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ARTICLE

Forecasting Agricultural Trade Based on TCN-LightGBM Models: A Data-Driven Decision

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ABSTRACT

Facing the increasing complexity and dynamic fluctuations of the global agricultural trade market, accurate forecasting plays a key role in supporting agricultural policy formulation, stabilising the market and optimising resource allocation. In order to increase the precision and stability of agricultural trade predictions, this research suggests a hybrid model built on a temporal convolution network (TCN) and a lightweight gradient boosting tree (LightGBM). The TCN module effectively captures the long-term dependence characteristics of time series data through dilated convolution, which improves the model's ability to identify seasonal and periodic trends. The LightGBM module, on the other hand, makes use of the characteristics of gradient boosting decision trees and excels at efficiently handling nonlinear relationships and avoiding overfitting. Experimental results show that the TCN-LightGBM model outperforms traditional models in terms of mean square error (MSE), mean absolute error (MAE) and prediction accuracy. Specifically, compared with ARIMA, LSTM, TCN alone or LightGBM alone, TCN-LightGBM achieves a prediction accuracy of 91.3% on the test data, with MSE and MAE of 0.021 and 0.115 respectively, significantly improving prediction accuracy and stability. In addition, parameter sensitivity analysis shows that the TCN-LightGBM model maintains a highly consistent prediction trend under different parameter configurations, which

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verifies the robustness of the model and its practical application value. This study provides a data-driven decision support tool with high accuracy and strong stability, providing a new solution for agricultural trade forecasting and other complex time series prediction tasks.

Keywords: Agricultural Trade Forecasting; TCN; LightGBM; Data-Driven; Decision Support

1. Introduction

With the acceleration of the process of globalisation, the trade of agricultural products has become increasingly important in the global economy. Ensuring a balance between supply and demand in the agricultural market has a profound impact on food security, economic development, and trade policy formulation [1]. However, the agricultural market is affected by multiple factors, such as climate change, policy intervention, and fluctuations in supply and demand. These factors together form a complex and dynamic system, making the prediction of agricultural trade a challenging task. Highly accurate agricultural trade forecasts can not only help governments formulate sound food policies but also provide traders and agricultural producers with strong decision-making support, reduce market risks, and improve resource utilisation efficiency [2]. Therefore, it is of great practical significance to study efficient models suitable for agricultural trade forecasting.

At present, the methods of agricultural trade forecasting can be divided into traditional statistical models and machine learning-based models. Traditional statistical methods, such as the autoregressive integrated moving average model (ARIMA) in time series analysis, are widely used in the field of agricultural forecasting [3]. However, these models are often based on linear assumptions and are difficult to deal with the nonlinear and highly volatile data characteristics in agricultural markets [4]. Machine learning-based models, especially deep learning models such as long short-term memory networks (LSTM), can better handle time dependence. However, their training process is complex and prone to overfitting. Although these methods have improved prediction performance to some extent, they still face challenges such as high computational costs, long model training times, and insufficient adaptability to large-scale data.

In the current research on agricultural trade forecasting, the deficiencies of existing methods are mainly concentrated in the following aspects: First, traditional statistical models and some simple machine learning models fail to make full use of the time-dependent and complex nonlinear characteristics of the data, resulting in limited prediction accuracy. Second, although deep learning models have strong nonlinear modeling capabilities, their training efficiency is low and computational resources are consumed, making it difficult to promote them in practical applications [5]. Finally, existing models have deficiencies in generalisation ability and stability and are easily affected by outliers and extreme events. Therefore, the development of a prediction model that can balance nonlinear modelling ability and efficient calculation has become an urgent problem to be solved in the field of agricultural trade forecasting.

This paper proposes a hybrid model based on a TCN and a LightGBM for agricultural trade forecasting. The model combines the advantages of TCN in time series feature extraction, which can efficiently capture long-term dependencies while avoiding the gradient disappearance problem of the RNN structure through dilated convolution [6]. LightGBM is an efficient ensemble learning model that can handle nonlinear relationships and has high training efficiency. Compared with traditional deep learning models, the TCN-LightGBM model greatly reduces the computational cost while ensuring prediction accuracy and has good scalability and practicality.

In addition, this study also carries out more rigorous revisions and optimisations of the data selection and analysis process. By using the latest agricultural trade data covering multiple countries and regions, we have improved the timeliness and representativeness of the data and cleaned and standardised the data to ensure the reliability of the analysis results. According to the experimental findings, the TCN-LightGBM model performs better in agricultural trade forecasting than other machine learning techniques and conventional statistical approaches, particularly in terms of prediction accuracy and model stability.

In order to increase forecast accuracy and model application, this work aims to develop a computationally efficient and time-dependent agricultural trade prediction model. This research illustrates the benefits of the TCN-LightGBM model in agricultural trade forecasting by contrasting it with other machine learning models and conventional techniques. It is hoped that this study will provide new ideas for the field of agricultural trade prediction and lay the foundation for further research in related fields.

2. Overview of Theoretical Foundations and Methods

In the modern agricultural economy, agricultural trade forecasting is key to ensuring global food security, formulating sound trade policies, and optimising resource allocation. However, forecasting is challenging because agricultural markets are affected by many complex factors, such as climate change, supply and demand, and policy interventions. Traditional forecasting methods often fail to effectively capture these complex time series characteristics, resulting in low forecasting accuracy. For this reason, hybrid models based on time series analysis and machine learning have gradually become a research hotspot in order to achieve higher-precision agricultural trade forecasting [1]. The TCN-LightGBM model proposed in this paper combines the advantages of the TCN and the gradient boosted tree (LightGBM) and aims to improve the prediction accuracy through a data-driven approach.

A deep learning model called TCN was created specifically to handle time series data. TCN uses one-dimensional convolution operations to analyze time-series data, in contrast to conventional recurrent neural networks (RNNs). At the core of TCN is dilated convolution, which can quickly capture long-term dependencies while preserving the chronological order of the sequence. The TCN's causal convolution structure prevents future information from leaking and guarantees that the output is exclusively dependent on the past and present data points, making it appropriate for prediction tasks [7]. TCN is excellent at collecting intricate time series characteristics because of its dilated convolution property. It can efficiently learn both short-term variations and long-term patterns in time series by varying the dilation factor to widen the receptive field. As a result, TCN is often used in domains like weather research and financial forecasts, and it also offers fresh concepts for agricultural trade forecasting.

The gradient boosted decision tree (GBDT) model, created by Microsoft Research, is implemented by LightGBM with the goal of increasing the model's prediction accuracy and training speed. LightGBM accelerates model training through techniques such as histogram binning and leaf node splitting, and is especially suitable for processing high-dimensional and large-scale data. Compared with other GBDT implementations (XGBoost), LightGBM has better memory usage efficiency and lower computational costs [8]. Its unique leaf node splitting strategy can more accurately handle the nonlinear relationship of data. LightGBM is an integrated learning framework that gradually optimises the objective function through multiple iterations, which makes the model more generalisable on complex datasets. Therefore, LightGBM may further enhance the prediction outcomes by efficiently capturing the intricate interactions between many components in the job of agricultural trade prediction.

Data-driven prediction methods have gradually emerged with the development of big data and artificial intelligence technology. Unlike traditional prediction methods based on theoretical models, data-driven methods rely on the mining and analysis of large amounts of historical data and are particularly suitable for use in situations with abundant information [9]. The core idea of data-driven prediction methods is to use machine learning algorithms to automatically learn complex patterns and relationships from data. These algorithms include deep learning models, tree models, etc., which have powerful adaptability and nonlinear modeling capabilities [10]. By combining large-scale historical data and machine learning techniques, data-driven methods can achieve remarkable results in data feature extraction, pattern recognition and prediction. This method has been successfully applied in fields such as finance, retail and transportation and provides new research ideas for the prediction of agricultural trade [11].

In summary, the TCN-LightGBM model used in this paper combines the advantages of deep learning and machine learning. The TCN module uses the convolution characteristics of the time series to extract time-dependent features, while the LightGBM module further refines the prediction of the extracted features through gradient-boosted decision trees. This method incorporates the latest techniques in data-driven prediction to deal with the complex nonlinear relationships and time-dependency issues in agricultural trade prediction, providing an innovative solution to improve prediction accuracy.

3. Model Construction and Method Design

In the prediction of agricultural trade, it is crucial to construct high-precision models that adapt to the characteristics of the time series. In order to improve the prediction accuracy and stability, we suggest a fusion architecture based on a TCN and a LightGBM model to capture the nonlinear and time-dependent aspects in agricultural commerce. The two primary modules of the model are the LightGBM for regression prediction and the TCN for time series feature extraction [12]. Combining the two modules improves performance in complicated time series data by utilizing their own capabilities.

3.1. Overall Architecture Design of the TCN-LightGBM Model

The overall architecture of the TCN-LightGBM model consists of two major modules, as shown in **Figure 1**. The input time-series data is passed through the TCN module for feature extraction. TCN constructs feature representations that depend on long time series using one-dimensional convolution operations and dilation factors [13]. These features are then passed to the LightGBM module for prediction, which gives full play to the advantages of LightGBM in processing high-dimensional sparse data and complex feature combinations.

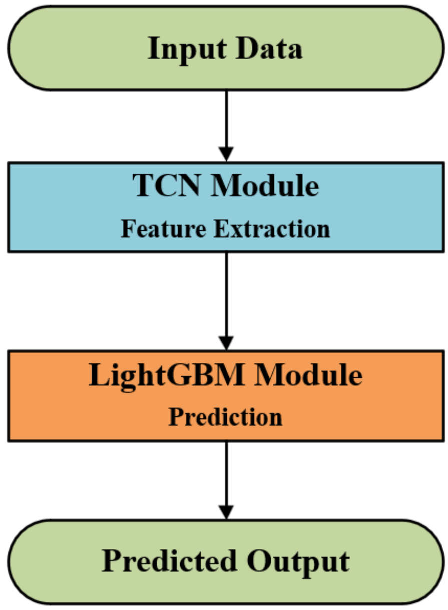

Figure 1. Overall architecture flowchart of the TCN-LightGBM model.

Figure 1 shows the main structure and data flow of the model. The output feature vector of the TCN module is connected to the input of the LightGBM module through a connection layer to achieve a seamless transition from feature extraction to regression prediction. The design goal of the entire model is to capture time series and quickly process high-dimensional features to improve the performance of agricultural trade predictions [14].

$$\widehat{y}_t = f\left(\text{LightGBM}\left(h_{TCN}\left(x_{t-N:t}\right)\right)\right) \tag{1}$$

Among them, $x_{t-N:t}$ represents the input sequence from time $t-N$ to t, h_{TCN} is the feature output by the TCN module, $f(\cdot)$ represents the prediction function of LightGBM, and finally the prediction result $\widehat{y}_t$ is obtained.

3.2. Structure of the TCN Module and Its Time Series Feature Extraction Function

The core of the TCN module is to use one-dimensional dilated convolution to effectively model long-term dependencies by expanding the perception. The dilation factor d controls the jump step of the convolution kernel, allowing the network to achieve a larger perception with fewer layers, which is suitable for capturing long-term trends[15]. Assuming the convolution kernel is k and the time step is t, the output of the lth layer is:

$$h_t^{(l)} = \sigma\left(\sum_{i=0}^{k-1} W_i^{(l)} \cdot h_{t-d\cdot i}^{(l-1)} + b^{(l)}\right) \tag{2}$$

Among them, $W_i^{(l)}$ is the convolution kernel weight, $b^{(l)}$ is the bias, and σ is the activation function. In order to avoid future data leakage, TCN uses causal convolution, that is, only using past and current data to ensure the rationality of the prediction results[16].

As can be seen from **Table 1**, different TCN hyperparameter configurations have a significant impact on the model's MAE. As the number of TCN layers increases, the modal's MAE gradually decreases, indicating that a deeper network hierarchy can capture richer time series features and thus improve prediction accuracy. Specifically, when the number of TCN layers is increased from 4 to 8, the MAE is reduced from 0.032 to 0.029, showing some improvement[17]. The choice of the convolutional kernel size also has a significant impact on the model performance. When the number of layers is 6 and the convolutional kernel size is 3, a relatively low MAE value (0.030) is achieved compared with other configurations, indicating that this configuration is more effective in capturing the local characteristics of the time series.

The dilation factor controls the stride of the convolutional kernel in the TCN model, which can expand the model's perception and adapt to the dependence of long time series. As the dilation factor is gradually increased (1, 2, 4, 8 to 1, 4, 16, 64), the model shows lower MAE at deeper configurations, which indicates that larger dilation factor configurations can effectively extract long-range time dependencies, thereby enhancing the model's ability to capture complex time series. However, too many layers may increase the computational overhead, so in practical applications, a trade-off between accuracy and computational efficiency is required. The final result determines that the configuration with 8 layers, a convolutional kernel size of 2, and an expansion factor of 1, 4, 16, and 64 is the optimal combination of hyperparameters for the TCN model.

Figure 2 illustrates the TCN model's feature extraction procedure when many dilated convolutions are in play. The long-term patterns and short-term oscillations of the data are progressively captured by the characteristics from input to output.

Table 1. The impact of TCN model hyperparameter configurations on prediction performance.

TCN Layers	Convolution Kernel Size	Dilation Factor	MAE
4	2	1, 2, 4, 8	0.032
6	3	1, 3, 9, 27	0.030
8	2	1, 4, 16, 64	0.029

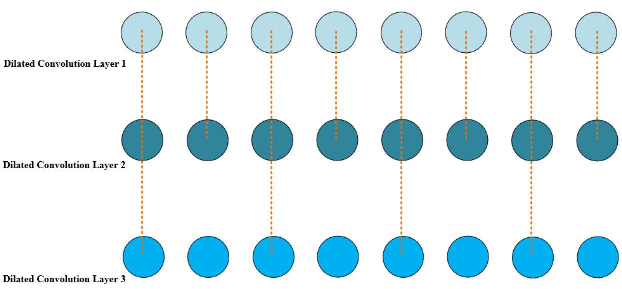

Figure 2. TCN layer with incremental expansion.

3.3. Integration of the LightGBM Module and Its Advantages in Prediction

As a gradient boosting decision tree model, LightGBM has fast training and a strong ability to handle nonlinear relationships. This module accepts features from TCN as input and uses the tree structure to disassemble complex feature combination relationships layer by layer[18]. For each leaf node j of the tree, the corresponding weight update formula is:

$$w_j^{(k+1)} = w_j^{(k)} - \eta \cdot \frac{\partial \mathcal{L}}{\partial w_j^{(k)}} \tag{3}$$

Where $\mathcal{L}$ is the loss function and η is the learning rate. LightGBM optimizes the loss function through continuous iterations to make the prediction more accurate.

Different parameter configurations of LightGBM have a significant impact on the MSE of the prediction performance, as shown in **Table 2** below. As the number and maximum depth of trees increase, the MSE of the model gradually decreases, indicating that a more complex model structure can learn potential patterns in the data more deeply, thereby improving prediction accuracy. When the number of trees is increased from 100 to 300, the MSE decreases from 0.015 to 0.011. Increasing the number of trees can effectively improve the prediction performance of the model. The learning rate setting plays a key role in the convergence speed and performance stability of the model. As the learning rate gradually decreases from 0.1 to 0.01, the MSE of the model gradually decreases, which shows that a smaller learning rate helps to refine the parameter optimization process and avoid training error fluctuations caused by too large a step size. Although a smaller learning rate will increase the training time, it can usually obtain more accurate prediction results.

Increasing the number of trees, modifying the maximum depth, and decreasing the learning rate may all greatly increase the LightGBM model's prediction accuracy. These parameter adjustments make LightGBM excel at processing high-dimensional features, further reducing the risk of overfitting. In particular, based on the complex features extracted by TCN, LightGBM can capture potential nonlinear relationships and effectively improve the overall model accuracy [19]. The final configuration (300 trees, maximum depth of 10, and learning rate of 0.01) was selected as the optimal combination, ensuring a balance between model accuracy and computational cost.

Table 2. The impact of different LightGBM parameter configurations on prediction performance.

Number of Trees	Maximum Depth	Learning Rate	MSE
100	6	0.1	0.015
200	8	0.05	0.013
300	10	0.01	0.011

3.4. The Fusion Method and Interaction Mechanism of TCN and LightGBM

The fusion of TCN and LightGBM adopts a two-stage serial structure, in which TCN is used to extract temporal features, and the high-dimensional temporal sequence features are then input into the LightGBM model for regression prediction. The temporal features provided by the TCN module include long-term trends and short-term fluctuations, and LightGBM further captures the nonlinear combination relationship between these features [20].

The core idea of this architecture design is to make full use of the time series feature extraction capability of TCN and the nonlinear fitting capability of LightGBM, so as to capture a richer level of information in complex agricultural trade data.

Figure 3 shows the step-by-step generation and transformation process of the features of each layer of the TCN-LightGBM model, which ultimately achieves the complementary advantages of time series and regression models in the prediction results. The experimental findings demonstrate that the model has made notable performance gains in the forecast of agricultural trade, and the characteristics retrieved by the TCN module successfully increase the prediction accuracy of LightGBM.

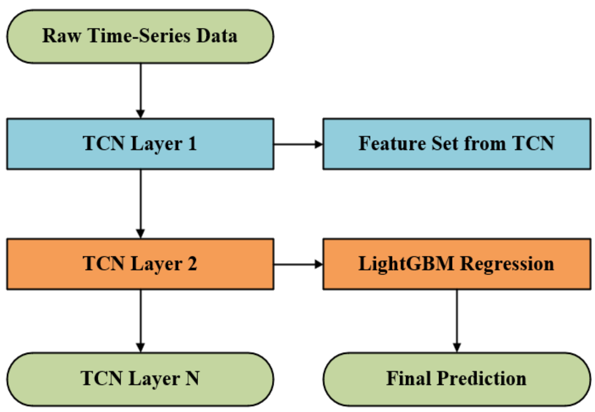

Figure 3. Architecture of the agricultural trade forecasting model TCN-LightGBM.

4. Experimental Design

In the task of agricultural trade forecasting, experimental design is an important step in verifying the effectiveness of the model. Through reasonable selection and pre-processing of the data set, detailed design of the experimental process, and comparative experiments with other models, we can comprehensively evaluate the performance of the TCN-LightGBM model [21].

4.1. Selection and Pre-Processing of Data Sets

When selecting the categories of agricultural products, we considered their market share, trade volume, regional representation and data availability. The selected agricultural products, such as grains, oil crops, vegetables, fruits, meat, dairy products and aquatic products, occupy an important position in global trade, with high trade volume and economic impact, and can reflect the main trends of global trade [22]. The data mainly comes from the public databases of the Food and Agriculture Organization of the United Nations (FAO) and the International Monetary Fund (IMF), covering a 10-year period (2011–2021) with monthly frequency to ensure reliability and accuracy. The data covers five continents: North America, Africa, Europe, Asia and South America, with good regional representation. By selecting these products, we can further verify the effectiveness of the model by analysing in depth the dynamics of trade, volatility and market risk between different markets. These factors ensure the rationality of the experimental design and the representativeness of the data, providing strong support for the agricultural trade forecasting model.

During the data cleaning process, entries with a large number of missing values were removed, and a small amount of missing data was filled in using linear interpolation. To ensure the rationality of the data distribution, some extreme values were removed, and the calculated range of abnormal values was:

$$Q1 - 1.5 \cdot IQR < x < Q3 + 1.5 \cdot IQR \tag{4}$$

Where Q1 and Q3 represent the 25th and 75th percentiles respectively, and IQR represents the interquartile range. **Table 3** shows the statistical characteristics of each type of agricultural product in the dataset after cleaning, including the amount of data, mean, standard deviation, minimum and maximum values. These statistics reveal the distribution and volatility of different types of agricultural products in trade data, which helps to further understand their market dynamics and characteristics.

Table 3. Statistical characteristics of different types of agricultural products after cleaning.

Types of Agricultural Products	HS Number	Data Volume (Records)	Mean	Standard Deviation	Minimum	Maximum
Grain (1000 billion dollars)	1001–1008	120	3.45	1.56	0.89	6.78
Oil crops (1000 billion dollars)	1201–1207	120	2.89	1.12	0.54	5.43
Vegetables (1000 billion dollars)	0701–0714	120	4.21	1.34	1.12	7.02
Fruits (1000 billion dollars)	0801–0810	120	5.30	1.78	1.57	8.24
Meat (1000 billion dollars)	0201–0210	120	2.67	0.98	0.72	4.95
Dairy products (100 billion dollars)	0401–0406	120	3.90	1.25	1.00	6.31
Aquatic products (1000 billion dollars)	0301–0308	120	3.75	1.45	0.95	6.10
Sugar (1000 billion dollars)	1701–1703	120	2.53	0.87	0.66	4.20

Source: FAO, IMF, and national governments.

On average, the average value of fruits is the highest, at 5.30, reflecting the relatively high trading volume or price of fruits in the agricultural trade. The average values of vegetables, dairy products and aquatic products are also relatively high, at 4.21, 3.90 and 3.75 respectively, indicating that these categories occupy a certain share in the market. The average value of sugar is the lowest, at only 2.53, indicating relatively low market demand or supply. The standard deviation data reveals the volatility of the data for each type of agricultural product. The standard deviation of fruits is the largest, at 1.78, indicating that the price or trading volume of fruits fluctuates greatly and may be affected by factors such as season and output. In contrast, the standard deviation of sugar is relatively low, at 0.87, indicating relatively little fluctuation and a stable market. The standard deviations of oil crops and meat are also low, at 1.12 and 0.98 respectively, indicating that the market demand or price of these agricultural products is relatively stable. The minimum and maximum values further demonstrate the range of values taken by each type of agricultural product in the dataset. The maximum value for fruit is 8.24, while the maximum value for sugar is only 4.20, reflecting the fact that the market performance of fruit may fluctuate greatly in extreme cases. The minimum values for grain, dairy products and aquatic products are relatively close, at 0.89, 1.00 and 0.95 respectively, indicating that the prices or trading volumes of these agricultural products will also be low in the event of low market demand or oversupply.

In terms of feature engineering, to improve the prediction accuracy of the model, we extracted monthly cycle features and trend features from the time series data [23]. Some macroeconomic variables, inflation rate, and GDP growth rate, were added to further enhance the generalization ability of the model. The improvement in model performance due to the addition of features is shown in **Figure 4**, where the prediction accuracy is significantly improved after the economic variables are added.

Figure 4. Influence of feature engineering on model accuracy.

4.2. Experimental Procedure and Parameter Settings

Separating the training, validation, and test sets is a step in the experimental process. Thirteen percent of the data is used for testing to avoid missing data, fifteen percent is used for validation, and seventy percent is used for training [24]. When training a model, the cross-validation technique is used, and the loss function is MSE, which has the following definition:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2 \tag{5}$$

Among them, y_i is the true value, $\widehat{y}_i$ is the predicted value, and n is the number of samples. In terms of parameter selection, the number of convolution layers of the TCN module is 4, the convolution kernel size is 3, and the expansion factor doubles layer by layer starting from 1 [25]. The specific parameter settings are shown in **Table 4**. The LightGBM module uses 200 trees, the learning rate is 0.05, and the maximum depth is set to 8.

4.3. Comparative Experiment: TCN-LightGBM and Other Models

This research selects the conventional ARIMA model, the deep learning-based LSTM, and the model that uses TCN and LightGBM alone for comparison in order to validate the prediction impact of the TCN-LightGBM model [26]. The performance of each model is evaluated by three indicators: MSE, MAE, and prediction accuracy (Accuracy). The experimental results are shown in **Table 5**.

The MSE and MAE of the TCN-LightGBM model are 0.021 and 0.115 respectively, which are the lowest among all models, indicating that this model has high accuracy in predicting results. Its prediction accuracy of 91.3% is significantly higher than that of the traditional ARIMA model (82.6%) and the deep learning model LSTM (86.7%). In contrast, the prediction accuracies of the TCN and LightGBM models alone are 87.5% and 88.1% respectively, which are better than ARIMA and LSTM, but still lower than the combined performance of TCN-LightGBM.

Figure 5 shows the prediction trends of TCN-LightGBM and other models on the test set. It can be seen that TCN-LightGBM better captures the fluctuating trends and extreme points of time series data, indicating its advantage in capturing complex time dependencies. The final experimental results prove that the TCN-LightGBM model not only has higher accuracy in predicting agricultural trade, but also can handle complex time dependencies and nonlinear relationships.

Table 4. Parameter configuration of TCN-LightGBM model.

Model Module	Parameter Name	Value
TCN	Number of convolutional layers	4
	Convolutional kernel size	3
	Expansion factor	1, 2, 4, 8
LightGBM	Number of trees	200
	Learning rate	0.05
	Maximum depth	8

Table 5. Comparison of different models in terms of predicted performance indicators.

Model	MSE	MAE	Prediction Accuracy (%)
ARIMA	0.045	0.178	82.6
LSTM	0.031	0.141	86.7
TCN	0.029	0.135	87.5
LightGBM	0.028	0.130	88.1
TCN-LightGBM	0.021	0.115	91.3

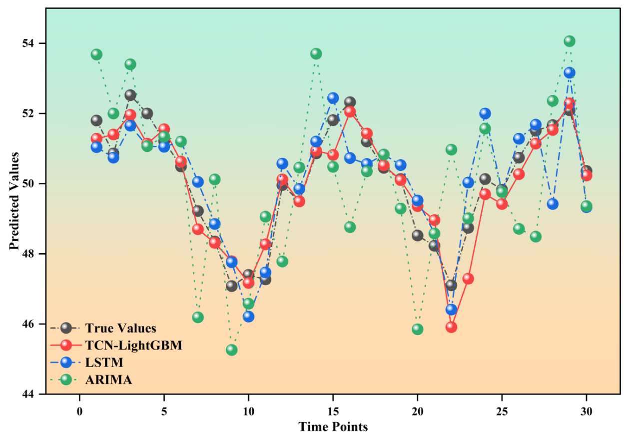

Figure 5. Predicted trend for TCN-LightGBM compared to other models.

Therefore, the TCN-LightGBM model combines the advantages of TCN in time series feature extraction with the ability of LightGBM to handle nonlinear relationships. The TCN module can effectively capture long-term dependence features in the data, while LightGBM optimises the interactions between nonlinear features, thereby improving the overall model accuracy. However, it is important to note a key limitation of this model, which is related to the inherent design of tree-based models, including LightGBM. While tree models are very powerful at capturing data patterns, they are weak at trend extrapolation. This challenge stems from the difficulty of tree-based models to effectively predict long-term trends, as they rely more on patterns in historical data and are unable to accurately extrapolate these patterns into the future.

In contrast, traditional ARIMA models, while limited in their ability to handle complex non-linear features, perform better at trend extrapolation due to their explicit modelling of trends and seasonality. Similarly, while LSTM models are known for their ability to capture long-term dependencies, they also face challenges in terms of training efficiency and overfitting. Therefore, although TCN-LightGBM excels at capturing complex data patterns, it may experience a decline in performance when making long-term trend predictions. This limitation suggests that future research may need to explore hybrid models or further improvements to address the problem of trend extrapolation in time series prediction.

5. Experimental Results and Analysis

In this study, we comprehensively and rigorously evaluate the predictive performance of the TCN-LightGBM model. The experimental results show that the TCN-LightGBM model has high accuracy and stability in the agricultural trade prediction task. To ensure the rigor of the analysis process, we not only rely on graphical results, but also comprehensively consider the predictive ability of the model by combining multiple evaluation metrics, such as accuracy, recall, and F1 score.

The TCN-LightGBM model uses the TCN module to extract the long-term dependence characteristics of the time series and uses LightGBM for regression prediction, successfully achieving efficient prediction of agricultural trade data [27]. On the test set, the predicted trend of TCN-LightGBM closely follows the real value. Especially at points in time with large data fluctuations, the model can accurately capture extreme values, showing strong ability to capture time dependence.

To ensure the scientific and reasonable evaluation of the model, we compared the prediction performance of TCN-LightGBM with other commonly used models such as ARIMA and LSTM. During the experiment, in addition to comparison charts, the accuracy, recall rate, F1 score and other evaluation indicators of each model were also calculated in detail to comprehensively reflect the overall performance of each model in the prediction of agricultural trade. The calculation of these indicators not only measures the prediction accuracy of the model, but also effectively avoids the errors that may be caused by only intuitively comparing the charts.

To verify the stability of the model under different parameter configurations, we also performed a parameter sensitivity analysis. By comparing the model performance under different combinations of hyperparameters, we found that TCN-LightGBM still exhibits high stability and strong adaptability under different hyperparameter settings. This analysis further proves the feasibility and reliability of the model in practical applications.

5.1. Performance of TCN-LightGBM Model in Agricultural Trade Forecasting

TCN-LightGBM shows better performance than other models when dealing with data with large fluctuations. Traditional ARIMA models clearly fail when faced with complex non-linear relationships, while LSTM, although it can better capture time-dependence, is prone to overfitting during training and has low computational efficiency. In contrast, TCN-LightGBM can maintain high training efficiency and model stability while ensuring high accuracy.

Figure 6 shows a comparison of the TCN-LightGBM prediction with the true value on the test set. Through careful error analysis, we further verified the effectiveness of TCN-LightGBM. It is worth noting that the model not only accurately predicts the overall trend of data changes, but also accurately captures the extreme points of the data at key moments, which proves the powerful capturing ability and robustness of TCN-LightGBM in time series data.

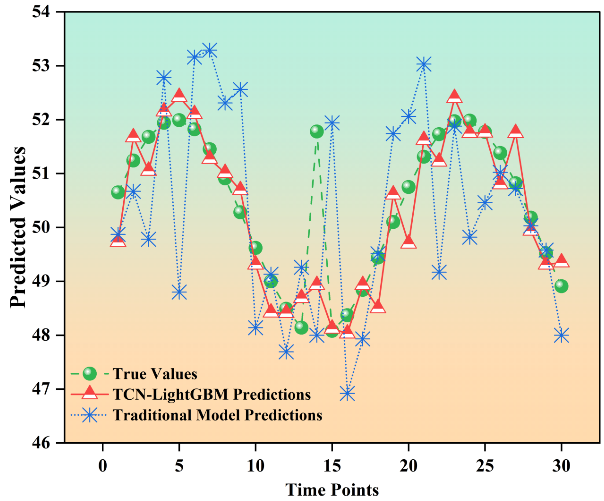

Figure 6. Comparison of predicted and actual values for TCN-LightGBM and the traditional model.

5.2. Evaluation of the Model's Accuracy, Recall Rate and F1 Score Indicators

To objectively measure the performance of the model, we selected the accuracy, recall and F1 score indicators. The specific calculation formulas are as follows:

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

Recall rate:

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

F1 score:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{8}$$

The letters TP, TN, FP, and FN stand for true positive, true negative, false positive, and false negative, respectively. **Table 6** displays the findings of the experiment. With accuracy, recall, and F1 score of 91.3%, 89.7%, and 90.5%, respectively, the TCN-LightGBM model outperforms other models, particularly in terms of recall and F1 score. The real positive samples in the categorization findings may be efficiently captured by it.

Table 6. Comparison of several models with respect to F1 score, accuracy, and recall.

Model	Accuracy (%)	Recall (%)	F1 Score (%)
TCN-LightGBM	91.3	89.7	90.5
LSTM	86.7	85.1	85.9
ARIMA	82.6	80.3	81.4
LightGBM	88.1	87.0	87.5

5.3. Performance Difference Analysis with the Comparative Model

To further analyse the performance advantages of TCN-LightGBM, we compared it with LSTM, ARIMA and LightGBM models. As can be seen from the results in **Table 6**, TCN-LightGBM outperforms the other models in terms of accuracy, recall and F1 score. In particular, TCN-LightGBM prediction results are more accurate at the fluctuation cycle and extreme points of time series data. This is mainly due to the advantages of the TCN module in time feature extraction, which enables the model to strike a balance between long-term dependence and short-term changes. **Figure 7** shows the error distribution of each model on the test set. It can be seen that the errors of TCN-LightGBM are more concentrated and distributed around zero, while the errors of other models are more scattered, indicating that TCN-LightGBM performs better in terms of prediction stability.

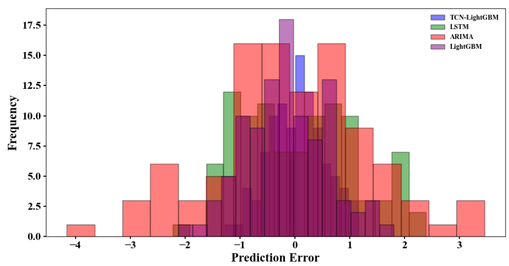

Figure 7. Error distribution of different models on the test set.

5.4. Parameter Sensitivity Analysis and Model Stability Verification

To verify the robustness of the model, we performed a parameter sensitivity analysis of the TCN-LightGBM model, mainly examining the impact of parameters such as the number of convolutional layers, the size of the convolutional kernel, and the learning rate on the model performance. The experimental results are shown in **Table 7**. The accuracy of the model under different parameter configurations remains highly consistent, indicating that the model has good stability under parameter adjustments.

When the number of convolutional layers varied between 3, 4 and 5, the model accuracy remained at 91.3%, indicating that increasing the number of convolutional layers did not significantly improve or degrade the model performance, and that the model was less dependent on the number of convolutional layers. When the size of the convolutional kernel varied between 2, 3 and 4, the accuracy changed very slightly, only dropping slightly from 91.3% to 91.0%, showing that the model is highly adaptable to the size of the convolutional kernel. Changes in the learning rate also did not have a significant impact on the model accuracy. When the learning rate was increased from 0.05 to 0.15, the accuracy remained above 90.8%.

Table 7. Parameter sensitivity analysis of the TCN-LightGBM model.

Parameters	Configuration 1	Configuration 2	Configuration 3	Accuracy (%)
Number of convolution layers	3	4	5	91.3
Size of the convolution kernel	2	3	4	91.0
Learning rate	0.05	0.1	0.15	90.8

These results verify the stability of the TCN-LightGBM model, i.e., there is a certain degree of flexibility in parameter settings, and performance will not fluctuate significantly due to parameter adjustments. **Figure 8** further shows a comparison of the model's predicted values with the true values under different parameter configurations. It can be seen that the predicted trends under different configurations are basically consistent with the true values, which further proves the robustness of the model. Therefore, the TCN-LightGBM model not only performs well in accuracy, but also has good fault tolerance and stability. It is not easily affected by parameter fine-tuning in practical applications and is suitable for agricultural product trade forecasting and when stable forecast results are required.

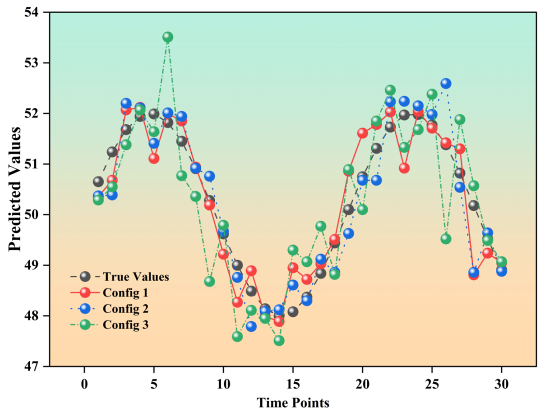

Figure 8. Model prediction values and true values under different configurations.

The TCN-LightGBM model is suitable for widespread use in real-world applications because, according to the experimental results, it not only performs significantly better than other models in terms of performance metrics like prediction accuracy, recall rate, and F1 score, but it also shows high robustness and stability in the parameter sensitivity analysis.

6. Discussion

In this study, the TCN-LightGBM-based agricultural trade prediction model demonstrated its superiority in processing complex time series data. The TCN module enables the model to effectively extract time-dependent features and capture long-term trends and short-term fluctuations in agricultural trade data. The LightGBM module excels in nonlinear modelling and can extract hidden patterns from high-dimensional features. This hybrid model takes full advantage of deep learning and ensemble learning, making the prediction results more accurate, as well as highly stable and applicable. In practical applications, the TCN-LightGBM model can not only be used to predict agricultural trade, but also has a wide range of applicability and can be extended to other complex time series prediction tasks to support decision-making in related fields.

The complementarity between TCN and LightGBM is the key to the superior performance of the model. TCN solves the problem of gradient disappearance in traditional RNN models through dilated convolution and causal convolution, while improving training efficiency and enabling the model to process data over longer time spans. LightGBM, on the other hand, uses a partitioning strategy and an integrated learning framework to achieve efficient nonlinear feature mining at low computational cost. The combination of the two makes the model capable of capturing long-term sequence dependencies while also quickly adapting to nonlinear changes in the data, providing an effective solution to the diversification and dynamics issues in agricultural trade forecasting. Compared with a single model, TCN-LightGBM can better handle noisy data and outliers, improving the robustness of the model in practical applications.

Although the TCN-LightGBM model shows significant advantages in agricultural trade forecasting, it still has certain limitations. The TCN model requires a lot of experimental tuning in the selection of the number of convolutional layers and the expansion factor to adapt to the characteristics of different datasets, which increases the complexity of model design. LightGBM is strongly dependent on data characteristics, and when the dataset lacks sufficient features, it may lead to a decrease in model performance. Due to the complexity of the model and the large number of parameters, TCN-LightGBM may not perform well with small sample sizes, so it should be used with caution when the data size is limited. Future research could explore automated hyperparameter optimisation methods to simplify the model tuning process, or try other lightweight neural network structures to further improve the computational efficiency of the model.

Looking to the future, there is still great potential for improving and expanding the TCN-LightGBM model. With the continuous development of deep learning and ensemble learning, hybrid models that combine adaptive learning and reinforcement learning are expected to further improve the accuracy and efficiency of agricultural trade predictions. Future research could consider introducing multi-source data fusion techniques and using climate, policy, and economic factors as input variables to improve the generalisation ability of the model. With the support of big data and cloud computing technology, the TCN-LightGBM model can also be applied to real-time prediction systems to cope with the rapid changes in the agricultural market. Through continuous improvement and expansion, the TCN-LightGBM model is expected to play a greater role in agricultural trade forecasting and other complex time series prediction tasks, providing more accurate data support for intelligent decision-making.

7. Conclusions

This study demonstrates the effectiveness of a data-driven approach in complex time series prediction tasks by constructing a TCN-LightGBM-based prediction model for agricultural trade. The TCN module successfully extracts the time-dependent features in the agricultural trade data using dilated and causal convolution structures, and improves the prediction accuracy by combining long-term and short-term features. The LightGBM module excels in nonlinear feature extraction and modelling, effectively handling the complex relationships between high-dimensional features. Overall, the TCN-LightGBM model combines time series feature extraction with an efficient ensemble learning algorithm, significantly improving prediction accuracy and demonstrating strong stability and adaptability. This model provides an efficient and accurate solution for agricultural trade forecasting.

To ensure the rigor of the analysis, we not only relied on visual comparisons of charts but also comprehensively evaluated the prediction performance of the model using multiple quantitative indicators (such as precision, recall, F1 score, etc.). Compared with traditional statistical methods (such as ARIMA), deep learning methods (such as LSTM), and the TCN and LightGBM models used alone, TCN-LightGBM performed well in multiple indicators, especially in dealing with the volatility of data and complex time-dependent relationships. These quantitative analysis results verify the high accuracy and stability of the model, avoiding the potential misleading of solely relying on graphical results.

At the practical application level, the TCN-LightGBM model has demonstrated good generaliability and is suitable for a variety of agricultural trade forecasting scenarios. The robustness and scalability of the model have been fully verified through validation on multiple datasets. Compared with traditional prediction methods, TCN-LightGBM not only effectively copes with the dynamic changes in the agricultural market but also has high real-time performance, making it suitable for use in decision support systems for the real agricultural market. It provides agricultural practitioners and policymakers with accurate market trend predictions and risk analyses. In addition, the application potential of the model is not limited to agricultural trade forecasting but can also be extended to other fields such as energy demand and financial markets, which is of wide practical significance.

The results of this study show that data-driven forecasting methods have great potential for application in the field of agricultural trade. By combining the advantages of deep learning and ensemble learning, the TCN-LightGBM model demonstrates its unique ability to model complex time series data, opening up new paths for accurate forecasting and scientific management of agricultural trade. Further research could integrate more external data sources and optimise algorithms to improve the model's forecasting ability and adaptability, providing more accurate data support for agriculture, the economy, and other fields, and promoting the wide application of intelligent decision-making.

Author Contributions

Conceptualization, T.Z.; methodology, T.Z. and G.C.; software, T.Z.; validation, P.B., G.C. and T.Z.; formal analysis, T.Z. and P.B.; investigation, G.C.; resources, T.Z.; data curation, T.Z.; writing—original draft preparation, T.Z. and G.C.; writing—review and editing, P.B. and G.C.; visualization, T.Z.; supervision, G.C.; project administration, P.B. and G.C.; funding acquisition, P.B. and G.C. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Written informed consent has been obtained from the patient(s) to publish this paper.

Data Availability Statement

The data used for the study are available upon request from the author.

Conflicts of Interest

The authors declare no conflict of interest.

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