshi et al. (2022) fully studied several factors that affect performance at work and quantified them into some indicators. Through these indicators, they used the XGBoost algorithm to achieve an objective evaluation of performance.

GREEN FINTECH INNOVATION PERFORMANCE METHOD BASED ON MACHINE LEARNING

Feature Selection of Green Fintech Innovation

In the realm of green finance, scientific and technological innovation (STI) finds manifestation in diverse facets, including R&D investments, intellectual property rights, innovation capacity, innovation culture, technological prowess, innovation outcomes, adaptability to external environmental changes, technology transformation, and commercialization capabilities, among others. To holistically assess scientific and technological innovation in the context of green finance, the authors have quantified four essential characteristics of green fintech-related papers: number of relevant papers, projects, technology transformation level, and commercialization value. These characteristics are derived from the aforementioned aspects and are depicted in Figure 1.

The amount of relevant papers can indicate the innovation capability of green fintech. This feature can reflect the research and academic output of an organization or individual in the field of green fintech, indicate the overall scale of academic research activities in the field, and also reflect the contribution and popularity of an organization or individual in the academia as well as the influence and leading role of academia. The number of papers in top journals or conferences can best reflect the innovation ability of science and technology, which directly reflects the recognition of academia and the output of high-quality research.

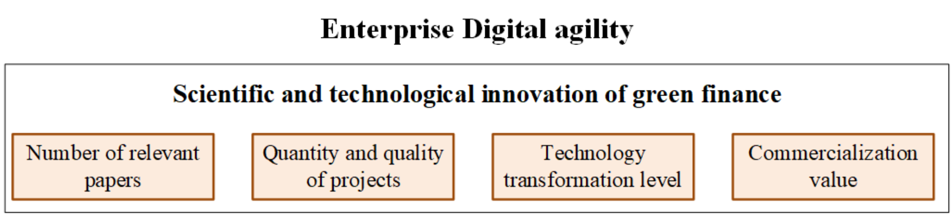
The number and quality of projects can reflect the level of activity and research investment in green fintech innovation as well as the importance and resource support of the organization to green fintech innovation. At the same time, it also indirectly reflects the level of scientific research, innovation, theoretical contribution, practical application, etc.

The feature of technology transformation level is a comprehensive feature, which can evaluate the technology transfer of green fintech research results and show the application scope and influence of research results in the market. It can help evaluate the practical application and commercialization degree of green fintech innovation, further guide the technology transformation strategy, and improve the effect of technology transformation.

The attributes of commercialization capability serve as a direct and compelling means to gauge the accomplishments of scientific and technological innovation in the field of green finance. It aptly portrays the positioning of the green finance market, the precise comprehension of market demands, the capacity for market expansion, and the extent of business model innovation.

This feature can help evaluate the commercialization potential and effect of the organization, guide the commercialization strategy, and improve the commercialization capability so as to realize the commercialization value of green fintech innovation.

Figure 1. Features of STI in green finance



Green Fintech Innovation Feature Processing Method Based on Improved Attention Mechanism

The assessment task of scientific and technological innovation in green finance needs to be comprehensively evaluated from multiple perspectives and aspects. Therefore, from different perspectives, the authors extracted four characteristics: the number of green fintech-related papers l, the number and quality of projects p, the level of technology transformation t, and the commercialization value f. In order to explore the relationship between these features and further express the level of scientific and technological innovation in green finance, the authors propose a feature processing method based on improved attention mechanism.

For the four different features of l, p, t, and f, the authors first perform a stitching operation, and the formula is as follows:

$$V = Cat\left[l, p, t, f\right] \quad (1)$$

where Cat represents the feature splicing function. Using the stitching operation, the authors retain all the features of the four features and also retain the window for deep mining of feature depth information.

First, in the process of encoding feature V by using the improved self-attention mechanism, feature v_i of different groups is assigned a number $p = (p_1,..., p_n)$, as shown in the formula:

$$v_i = v_i + p_i \quad (2)$$

However, considering that feature V is the result of splicing, absolute position coding is not applicable. Thus, the authors design a feature relative position coding.

For any feature v_i and v_j, the distance is computed as follows:

$$I^v = g\left(v_i - v_j\right) \quad (3)$$

where g(x): R→{ρ∈zl-β≤ρ≤β}. a learning characteristic parameter $r_{i,j}$ is intended to be set up to express the relative position of v_i and v_j, as shown in the formula:

$$r_{i,j} = p_{I^v} \quad (4)$$

Then, when implementing the self-attention mechanism of features, location coding can be added as shown in the formula:

$$b_{i,j} = \left(v_i W^Q\right) r_{i,j}^T \quad (5)$$

$$e_{i,j} = \frac{\left(v_i W^Q\right)\left(v_j W^V\right)^T + b_{i,j}}{\sqrt{d_c}} \quad (6)$$

$$z_i = \sum_{j=1}^{n} softmax\left(e_{i,j}\right)\left(x_j W^V + p_{i,j}^V\right) \quad (7)$$

where z_i represents the coding result of feature self-attention mechanism.

After the feature spatial position coding is completed, firstly, the self-attention mechanism is improved by using the relative position coding results, and the structure is shown in Figure 2. The position information of image visual features is fully utilized to realize the feature enhancement. Then, the improved self-attention mechanism is used to form the multi-head attention module (MHSA), and the process is shown in the formula:

$$MultiHead(Q,K,V) = [head_1,\ldots,head_n] \tag{8}$$

$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V) \tag{9}$$

where *Attention* represents the improved self-attention mechanism. Finally, the MHSA module is used to design the Transformer coding architecture based on convolution. The architecture includes Transformer branch and convolution branch, and the structure is shown in Figure 3. Through the extracted global features, interpolation, pooling, and other algorithms, the mutual

Figure 2. Improve self-attention structure

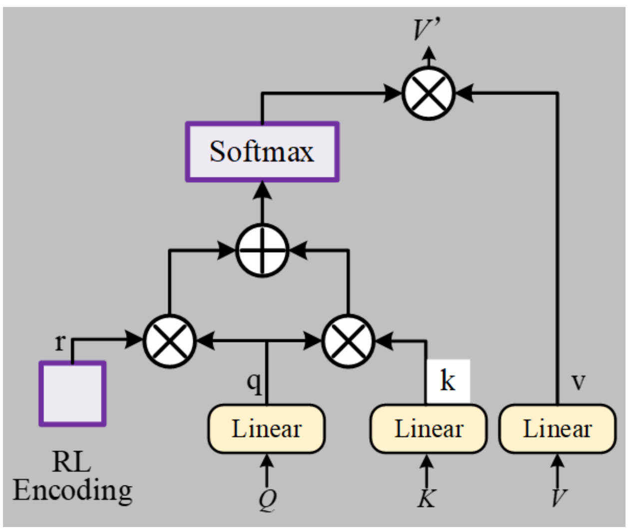
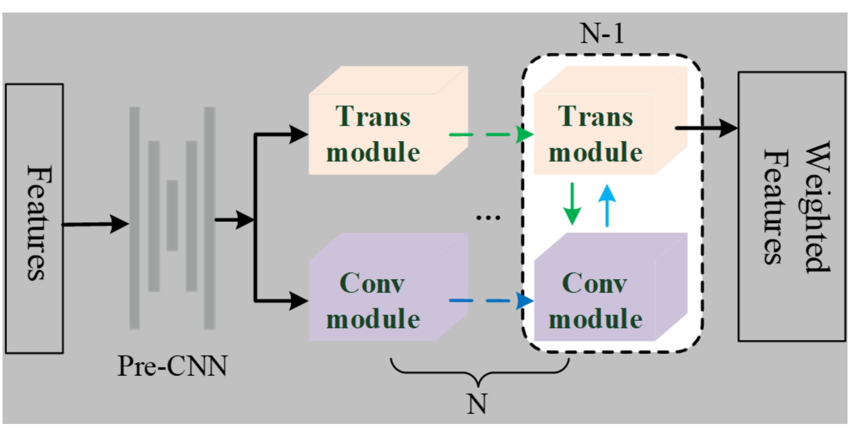


Figure 3. Structure of Transformer branch and convolution branch



guidance of global and local features is realized to enhance the saliency of local features of Transformer branches.

Performance Appraisal Method Based on TCN

In obtaining the enhanced features, the authors still need to fully consider the performance of STI in different periods. Therefore, they propose a performance appraisal method by TCN.

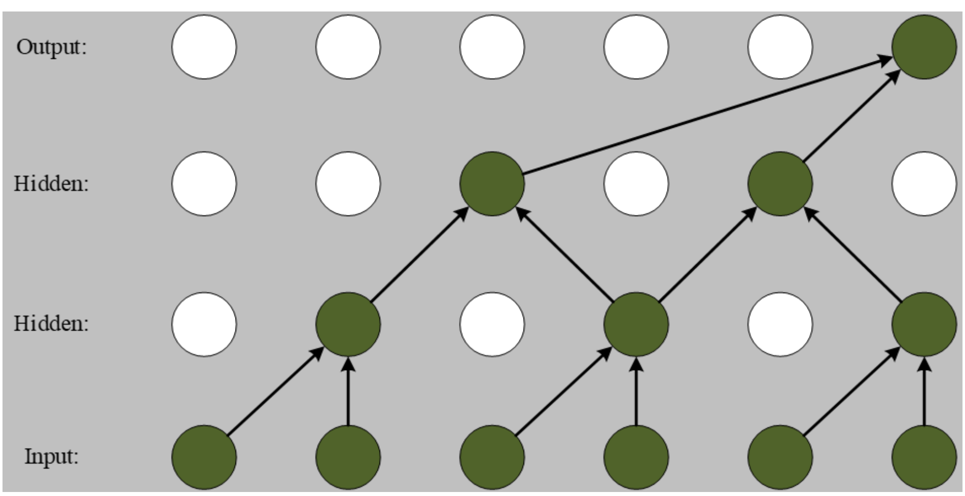
The network structure of TCN is composed of stacked one-dimensional fully connected convolutional layers, each of which has a unique causal convolutional structure, as shown in Figure 4. It can accept input sequences of any length and output the same length. The output at time T is convoluted only with elements before T, which avoids the influence of future information.

$$F\left(s\right)=\sum_{i=0}^{k-1}f\left(i\right)z_{s-i} \tag{10}$$

where z is the input, f is the filter, and k is the size of the convolution kernel.

Considering the continuously adding layers, the amplitude of the gradient update of the neural network is too large during the training process, resulting in the weight changing too fast, which leads to the network degradation effect of the model; that is, the model performs poorly when processing new data, because it does not capture the potential relationship between the training data well. The convolutional layer in TCN is used to capture the dependencies of sequences and reveal the hidden relationships within the data. Meanwhile, the residual connection reduces the network depth and parameters and improves the generalization ability and training efficiency of the model. The model can give priority to the important feature information related to the data in the hidden layer and ignore other irrelevant information. By calculating the importance of each element in the feature and assigning different weights to different features according to the importance, the model can pay attention to the content of other positions in the time series and use this content as help guidance to increase the prediction accuracy. Finally, the calculation results of the TCN network layer are output through the dense layer, and the output results are the prediction value of the innovation performance for green fintech.

Figure 4. Structure of TCN



EXPERIMENTS

Dataset and Implement Detail

The authors use the green finance dataset (https://www.zenodo.org/record/4592559, doi: 10.5281 / zenodo. 4592559) to test the effectiveness of the method. Their experimental setup is shown in Table 1. The authors set the weight decay term of the model to 0.0001 and used Adam as the optimizer.

Since the authors' method will directly obtain an evaluation value of performance, this becomes a regression task. They use precision, recall, and H-mean as the evaluation criteria of their method. Among them, the calculation formula of positive and negative samples of regression prediction is as follows:

$$V_P = \frac{V\left(N_{gt} \cap N_{pr}\right)}{V\left(N_{pr}\right)} \tag{11}$$

$$V_R = \frac{V\left(N_{gt} \cap N_{pr}\right)}{V\left(N_{gt}\right)} \tag{12}$$

$$V_{H-mean} = \frac{V_P \times V_R}{V_R + V_R} \tag{13}$$

where *pr* represents the value predicted by the model and *gt* represents the real value labeled by the dataset. The higher the values of precision, recall, and H-mean are, the better the model is.

Comparison With Other Methods

The authors conduct the performance experiments of their methods on the green finance dataset. Firstly, according to the model structure in Figure 3, they train four feature models. The model input is the number of papers related to green fintech, the number and quality of projects, technology transformation level, and commercialization value. The loss function curve is shown in Figure 5. It can be found that the authors' model basically meets the training expectation in the 25th epoch.

At the same time, the authors selected some excellent regression models, such as CNN-LSTM (Livieris et al., 2020), MLP (Tolstikhin et al., 2021), and Transformer (Han et al., 2021). The performance of Informer (Zhou et al., 2021) and Dlinear (Zeng et al., 2020) are compared in Table 2 and Figure 6. When compared with other methods, the authors' method can obtain higher precision, recall, and H values, and these can reach 0.846, 0.869, and 0.851, respectively. Compared with CNN-LSTM and MLP, their method can improve the precision, recall, and H value by more than 0.1. Compared with Transformer, the H value of this method is also superior by nearly 0.05. Finally,

Table 1. Implementation parameters

Types	Parameters
CPU	i7-13700h
GPU	Rtx 3060
Deep learning method	Pytorch
Epochs	30
Batch size	64
Initial learning rate	0.008
Momentum	0.98

Figure 5. The loss of the trained model for features

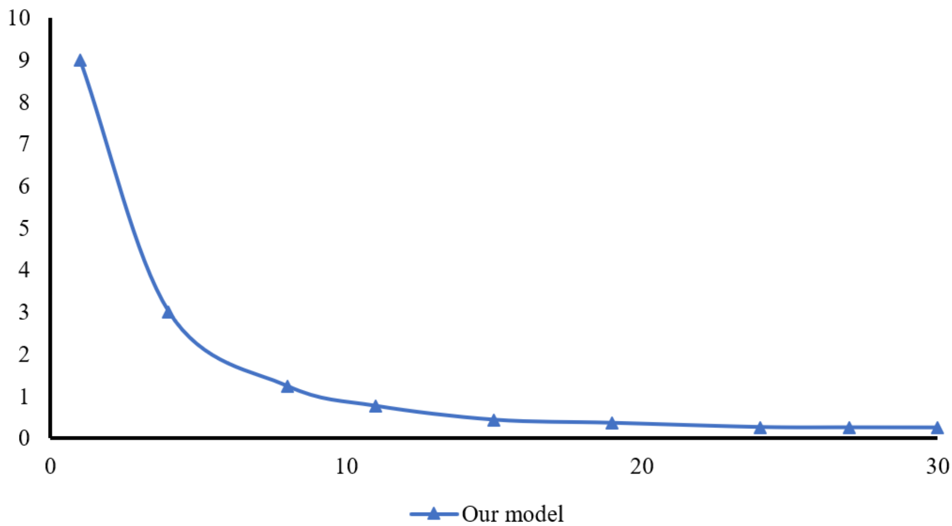
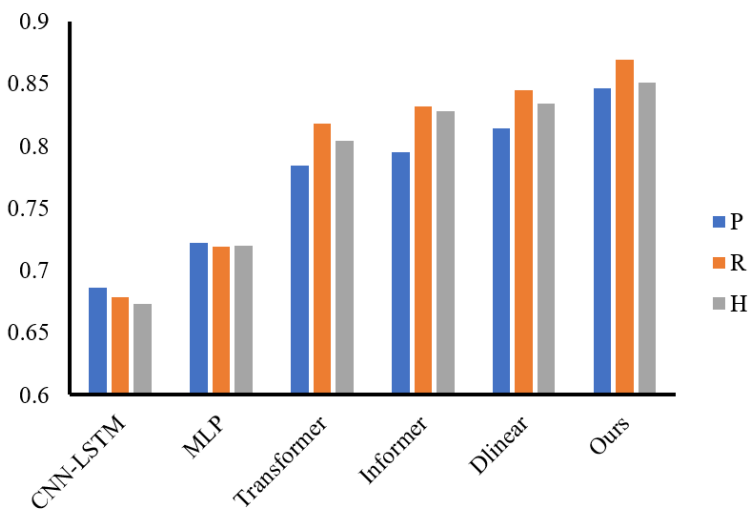


Figure 6. The loss of the trained model for features



when compared with the advanced Informer and Dlinear, this method still outperforms them, with a lead of more than 0.015 in each metric.

Ablation Experiments

The authors used four characteristics: number of green fintech-related papers, number and quality of projects, level of technology transformation, and value of commercialization. To verify the role of these features in the methodology, they performed ablation experiments on these four features.

The results in Table 3 can conclude that this model can get better performance with more and more features, which means that the authors promote the accuracy of the model by fusing four different features and also proves the effectiveness of the selected features.

Table 2. Model comparison

Methods	P	R	H
CNN-LSTM	0.686	0.678	0.673
MLP	0.722	0.719	0.720
Transformer	0.784	0.818	0.804
Informer	0.795	0.832	0.828
Dlinear	0.814	0.845	0.834
Ours	0.846	0.869	0.851

Table 3. Results of different time for prediction

Number of papers	Quantity and quality of projects	Level of technology conversion	Commercialization value	H-mean
○				0.786
	○			0.781
		○		0.776
			○	0.769
○	○			0.802
○		○		0.817
○			○	0.814
	○	○		0.809
	○		○	0.813
		○	○	0.803
○	○	○		0.835
○		○	○	0.839
○	○		○	0.841
	○	○	○	0.837
○	○	○	○	0.851

Discussion

Through the experiments referenced in prior sections, the authors fully demonstrated the performance of the method. Firstly, the method achieved the highest evaluation index value. Compared with Transformer and other methods, the authors further explored the relationship between different features and different weights by constructing the connection between Transformer and CNN, which was the reason why their method was better. In addition, when comparing the performance of different features, the authors could also clearly indicate the improvement brought by each feature. Through the improved attention mechanism and relative position coding, the authors strengthened the internal relationship between features and optimized the performance of STI in green finance through the internal relationship. The proposed method was very convenient and accurate, and it fully met the performance task of STI in green finance, as well as improved enterprise digital agility.

CONCLUSION

In order to help enterprises strengthen their management ability and improve the convenience of electronic innovation, the authors propose the prediction method of STI performance based on machine learning. By analyzing the characteristics of STI, four different features are obtained to achieve effective quantification of STI. Then, a feature processing method based on an improved attention mechanism and a performance assessment method based on the temporal convolution network (TCN) are proposed to predict the performance of STI in green finance by four features. The experiment's results show that the method can reach the precision of 0.846, the recall of 0.869, and the H value of 0.851, which exceeds the advanced methods in the world. In the future, the authors will further explore more information that affects the performance of STI and will focus on the role of the attention mechanism on multi-features.

CONFLICTS OF INTEREST

All the authors declare that they have no conflict of interest.

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