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A new probability forecasting model for cotton yarn futures price volatility with explainable AI and big data

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Abstract
Cotton, cotton yarn, and other cotton products have frequent price volatility, increasing the difficulty for industry participants to develop rational business decision plans. To support cotton textile industry decision-makers, we apply data mining methods to extract the main influencing factors affecting cotton yarn futures prices from big data and build a probabilistic forecasting model for cotton yarn price volatility with uncertainty assessment. Based on Explainable Artificial Intelligence (XAI) and data-driven perspectives, we use the LassoNet algorithm to extract 18 features most relevant to the target variable from the massive data and visualize the importance values of the selected features to improve the reliability. Moreover, by combining conformal forecasting (CP) with quantile regression (QR), the uncertainty measure of the point estimation results of the long and short-term memory (LSTM) model is applied to improve the application value of the model. Finally, SHAP (SHapley Additive exPlanations) is introduced to analyze the SHAP values of the input features on the output results and to explore in depth the interaction and mechanism of action between the input features and the target variables to improve the explainability of the model. Our model provides a "big data-forecasting model-decision support" decision paradigm for real-world problems.

KEYWORDS
big data mining, forecasting, probabilistic modelling, XAI

1 | INTRODUCTION

Forecasting plays a crucial role in the domain of operational research. It allows businesses to anticipate future trends and optimize their strategies and resources, thereby improving their competitiveness and reducing potential losses. In the field of operational research, forecasting is used to make informed decisions about production lines, logistics, credit analysis, and supply chain management, helping companies achieve maximum efficiency and cost-effectiveness (Chai et al., 2024; Fan et al., 2023; Karimi & Zaerpour, 2022; Sarlo et al., 2023; Sroginis et al., 2023). Furthermore, forecasting is of utmost importance for the cotton textile market, as it enables market participants to make informed decisions regarding production, procurement, and other aspects based on expected market trends (Wang, He, et al., 2021). Cotton yarn, as an important product in the cotton textile supply chain, is crucial to the operation of upstream and downstream industries (Venkataraman et al., 2016). Considering this crucial role, the study will delve into the forecasting of cotton yarn futures prices as a case study, providing more decision support for decision-making in the field of operations research and market participants.

The cotton textile industry is a deeply rooted basic industry in China. China is the largest producer and exporter of textiles and apparel (Muhammad et al., 2021). According to data from the National Bureau of Statistics and the World Trade Organization (WTO), in 2020, the operating income of large-scale enterprises in the cotton textile industry reached 967.95 billion Yuan, accounting for 21.4% of the national textile industry. The total profit amounted to 33.65 billion yuan, representing 16.3% of the national textile industry. Textile and apparel exports reached 296 billion US dollars, holding a substantial share of 36.9% in the global textile export market, maintaining its position as the world's leading exporter. In recent years, the uncertainty of the cotton textile industry has greatly increased because of the dual pressure of international geopolitical conflicts, volatility in commodity prices, slow global economic recovery, as well as the unsmooth operation of supply chains, and the need for further recovery in the domestic consumer market. This has led to violent volatility in commodity prices (Muhammad et al., 2021), such as cotton and cotton yarn, in the industrial chain. The price volatility of cotton products will not only affect the normal operation of the cotton textile market but may also affect other markets, thereby affecting the healthy operation of the entire national economy. Therefore, it is necessary and meaningful to article the volatility pattern of cotton yarn prices. With the rapid development of the big data era, data mining and AI technology can reveal potential distribution patterns from the huge amount of data (Bouteska et al., 2023; Jalota et al., 2023; Meng et al., 2022), so this paper follows the data-driven decision paradigm of "big data-forecasting model-decision support" to provide decision support for OR stakeholders and market participants.

Cotton yarn futures price volatility forecasting is an important area of operational research. By analyzing and modeling various factors such as cotton cultivation, harvesting, processing, and sales, researchers can forecast the trends in cotton yarn prices (Xu & Zhang, 2022). This is crucial for both textile manufacturers and investors as it provides key information about future market changes, supporting more informed decision-making. For textile manufacturers, the ability to adjust raw material procurement strategies based on anticipated price forecasting is paramount. This allows them to minimize the risks associated with high-cost purchases or shortages caused by low prices. In dynamic market conditions, manufacturers can adapt more flexibly to supply and demand forecasting, enhancing production efficiency, ensuring stable operation of production lines, and effectively reducing production costs. Investors, on the other hand, rely on these forecasting insights as crucial references for making informed trading decisions. They can dynamically adjust their investment portfolios based on market expectations, seize favorable trading opportunities, and consequently achieve higher returns. For investors, a deep understanding of the trends in cotton yarn futures prices signifies a better grasp of market dynamics, facilitating more prudent, data-driven investment decisions (Marfatia et al., 2022).

In order to reduce uncertainty, scholars have conducted multi-angle research on commodity price volatility, but relatively less in the cotton textile field. Current research mainly relies on methods such as autoregressive moving average (ARMA) models, back-propagation (BP) neural networks, and basic machine learning models. There is limited research that utilizes deep learning methods (Jiang et al., 2021; Venkataraman et al., 2016; Wu et al., 2018). Additionally, cotton yarn price prediction predominantly focuses on accurately forecasting the price for a specific future day rather than predicting the distribution range of cotton yarn prices. For instance, Venkataraman et al. (2016) combined ARMA and K-nearest neighbors (KNN) to predict cotton yarn prices. In this research, the ARMA algorithm was used to forecast the influencing factors of cotton yarn price fluctuations, such as cotton prices, yarn production, and other features' future prices. Subsequently, the KNN algorithm utilized the predicted values of these influencing factors to forecast future cotton yarn prices. Wu et al. (2018) collected 13 factors influencing cotton yarn price fluctuations and investigated the predictive performance of the mean impact value, genetic algorithms, and BP neural networks in predicting cotton yarn prices in China. They concluded that the proposed predictive model demonstrated high accuracy. In comparison to forecasting studies in the financial domain, the development of cotton yarn price prediction has been relatively slow (Du et al., 2022; Hu et al., 2020; Li et al., 2017; Vidal & Kristjanpoller, 2020). The existing research on price volatility mainly includes two aspects: (1) analysis of influencing factors and (2) price volatility forecasting. In terms of analyzing influencing factors, econometric methods are mainly used (Guo et al., 2019; Karasu et al., 2020). The above methods involve only a few variables and cannot fully explore the influencing factors of the target variable from a big data perspective (Besbes & Mouchtaki, 2023). In terms of constructing volatility forecasting models, most existing research is based on point forecasting at the numerical level, that is, providing accurate forecasting results (Herwartz, 2017; Hu et al., 2020; Jabeur et al., 2021; Kim & Won, 2018; Lee & Ryu, 2019; Li et al., 2019; Tschora et al., 2022). From the results of existing articles, we find that point forecasting models, whether they are econometric models or deep neural network models that can handle complex information, have some degree of discrepancy between their forecasting results and actual values. There are two reasons for this finding. First, the market environment is complex and changeable, and there is a large amount of uncertainty that cannot be eliminated by quantification. Second, when collecting and processing data, we started from a big data perspective and collected the factors related to the target variable as much as possible, but there is still a gap with the actual influencing factors (Hüllermeier & Waegeman, 2021; Jalota et al., 2023). From the analysis of the above two aspects, we can know that precise and fixed-point forecasting results are unreliable and difficult to achieve. In consideration of the limitations of point forecasting, researchers have extended the forecasting model to interval forecasting models and probability forecasting models (Baştürk et al., 2019; Hajek et al., 2020; Jensen et al., 2022; Li et al., 2022; Liu & Ma, 2022; Sun et al., 2018). Unlike point forecasting, the output results of interval forecasting and probability forecasting are not a determined point estimation value but an interval range with uncertain estimates, which not only quantifies the price volatility range but also corrects the point forecasting results. Therefore, in contrast to point forecasting, probability forecasting is more in line with the actual situation and has a higher practical value (Hüllermeier & Waegeman, 2021; Zhang et al., 2020).

In the research, for the analysis of influencing factors on cotton yarn futures prices, we combined residual neural networks with regularization (Lasso) from a data-driven perspective to construct a LassoNet algorithm that can handle complex, nonlinear regression. The algorithm was used to extract 18 most relevant factors from a collection of 148 potential influencing factors. Different from the commonly used principal component analysis (PCA) feature extraction method, LassoNet returns specific features, not only extracts features but also provides importance scores of the features and visualizes them, thus improving the interpretability of the research (Jalota et al., 2023; Lemhadri et al., 2021). In terms of analyzing price volatility patterns, we proposed a CP-QR-LSTM probability forecasting model, which combines CP and QR to calibrate the point estimator output by LSTM, generating a forecasting interval with a given confidence level. This mixed model quantifies the uncertainty of point estimation results, and the final output is the distribution range of the point estimation value under certain probability conditions. Specifically, the primary focus of this article is to address the following research questions:

RQ1: *What is the pattern of cotton yarn futures price volatility driven by data (three types of data)?*

RQ2: *What is the relationship between data empowerment of XAI and cotton yarn price futures volatility?*

To address these research questions, we propose a data-driven research paradigm based on big data and XAI, which is called the "big data-forecasting model-decision support" framework. First, to identify the factors that influence cotton yarn feature prices, we use the LassoNet algorithm to extract highly correlated feature variables from massive datasets related to the target variable. The important scores of these features were visualized to help OR stakeholders and market participants to understand and analyze the reasons for cotton yarn futures price volatility. Second, the CP-QR-LSTM probability forecasting model was constructed to explore the patterns of cotton yarn futures price volatility under data-driven contexts. This model provides uncertain probability measurements of future cotton yarn futures price distribution. Finally, after the model training, we introduce the SHapley Additive exPlanations (SHAP) algorithm to quantify the contribution of each input feature to the LSTM point estimate results. On this basis, we further reveal the interaction relationship between feature variables and the target variables to further improve the explainability of the proposed model. It aims to provide reasonably accurate price volatility forecasting schemes for the cotton textile industry and related enterprises, helping stakeholders in the cotton textile market make decisions and plans in high-risk and high-uncertainty markets and enhancing their competitiveness.

The other sections of this article are organized as follows: first, a literature review and research framework were established; second, the required data for model validation was collected, and the model was tested; third, important findings were drawn; finally, a summary and discussion were presented.

2 | LITERATURE REVIEW AND RESEARCH FRAMEWORK

In this article, we will answer the proposed research questions through two main themes: price volatility forecasting and explainable AI. In this section, we will discuss the existing literature on these two themes and propose our own research framework.

2.1 | Research on price volatility

The forecasting of commodity price volatility has received extensive research attention in recent times in operational research and management science (Chen et al., 2021; Karimi & Zaerpour, 2022). In literature, predictive models can be broadly classified into three categories, as shown in Table 1.

Initially, traditional econometric models (Herwartz, 2017) were widely used for price forecasting. These models typically analyze linear relationships between variables based on strict assumptions and piecewise functions. However, with a better understanding of the nonlinear relationships between factors that influence commodity prices and their financial properties, it has been shown that traditional econometric models are unable to meet the needs of highly complex datasets (Chen et al., 2021; Hajek & Abedin, 2020; Ma et al., 2019; Svetunkov et al., 2023).

On the other hand, machine learning models have deep network hierarchies that can handle nonlinear and complex structures, learn from data, and reflect actual commodity price volatility patterns. Prior articles (Li et al., 2017; Li et al., 2019) combine LSTM and convolutional neural networks (CNN) to explore the impact of unstructured data on oil and stock price volatility trends. Results find that LSTM and CNN are superior to traditional linear methods in terms of forecasting accuracy and performance. However, they only compared single models and not hybrid models.

Finally, hybrid models, which combine econometric and machine learning models (Kim & Won, 2018; Venkataraman et al., 2016), artificial neural networks and machine learning (Hu et al., 2020), or multiple machine learning models (Svetunkov et al., 2023; Vidal & Kristjanpoller, 2020), have shown significant improvements in forecasting performance compared with single models. However, existing articles have some limitations. Many articles focus on point data, such as predicted closing prices (Jabeur et al., 2021; Liu & Ma, 2022) and volatility (Vidal & Kristjanpoller, 2020) without exploring the uncertainty of predicted results, leading to weak robustness and effectiveness of the models.

Considering these limitations, few articles have started expanding forecasting objects to include interval data (Hajek et al., 2020; Kang et al., 2022; Li et al., 2022), functional data, and density distribution (Baştürk et al., 2019), among other fields. In the limited interval

TABLE 1 Overview of price volatility research.

Research model	Research content	Research subject	Reference
Econometric model	Constructed an improved GARCH-based stock return prediction model	Point data	Herwartz, 2017
Machine learning model	Constructed an LSTM-based stock closing price prediction model using investor sentiment	Point data	Li et al., 2017
	Using CNN to process textual information and the random Forest model to predict crude oil prices	Point data	Li et al., 2019
	Predicting gold prices using XGBoost	Point data	Jabeur et al., 2021
	Predicting stock closing prices using artificial neural networks	Point data	Liu & Ma, 2022
Hybrid model	Predicting stock price volatility using LSTM and three hybrid GARCH models	Point data	Kim & Won, 2018
	Forecasting yarn price volatility using the ARIMA-KNN model	Point data	Venkataraman et al., 2016
	Constructed GARCH-ANN-LSTM model for copper price volatility prediction	Point data	Hu et al., 2020
	Predicting gold prices using the CNN-LSTM model	Point data	Vidal & Kristjanpoller, 2020
	Developed a multi-scale nonlinear interval prediction paradigm and constructed interval predictions of raw stock signals using Gaussian process regression	Interval data	Wang, He, et al., 2021
	Proposed an interval data prediction method based on a fuzzy cognitive map and applied it to 10 public datasets, showing the high efficiency of the method	Interval data	Hajek et al., 2020
	Used fuzzy information granulation to process interval data and predicted interval data using an ALSTM	Interval data	Li et al., 2022
	Proposed a data-driven dynamic combination model to predict the distribution of profit function	Distribution of function	Baştürk et al., 2019

forecasting or probabilistic forecasting literature, most articles granulate the original time series datasets directly into interval datasets based on fuzzy granulation theory (Goltsos et al., 2022; Sun et al., 2022), and the quality of granulation is difficult to measure and prone to large errors. There are also articles based on Gaussian regression and quantile regression, among others (Liu et al., 2015; Panagiotelis et al., 2023; Wang, Wang, et al., 2021), but this type of article is weak in terms of coverage and cannot meet the decision-making needs.

2.2 | eXplainable Artificial Intelligence (XAI)

With the growing demand for XAI techniques, many different studies have recently been conducted, which can be mainly divided into two types: (1) model explainable and explainable and (2) model uninterpretable but explainable, as shown in Table 2. Model explainable and explainable techniques focus on constructing models that are inherently transparent and understandable. This means that the internal workings of the model are designed to be user-friendly, allowing users to delve into how the model arrives at specific predictions (Jiang et al., 2024; Lisboa et al., 2023). On the other hand, model uninterpretable but explainable techniques acknowledge that the underlying model might be complex or a "black box." These methods generate explanations after the model has made predictions, revealing why certain decisions were made without necessarily disclosing the complexity of the model (Dwivedi et al., 2023). Existing literature on explainable models mostly uses federated learning and rule extraction methods. For example, researchers embed complex "black-box" models into decision trees or regression trees that are inherently explainable by using techniques such as federated learning and rule extraction to extract explainable regression and classification models from "black-box" models and demonstrate the effectiveness of extracting models on 20 public datasets (Haffar et al., 2023; Johansson et al., 2022).

However, the aim of this article on explainability is to explore the important factors affecting volatility in cotton yarn futures prices. Therefore, on the interpretability level, we will focus on the uninterpretable but explainable models. Common methods of XAI techniques in this category include (1) SHAP and (2) Local Interpretable Model Agnostic Explanations (LIME). In this context, the SHAP method is based on cooperative game theory and aims to fairly distribute the "value" of each feature among the contributing features in a prediction. It provides a way to attribute the contribution of each feature to a specific prediction instance, offering a comprehensive understanding of how each feature influences the model's output. SHAP values highlight the impact of each feature on the target variable, revealing whether a specific feature contributes positively or negatively to the prediction (Lundberg & Lee, 2017; Yang et al., 2023). On the other hand, LIME generates local explanations by

TABLE 2 Common XAI techniques.

Classification	Research methods	Research content	Reference
Model explainable and explainable	Federated learning	Based on Federated Learning technology, we can construct a surrogate model of black-box models and use the combination of these two models to interpret the black-box model.	Haffar et al., 2023
	Rule extraction	We can use explainable models with weaker functionality to approximate opaque models and extract explainable regression models from these opaque models.	Johansson et al., 2022
Model uninterpretable but explainable	SHAP	The SHAP method is proposed to verify the benefit of various gold prices.	Jabeur et al., 2021
		Results show that SHAP are beneficial for the collaboration between human workers and artificial intelligence.	Yang et al., 2022
	LIME	LIME is used to perform explainability analysis on the results of AI medical diagnosis.	Elshawi et al., 2021
		LIME technology is applied to the early stage of an engineering change to explain the reasons for the change request. After evaluation by industry experts, LIME improves the transparency of the model.	Pan & Stark, 2022
		LIME is used to derive and evaluate the predicted results of model forecasting, improving the transparency of the established model.	Wang et al., 2022

training a locally simplified model around a specific instance. It perturbs input data and observes changes in the predicted outcomes, thus understanding the impact of different features on the model's decision for a specific instance. This approach makes it easy to comprehend the local behavior of the model (Dwivedi et al., 2023). As shown in Table 2, SHAP's biggest advantage is its ability to reflect the degree of influence of features and indicate their positive or negative impact. Researchers have used SHAP to visualize the Shapley values of different input features to help decision-makers understand the forecasting of complex machine learning (Jabeur et al., 2021; Yang et al., 2022). Results show that the combination of machine learning methods with SHAP can significantly improve model explainability, but the computational cost of SHAP is high when there are many features. Results have found that the LIME method can improve the overall explainability of models, but it relies on an alternative linear model, explaining the local impact of each variable through multiple random perturbation terms of instances, and has high instability (ElShawi et al., 2021; Pan & Stark, 2022; Wang et al., 2022).

The methods mentioned above can improve model explainability to varying degrees, but they are all performed after model training. In actual situations, there are many factors affecting cotton yarn futures prices, so there are many features in this article. Directly inputting these variables into the forecasting model will surely increase computational costs. Traditional feature extraction methods based on linear regression, such as Lasso, Pearson correlation coefficient, and PCA, have limitations in handling nonlinear problems (Fan et al., 2014; Lockhart et al., 2014). First, the above traditional feature extraction methods generally target linear problems and perform poorly on nonlinear problems. Second, the returned values after feature processing are not individual features (such as PCA), which makes commonly used explainable methods such as SHAP and LIME ineffective.

Therefore, this paper will use LassoNet and SHAP algorithms to explain the causal relationships between the feature variables and the target variables before and after model training, respectively. First, the LassoNet feature sparsity method was introduced before model training to analyze the degree of influence between the target and feature variables. LassoNet not only meets the demand for feature extraction but also reduces computational effort. Moreover, the algorithm is also able to calculate the importance scores of the input variable, quantify the importance of each variable on the target variable, and improve the interpretability of the whole article. Second, after the model training, the SHAP algorithm is introduced to analyze the marginal contribution rate of the input features to the forecasting results.

2.3 | Research framework

In the big data scenario, there are numerous and dynamically variable factors affecting cotton yarn futures price fluctuations, resulting in large volatility in the cotton yarn futures market. Considering that it is impossible to collect all the data related to cotton yarn futures prices in actual research, this paper provides a data-driven research paradigm to explore the price volatility of cotton yarn futures in this dilemma, that is, "big data-forecasting model-decision support." The framework of this article is shown in Figure 1.

In this article, we divide influencing factors into three types of data from the big data perspective: trading data, measurement data, and interaction data, which contain characteristic variables that are dynamic. Second, XAI is introduced to extract the typical features affecting the fluctuation of cotton yarn futures prices interpretably from the dynamically changing feature variables, which do not change with the amount of original data, and thus can reflect the fluctuation pattern of cotton yarn futures prices to a certain extent. Next, the CP-QR-LSTM model is built to extract the fluctuation pattern of cotton yarn futures from the extracted typical features and predict the distribution of cotton yarn futures prices in the future period. Because of the incompleteness of the data collected in the context of big data, the proposed model gives a range of future price distributions at different confidence levels to improve the generalization and stick-filtering ability of the model. The final model will produce the volatility range of cotton yarn futures prices under certain confidence level conditions to provide decision support for OR stakeholders and market participants.

3 | DATA COLLECTION AND DATA ANALYSIS

3.1 | Data collection

In order to explore the volatility pattern of cotton yarn prices, we selected the daily closing prices of cotton yarn futures (CCYc1_C) as the research target, which were obtained from the Zhengzhou Commodity Exchange (www.czce.com.cn). Research shows that cotton yarn, as the most direct downstream product of cotton, is not only affected by the supply and demand relationship in the cotton textile market. It also has financial and political attributes (Besbes & Mouchtaki, 2023; Huchet & Fam, 2016). To better simulate the cotton yarn futures trading environment, we collected 148 feature variables that may affect the volatility of cotton yarn futures prices from three aspects: commodity attributes,

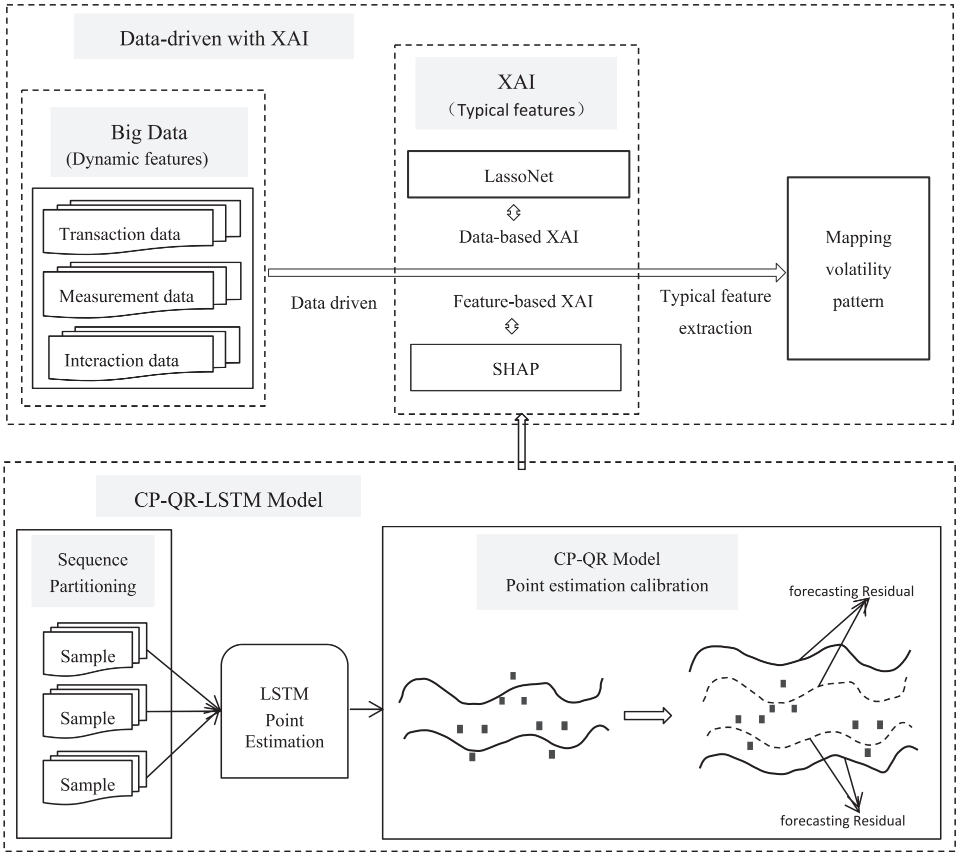


FIGURE 1 Flowchart of the proposed framework.

TABLE 3 Descriptive statistical analysis of the datasets.

	CCYc1_C	CCFc1_C	MCOTc1_C	CT_C	SSEC_C	CSI100I_C
count	1353.0000	1354.0000	1426.0000	1410.0000	1354.0000	1354.0000
mean	22,837.5683	15,258.2274	25,372.6437	82.6450	3167.9729	6350.2288
std	2858.2706	2774.8660	9587.6935	19.9610	289.9971	908.6182
min	15,970.0000	10,280.0000	15,020.0000	48.8500	2464.3600	4149.4400
25%	508.5000	13,542.5000	19,610.0000	68.6525	2936.2425	5562.8700
50%	1017.0000	14,880.0000	21,470.0000	79.1750	3213.9850	6493.0450
75%	1525.0000	15,760.0000	29,822.5000	88.3000	3395.4850	7000.3850
max	2034.0000	22,390.0000	64,200.0000	154.7400	3715.3700	8055.5300

financial attributes, and political attributes. Our data collection is not only limited to trading data but also includes interaction data and measurement data. The time span of the data is from August 21, 2017, to March 17, 2023, for a total of 301,180 records. Table 3 shows the descriptive statistical analysis of some of the data. In addition, we summarize data classification and source information in Table 4.

3.2 | Data analysis

To achieve the forecasting target and make the collected datasets match the model, three steps of data preprocessing are performed before model validation, as shown in Figure 2. Moreover, we introduce the LassoNet algorithm and SHAP algorithm to analyze how features affect the forecasting results from both data and feature perspectives, respectively, during the experiment. In this section, only data-based XAI is covered. Feature-based XAI will be elaborated on in Section 4.3.

3.2.1 | Data analysis

Missing value imputation stage

Through analysis of the original data, we found that missing values are generally caused by holidays. In actual

TABLE 4 Data classification and sources.

Attribute classification		Measurement indicators	Data sources
Commodity attributes	Supply and demand	Cotton yarn futures (CCYc1)	www.czce.com.cn
		Cotton futures (CCFc1)	
		PTA futures (CTAc1)	
		US cotton no. 2 futures (CT, CTc1, CTc2, CTc3)	cn.investing.com
		US soybean futures	
		China soybean no. 1 futures	
		Indian cotton futures (MCOTc1)	www.mcxindia.com
Financial attributes	Exchange rate	USD/CNY	cn.investing.com
		EUR/CNY	
		INR/CNY	
	Public attention	Baidu search (Keywords: cotton, cotton yarn, yarn, textile, Xinjiang cotton)	index.baidu.com
		Baidu news (Keywords: cotton, cotton yarn, yarn, textile, Xinjiang cotton)	
	Macroeconomic indicators	SSE Composite Index (SSEC)	cn.investing.com
		CSI 1000 Index (CSI1000I)	
		SZSE Component Index (SZI)	
		FTSE China A50 Index (FTXIN9)	
		Nasdaq 100 Index (NDX)	
		Nasdaq Composite Index (IXIC)	
		S&P 500 Index (SPX)	
		Dow Jones Industrial Average (DJI)	
		FTSE 100 Index (FTSE)	
		WTI crude oil futures	
		London Brent crude oil futures	
		Gold futures	
Political attributes	Economic Policy Uncertainty Index	daily_policy_index EPU	www.policyuncertainty.com
		China_Mainland_Paper EPU	
		China news-based EPU	
		China_Mainland_Paper TPU	
		Twitter EPU	
	VIX Fear Index	VIX	cn.investing.com

trading, the problem of missing data caused by holidays is generally supplemented based on the previous day's trading data. Therefore, in this article, the upward-filling method will be adopted to fill in the missing values in the original datasets.

Normalization stage

The dimensional and dimensions of various features in the original datasets are different, which leads to imbalanced weights of feature variables in the model, which will affect the accuracy of the research. In order to reduce that influence, the StandaraScaler class is used to normalize the feature values to the same dimension before modeling. The mathematical principle of the normalization process is shown in Formula (1).

$$x^* = \frac{x - \overline{x}}{\sigma} \tag{1}$$

where $\overline{x}$ denotes the mean of the feature value and σ denotes the standard deviation of the feature value. After normalization, the mean of the feature value in the original datasets is 0, and the standard deviation is 1.

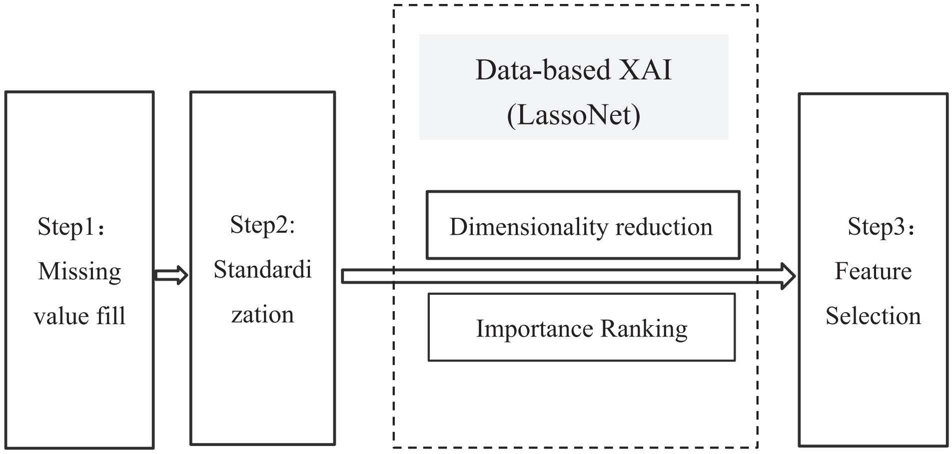


FIGURE 2 Data analysis process flowchart.

Feature selection stage

In many research problems, there are some feature variables in the original datasets that are unrelated to the forecasting target. Feature selection can not only achieve a deep understanding of the relationship between input features and forecasting results before model validation and improve the interpretability of the model but also eliminate redundant or noisy features, thus reducing computational costs and improving the generalization ability of the model. Considering that there is a nonlinear relationship between cotton yarn futures prices and feature variables, traditional feature extraction methods based on linear regression, such as Lasso, Pearson correlation coefficient, and PCA, have limitations in dealing with nonlinear problems (Fan et al., 2014; Lockhart et al., 2014). Therefore, we introduced an arbitrary feed-forward network and residual layer into the Lasso regression model, forming a feature extraction model, LassoNet, that can handle highly nonlinear regression (Lemhadri et al., 2021). Moreover, the process of LassoNet feature extraction is also the process of analyzing the causal relationship between input features and forecasting results, and the specific implementation process is described in Section 3.2.2.

3.2.2 | Data-based XAI

We use LassoNet as an interpretable technique for the model, which can mine the features with strong influence on the target variables from a large amount of data, give explanations, and provide strong support for decision-making. The LassoNet algorithm is achieved by combining Lasso and neural networks, as shown in Figure 3, where the green part represents the residual layer, and the black part represents a feed-forward network. It can effectively select the features most relevant to the output variable and shrink the weights of other features to zero. In addition, the LassoNet algorithm can rank the importance of each feature by training the datasets, calculating the weight of each feature, and visualizing the results.

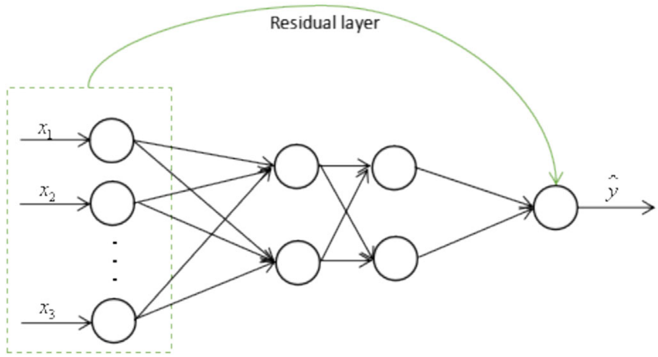


FIGURE 3 LassoNet structure diagram.

In addition to the target variable of cotton yarn futures prices, we collected 147 exogenous variables. If all variables are input into the model, it would be difficult to identify the features that significantly impact results. LassoNet utilizes Lasso to reduce model complexity while retaining important features, which can not only reduce training time and computational costs but also effectively identify the key variables in the input data. The working principle of LassoNet is shown in Equation (2).

$$\begin{aligned} &\min_{\theta,w} imizeL(\theta,w)+\lambda\|\theta\|_1 \\ &\text{subject to } \left\|w_j^1\right\|_\infty \le M\|\theta_j\|, j=1,\dots,d \end{aligned} \tag{2}$$

In the formula, $L(\theta,w)=\frac{1}{n}\sum_{i=1}^{n} l(X_i,y_i;\theta,w)$ represents the loss function and $\lambda\|\theta\|_1$ represents the Lasso. The LassoNet algorithm contains two hyper-parameters λ and M. A larger λ value leads to sparser models and M is used to control the relative strength between linear and

Algorithm 1 LassoNet for data-based XAI

Input: Time-series data X, feed-forward neural network $gw(\cdot)$, number of epochs B, hierarchy multiplier M, path multiplier ε, learning rate α.

```
Initialize and train gw(·) on the loss L(θ,W)
Initialize the penalty, λ = λ_0, and the number of active features, K = d
While K > 0 do
  Update λ ← (1+ε)λ
  for b ∈ 1...B do
    Compute the gradient of L(θ,W) using back-propagation
    Update θ ← θ − α∇_θ L and W ← W − α∇_W L
    Update (θ,W^(1)) ← hier − prox(θ,W^(1),αλ,M)
  end for
  Update K to be the number of non-zero coordinates of θ
end while
```

nonlinear components. When $M \rightarrow 0$, LassoNet reduces to linear regression with Lasso regularization, whereas when $M \rightarrow \infty$, it becomes a standard feed-forward neural network. Algorithm 1 presents the working mechanism of LassoNet.

In our article, we set $M = 10$ and obtained the relationship between candidate feature variables and loss values, as shown in Figure 4. Experimental results show that when extracting 18 features from the original datasets, the loss value can be minimized. Using more than 18 features decreases the accuracy of the experimental results. Therefore, we chose 18 features from the original datasets as input features in our article.

In the above experiments, we concluded that loss minimization could be achieved when 18 features are input, but it is impossible to know exactly which 18 features. Moreover, the feature-based explainable technique can solve this problem. LassoNet can compute the absolute values of the input feature coefficients to determine their importance, with higher coefficients indicating greater importance. By leveraging this approach, we can identify the features that have the greatest impact on the target variable and visualize them, which is critical for data interpretation and deeper analysis. Since the original dataset contains 148 features in total, it cannot be clearly displayed on a single image, so we only show the top 18 sorted feature variables in terms of importance, as shown in Figure 5.

From the feature importance ranking graph, it can be seen that the factors affecting cotton yarn futures price volatility are quite complex, including not only cotton yarn futures prices themselves but also the prices of their upstream and downstream products (e.g., CCFc1_c and CTAc1_C), as well as macroeconomic indicators (e.g., LCOK3_C and SZI_F) and market sentiment indicators (VIX_L, ETU_SCA, etc.).

4 | MODEL CONSTRUCTION AND VALIDATION

4.1 | Construction of probability forecasting models

In this article, we combined CP (Lei et al., 2018), QR (Liu et al., 2015), and LSTM (Du et al., 2022) to develop a hybrid probability forecasting model called CP-QR-LSTM, which was applied to investigate the volatility patterns of cotton yarn futures prices. The CP-QR-LSTM model combines the strengths of CP, QR, and LSTM

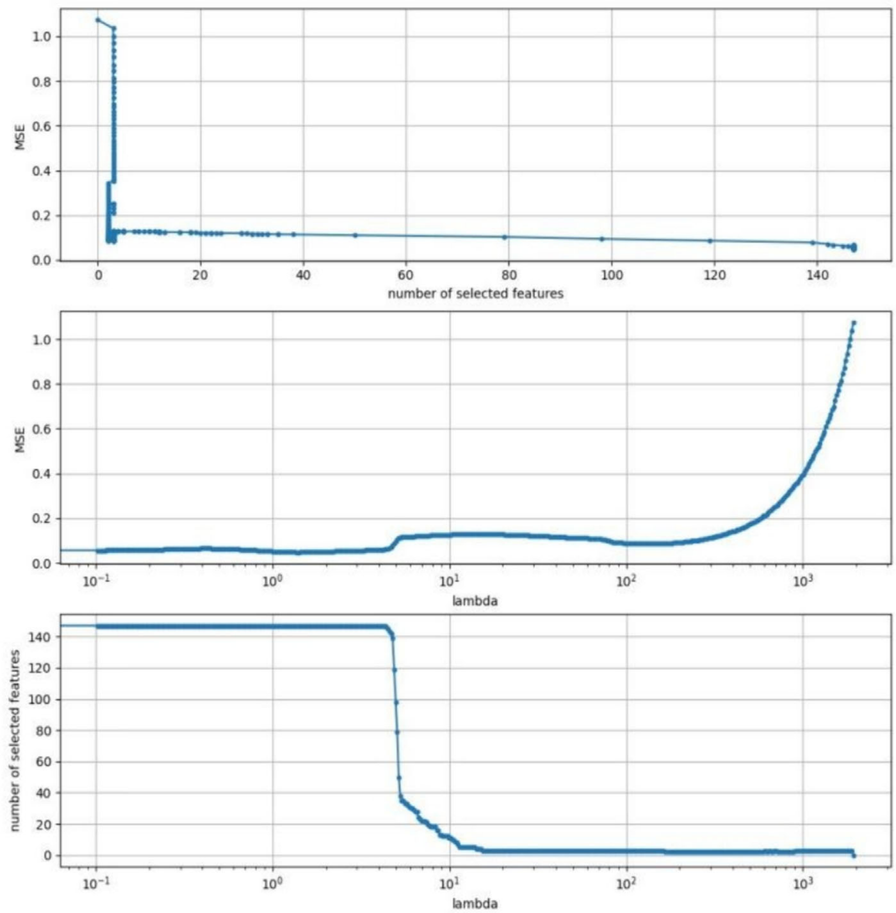


FIGURE 4 The relationship between the number of features and the loss value.

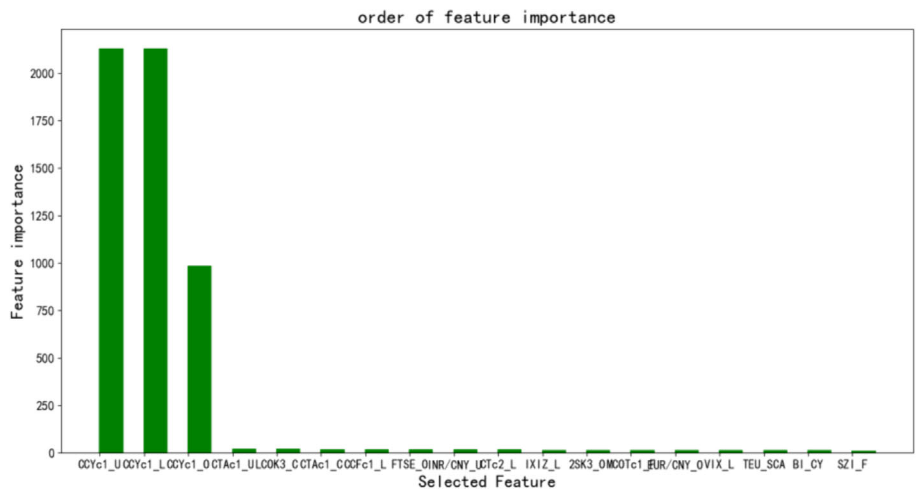


FIGURE 5 Feature importance ranking.

(Jensen et al., 2022), enabling it to handle the hidden complexities in time series data while providing reliable and effective interval forecasting with confidence levels. Furthermore, since the model takes historical errors into account and dynamically updates the threshold needed for quantile forecasting, it can deceptively handle potential Heteroskedasticity or noise issues (Schecter et al., 2022). The research framework is illustrated in Figure 6.

In the above framework, the LSTM model learns hidden features in time series data using the back-propagation algorithm and provides point estimates corresponding to a one-time step into the future. These point estimates can provide some time series trend information, which is often misunderstood as precise values. However, in practical forecasting tasks, precise point forecasting cannot be achieved. We hope to provide a reliable confidence interval while giving point forecasting to reflect the uncertainty

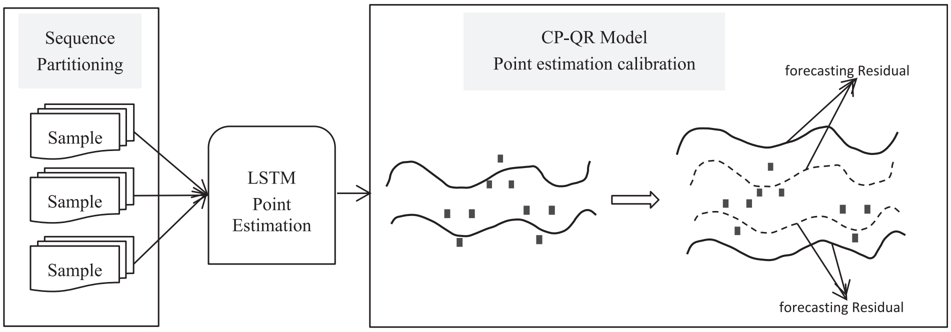


FIGURE 6 Architecture diagram of CP-QR-LSTM model.

of forecasting results (Schecter et al., 2022). In this article, we trained three CP-QR models simultaneously and combined them into a single model (named CP-QR model) to calibrate the point estimates output by the LSTM model and generate forecast intervals that satisfy the specified confidence level. Next, we will introduce the working principle of CP-QR in detail.

CP is a non-parametric method for predicting confidence levels, which can ensure that predicted results are effectively covered within a confidence interval (Lei et al., 2018). The mathematical principle of the CP algorithm is as follows. First, the given datasets $X \in R^d$ are divided into three datasets, which are the LSTM point estimation training set ξ_1, the calibration set ξ_2, and the test set ξ_3. For results forecasted Y_{n+1} by $\widehat{h_{lstm}}$ in ξ_1, we require a forecast interval $\widehat{C_\alpha}(x)$ to satisfy the following equation.

$$P\left\{Y_{n+1} \in \widehat{C_\alpha}(X_{n+1}=x)\right\} \geq 1-\alpha \tag{3}$$

$$\widehat{C_\alpha}(x) = \left[\widehat{h_{lstm}}(x) - Q_{1-\alpha}(R,\xi_2), \widehat{h_{lstm}}(x) + Q_{1-\alpha}(R,\xi_2)\right] \tag{4}$$

where α is the miscoverage rate, R is residual set in ξ_2, and $Q_{1-\alpha}(R,\xi_2)$ is the $(1-\alpha)th$ quantile of R.

QR is a quantile regression method that models uncertainty in predicted results and can deal with heteroskedasticity data exhibiting local variability (Liu et al., 2015). First, the purpose of QR is to estimate the conditional quantile function of Y given X at a specified α, which is defined as

$$\widehat{q_\alpha}(x) = \inf\{y \in R : F_Y(y|x) \geq \alpha\} \tag{5}$$

$$\widehat{C_\alpha}(x) = \left[\widehat{q_{\frac{\alpha}{2}}}(x), \widehat{q_{1-\frac{\alpha}{2}}}(x)\right] \tag{6}$$

By utilizing the advantages of these two algorithms, the proposed CP-QR algorithm is a calibration method based on confidence levels and quantile regression, which can perform conditional probability analysis on the distribution of forecasting results of the LSTM point forecasting model. The forecast interval $\widehat{C_\alpha}(x)$ of CP-QR-LSTM satisfies the following equation. Algorithm 2 is the pseudo-code of the CP-QR-LSTM model.

$$\widehat{C_\alpha}(x) = \left[\widehat{q_{\frac{\alpha}{2}}}(x) - Q_{1-\alpha}(\varepsilon,\xi_2), \widehat{q_{1-\frac{\alpha}{2}}}(x) + Q_{1-\alpha}(\varepsilon,\xi_2)\right] \tag{7}$$

where $\varepsilon \triangleq \max\left\{\widehat{q_{\frac{\alpha}{2}}}(x_i) - y_i, y_i - \widehat{q_{1-\frac{\alpha}{2}}}(x_i)\right\}, i \in \xi_2$.

4.2 | Model validation

In order to demonstrate the effectiveness and accuracy of the proposed CP-QR-LSTM model, this section validates the model in two stages, as shown in Figure 7. In the first stage, we visualize the results of the proposed probability forecasting model and the point forecasting (LSTM-Attention) model to verify the effectiveness of the model. In the second stage, the proposed model is compared with the CP-QR-TCN (TCN: Temporal Convolutional Network) probability forecasting model and the CP-QR-RF (RF: Random Forest) probability forecasting model to validate the accuracy of the model.

4.2.1 | Validity test

In this article, we use mean absolute percentage error (MAPE), root mean square error (RMSE), and mean absolute error (MAE) as evaluation metrics. The ranges of these three indicators are all (0, $+\infty$), and the larger the indicator value, the worse the model's performance. The calculation formulas are shown in Equations (8), (9), and (10), respectively.

$$MAPE = \frac{100\%}{m}\sum_{i=1}^{m}\left|\frac{\widehat{y_i}-y_i}{y_i}\right|, \tag{8}$$

Algorithm 2 The pseudo-code of the CP-QR-LSTM model

Input: Time-series data X, Prediction probability P, Selection of bias correction tool function M.

Output: Prediction intervals for each time point in the future prediction period.

Initialize a residual set $R = \{0\}$, an interval set $Q = \{\ \}$, and a set of confidence levels α.
for each confidence level α **do**
  Train LSTM model $h(X)$ using X, and make forecasting with it.
  Generate a prediction interval $C(X, P, h, \alpha)$ using Conformal Prediction on the training set, where P is the forecasting probability.
  Bias correction: subtract $M(C(X, P, h, \alpha))$ from all elements in the residual set R to obtain a new set of residuals R_{new}.
  Combine the intervals in Q with R_{new} and α to form a new interval set Q_{new}, and set it as Q.
for each t in the future prediction period, **do**
  Train a LSTM model $h_t(X_h)$ using the historical values in X_h up to and including time t.
  For each confidence level α, create an interval set $Q_t(\alpha)$ using $h_t(X_h)$, R, and α.
  Take the weighted average of the intervals in $Q_t(\alpha)$ at the given confidence level α to obtain the final interval set Q_t.
end for

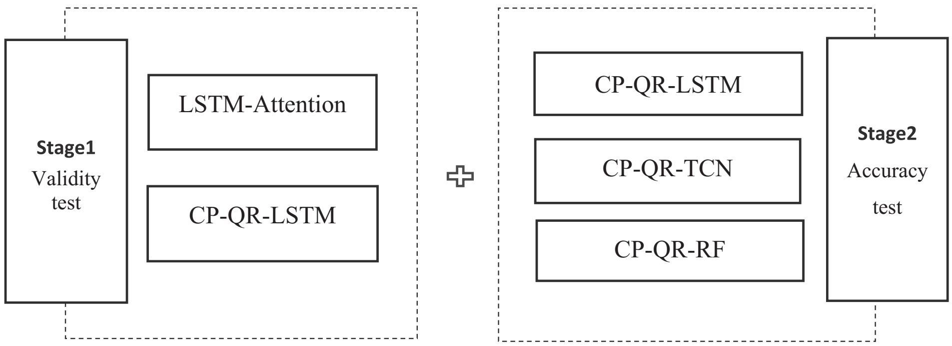


FIGURE 7 Two-stage model validation framework.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m} (\hat{y}_i - y_i)^2}{m}}, \tag{9}$$

$$MAE = \frac{\sum_{i=1}^{m} |\hat{y}_i - y_i|}{m}, \tag{10}$$

where $\hat{y}_i$ is the forecast value, y_i is the real value, and m is the total amount of data.

In this article, we built an LSTM model with an attention mechanism as the point forecasting model, and its quantitative forecasting results are shown in Table 5. The forecasting horizon in Table 5 represents the forecasting step length. Without loss of generality, we analyze the forecasting errors for five different forecasting step lengths: 1, 7, 14, 21, and 28. The final average of the errors of five different steps is calculated as the evaluation criterion. Here, in order to test the effectiveness of data mining in Section 3.2, we input the missing values and the original standardized dataset into the model for comparison tests. From Table 5, we conclude that the features mined by the LassoNet algorithm can better reflect the fluctuation pattern of cotton yarn futures prices, which greatly improves the accuracy of models. Nevertheless, the point forecasting model still has a large inaccuracy.

In order to intuitively verify the effectiveness of probability forecasting, we visualize experimental results of LSTM-Attention and CP-QR-LSTM, as shown in Figures 8 and 9. From Figure 8, we can see that the predicted values and actual values do not completely overlap, and there is even a significant error between the two around Time = 100, which leads to poor robustness of the model.

TABLE 5 Evaluation results of point forecasting indicators.

Point forecasting model	Forecasting horizon:1			Forecasting horizon:7			Forecasting horizon:14		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
LSTM-Attention (processed datasets)	691.9878	394.8949	1.7226	719.7284	424.1447	1.8276	744.5562	456.6801	1.9998
LSTM-Attention (original datasets)	1542.0669	1100.4785	5.3107	2029.1941	1586.5992	8.0224	3871.7548	2853.1217	17.2554

TABLE 5 (Continued)

Point forecasting model	Forecasting horizon:21			Forecasting horizon:28			Average value		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
LSTM-Attention (processed datasets)	644.5368	300.8113	1.3212	662.2473	316.5099	1.4096	**692.6113**	**378.6082**	**1.7762**
LSTM-Attention (original datasets)	3862.5280	2828.3595	17.0766	6851.7324	5187.8296	16.9008	**3631.4552**	**2711.2777**	**12.9132**

The reason for the above problem is due to the inherent limitations of point forecasting, which generates only a deterministic result and does not consider the uncertainties caused by complex market environments, data collection, and data processing, thus failing to provide uncertainty measures for the predicted results (Chen et al., 2023; Hüllermeier & Waegeman, 2021; Mullins & Sabherwal, 2022). Unlike point forecasting, the CP-QR-LSTM model delves into the distribution of point estimates generated by LSTM and calculates the forecasting interval at a given confidence level. Figure 9 shows the forecasting results at a confidence level of 90%, and the model's results are not a fixed value but rather within a certain range, providing an uncertainty measure for the predicted results. Therefore, in practical applications, probability forecasting has higher effectiveness, practical value, and potential than point forecasting.

4.2.2 | Accuracy test

The forecasting interval coverage probability (PICP) and normalized average width (PINAW) were selected as evaluation metrics for CP-QR-LSTM in this article. Their calculation formulas are shown in Equations (11) and (12), respectively. In this article, we aimed to ensure that the PICP reached the confidence level we set while minimizing the execution interval width, that is, minimizing the PINAW as much as possible.

$$PICP = \frac{1}{n}\sum_{i=1}^{n} C_i, \tag{11}$$

where $C_i = \begin{cases} 1, & y_i \in [\boldsymbol{L_i}, \boldsymbol{U_i}] \\ 0, & y_i \notin [\boldsymbol{L_i}, \boldsymbol{U_i}] \end{cases}$, L_i, U_i is the lower and upper bounds of confidence interval.

$$PINAW = \frac{1}{nR}\sum_{i=1}^{n}(U_i - L_i), \tag{12}$$

where $R = y_{max} - y_{min}$.

As shown in Table 6, in order to verify the accuracy of the CP-QR-LSTM model, we compared it with the CP-QR-TCN and CP-QR-RF models. To reduce the randomness of the experimental results, we conducted multiple experiments under the conditions of 90.0% and 95.0% confidence intervals, respectively, and took the average value of multiple experimental results as our basis for comparison. From Table 6, it can be seen that all three models are able to reach the corresponding confidence level, which is due to the introduction of the CP (conformal forecasting) algorithm in the models, which improves the coverage rate of the models. Because the LSTM algorithm has advantages in capturing long-term dependencies and nonlinear modeling of time series, the proposed model is significantly better than the other two comparison models in terms of coverage width. Specifically, under the condition of a 90.0% confidence interval, the coverage width of CP-QR-LSTM is reduced by about 61.43% compared with CP-QR-TCN and by about 44.31% compared with CP-QR-RF; under the condition of a 95.0% confidence interval, the coverage width of CP-QR-LSTM is reduced by about 44.13% compared with CP-QR-TCN and by about 3.09% compared with CP-QR-RF. Therefore, results show that the CP-QR-LSTM model has high accuracy in predicting the volatility patterns of cotton yarn futures prices.

4.3 | Feature-based XAI

SHAP approximates the importance of local features by using the Shapley values defined in cooperative game theory (Lundberg & Lee, 2017), and it interprets the results of models by evaluating the marginal contribution margin to the result of the model while visualizing the results. SHAP works as shown below. Moreover, Algorithm 2 presents the working mechanism of SHAP.

SHAP interprets the model output by calculating the Shapley value for each feature, as shown in Equation (13).

$$g\left(z'\right) = \varphi_0 + \sum_{j=1}^{M} \varphi_j \tag{13}$$

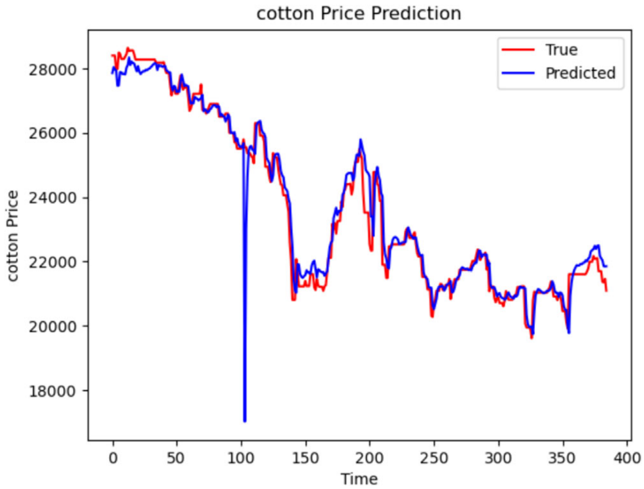


FIGURE 8 Visualization of point forecasting results of the LSTM-Attention model.

The Shapley value φ_j of j can be calculated for all possible combinations of features and then weighted and summed, as shown in Equation (14):

$$\varphi_j(val) = \sum_{s \subseteq \{x_1, x_2, \ldots x_p\} \setminus \{x_j\}} \frac{|s|!(p-|s|-1)!}{p!} \left(val\left(s \cup \{x_j\}\right) - val(s)\right) \tag{14}$$

where s is the subset of input features, x is vector of instance eigenvalues, p is feature's number, $val_x(s)$ is the output of s, and integral is calculated for features not included in the s, as shown in Equation (15). And Algorithm 3 is the pseudo-code of SHAP in this article.

$$val_x(s) = \int \hat{f}(x_1, x_2, \ldots, x_p) dp_{x \notin s} - E_x\left(\hat{f}(X)\right) \tag{15}$$

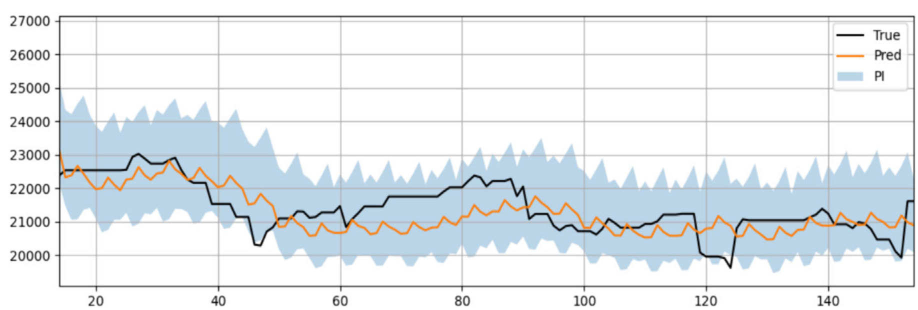


FIGURE 9 Visualization of probability forecasting results of CP-QR-LSTM model.

TABLE 6 Assessment results of probability forecasting indicators.

Confidence level	Interval forecasting model	Forecasting horizon: 10 PICP	Forecasting horizon: 10 PINAW	Forecasting horizon: 20 PICP	Forecasting horizon: 20 PINAW	Forecasting horizon: 30 PICP	Forecasting horizon: 30 PINAW	Average value PICP	Average value PINAW
90.0%	CP-QR-LSTM	90.0%	0.525	93.3%	0.536	97.1%	1.052	**93.47%**	**0.7043**
	CP-QR-TCN	100.0%	1.279	99.5%	1.312	99.4%	2.887	**99.63%**	**1.8260**
	CP-QR-RF	100.0%	0.968	100.0%	0.915	100.0%	1.911	**100.00%**	**1.2647**
95.0%	CP-QR-LSTM	98.4%	1.043	96.7%	1.182	98.3%	1.354	**97.80%**	**1.1930**
	CP-QR-TCN	99.5%	1.771	98.3%	0.992	100%	3.643	**99.27%**	**2.1353**
	CP-QR-RF	100%	1.069	100%	1.143	100%	1.481	**99.83%**	**1.2310**

Algorithm 3 SHAP for feature-based XAI

input: point forecasting model f_{lstm}, instance to explain X, reference datasets X' reference outputs Y', number of interpreters K

output: SHAP value S for each feature

Initialize $S = [0] * n$, where n is the feature's number

for $k = 1 \ldots K$ **do**

    Randomly select a sample x' from X', and compute its output value $f_{lstm}(x')$

    Compute the difference $f_{lstm}(x) - f_{lstm}(x')$

    for $j = 1 \ldots n$ **do**

        Randomly select a sample x_j' from X', and replace the j feature value with the corresponding value from x_j', then compute the output value $f_{lstm}(x_j')$

        Compute the difference $f_{lstm}(x) - f_{lstm}(x_j')$

        Accumulate the contribution to S_j as follows:

        $$S_j = \frac{1}{K} \sum_{k=1}^{K} (f_{lstm}(x^k) - f_{lstm}(x_j^{\ k}))$$

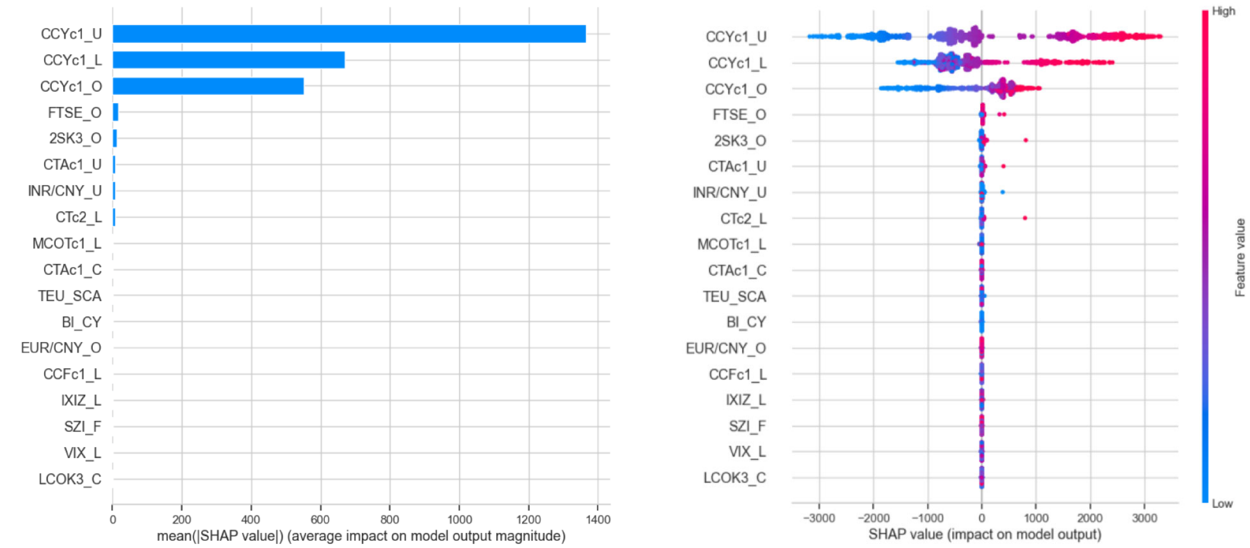
end for

return S

The remainder of this section introduces the SHAP algorithm for feature interpretable analysis of the point estimation part of the CP-QR-LSTM.

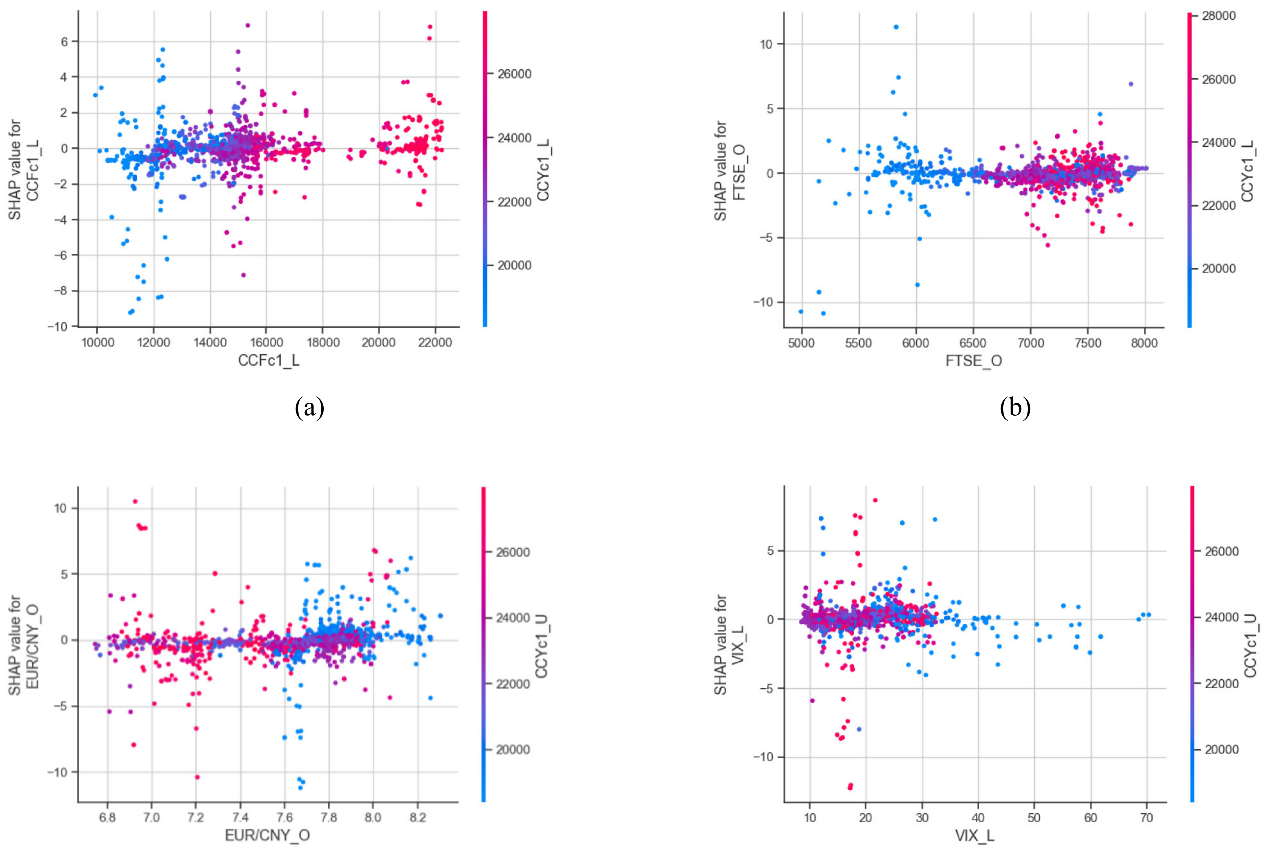
First, Figure 10 shows the SHAP feature importance analysis chart, which ranks the SHAP values of the factors affecting cotton yarn futures prices according to their elements. In Figure 10a, the ranking is based on the magnitude of the absolute value of SHAP values, and Figure 10b directly shows the degree and direction of the influence characteristics of each instance. From Figure 10, it can be found that the differences in the characteristics of CCYc1_U (highest of cotton yarn futures), CCYc1_L (lowest of cotton yarn futures), and CCYc1_O (opening of cotton yarn futures) have a more obvious impact on the model. This is the same as the top three important features calculated by LassoNet in Section 3.2.2. Figure 10b indicates that all three main features have a positive effect on CCYc1_C (closing of cotton yarn futures). When these characteristics have larger values, they correspond to higher SHAP values, which in turn are associated with higher CCYc1_C.

Compared with the three types of features mentioned above that have more significant effects, the effects of other features are difficult to observe visually in Figure 10. Therefore, we plot the interaction dependence of the two features by changing the specific features in the SHAP algorithm. Figure 11a,b shows the interaction dependence plots of CCFc1_L (lowest of cotton futures), FEST_O (FTSE 100 opening), and CCYc1_L, where the red dots represent the higher values of CCYc1_L (lowest price of cotton yarn futures), where the red dots represent the higher values of CCYc1_L and the blue dots represent the lower values of CCYc1_L. When the values of CCFc1_L and FEST_O increase, CCYc1_L increases, and the SHAP value also increases, indicating that CCFc1_L and FEST_O indirectly affect the CCYc1_C by interacting with CCYc1_L, and the effect is positive. Similarly, Figure 11c,d shows the interaction dependence plots of EUR/CNY_O (opening value of EUR/CNY), VIX_L (lowest value of VIX panic index), and CCYc1_L. Unlike the above two features, EUR/CNY_O and VIX_L affect the CCYc1_C by influencing CCYc1_U, indirectly



(a) Absolute value ordering of SHAP values (b) ordering of SHAP values

FIGURE 10 SHAP feature importance analysis.



(a) (b)

(c) (d)

FIGURE 11 SHAP dependence plots.

affecting CCYc1_C, and the effect is negative. Through the feature dependence chart, we find that the factors that have a positive effect on the CCYc1_C include CCFc1_F (lowest of cotton futures), FEST_O (the opening price of FTSE 100), CTAc1_U (highest of PTA futures), 2SK3_O (opening of US soybean futures),

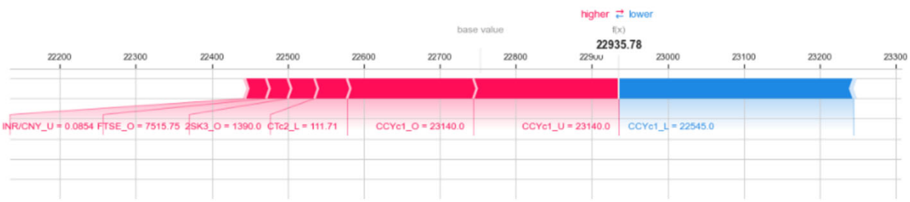


FIGURE 12 Explanation of the 23rd instance by SHAP.

TABLE 7 Descriptive statistical analysis of robustness test datasets.

	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)
count	70,091	70,091	70,091	70,091	70,091	70,091
mean	9.45048	283.4930	4.9564	76.0097	13.5765	9.5339
std	8.4233	8.5044	6.7300	16.4749	7.7398	4.1836
min	−22.76	250.85	−24.8	13.88	0.97	0.81
25%	3.35	277.44	0.24	65.21	7.77	6.22
50%	9.41	283.46	5.21	79.3	11.82	8.86
75%	15.48	289.53	10.08	89.4	17.61	12.36
max	37.28	311.21	23.06	100	63.77	28.25

LCOK3_C (closing of London Brent crude oil futures), CTc2 _L (highest value of US cotton futures No. 2 [CTc2]), IXIZ_L (lowest value of the Nasdaq Composite), and INR/CNY_U (highest value of the Indian rupee/yuan). Features that have a negative effect include EUR/CNY_O (EUR/CNY opening value), VIX_L (VIX Panic Index minimum), TEU_SCA (Twitter EPU [TEU_SCA]), SZI_F (SZI component index gain/loss), and MCOTc1_L (Indian cotton futures minimum).

Figure 12 shows the marginal contribution of the main features to the predicted values using SHAP analysis for the 23rd randomly selected estimate after the training of LSTM point estimation.

We can see from Figure 12 that the baseline value (mean predicted value) for the 29th sample is 22935.78. All the red bars on the left side of the model output represent features that have a positive effect on the deviation from the baseline value (mean predicted value), including INR/CNY_U, ….., and CCY1c1_U. Each of these features causes an increase in prediction, and the length indicates the extent of the effect. Similarly, all blue bars on the right side of the model output represent features that have a negative impact on the deviation of the predicted value from the baseline value. The length of the bar indicates the contribution of that element, indicating that CCYc1_L is the feature that causes a decrease in prediction results, with the largest effect originating at CCYc1_l = 22545.0.

Consequently, we can clearly understand the extent and direction of input features on the forecasting results, which significantly improves the interpretability of the "black box" model.

4.4 | Robustness test

To validate the strong generalization capabilities of the proposed probability forecasting model, we selected an open-source dataset from the meteorological domain to assess the model's predictive performance. The descriptive statistics for some variables in the datasets are presented in Table 7, where T (degC) represents the prediction target.

As the dataset is collected on an hourly basis, in our study, we set a sliding window of 24 h to predict the temperature change range within the next 6 h. The experimental results are presented in Table 8 and Figure 13. Table 8 displays the evaluation results of the model constructed in this study at 90% and 95% confidence levels. It is evident from the table that the model exhibits good coverage in meteorological forecasting, with relatively narrow prediction intervals.

Figure 13 illustrates the visual results of the testing set at a 90% confidence level, including actual values, point estimates, and prediction intervals. From the graph, we observe that the model developed in this research demonstrates applicability in meteorological forecasting with effective coverage.

5 | DISCUSSION

5.1 | Theoretical contribution

The probability forecasting model (CP-QR-LSTM) proposed in this paper is used to quantify the volatility

TABLE 8 Assessment results of robustness test datasets.

		Forecasting horizon: 24 h	
Confidence level	Interval forecasting model	PICP	PINAW
90.0%	CP-QR-LSTM	**94.3%**	**0.170**
	CP-QR-TCN	95.9%	0.602
	CP-QR-RF	92.7%	0.171
95.0%	CP-QR-LSTM	**96.6%**	**0.212**
	CP-QR-TCN	98.3%	0.714
	CP-QR-RF	89.0%	0.288

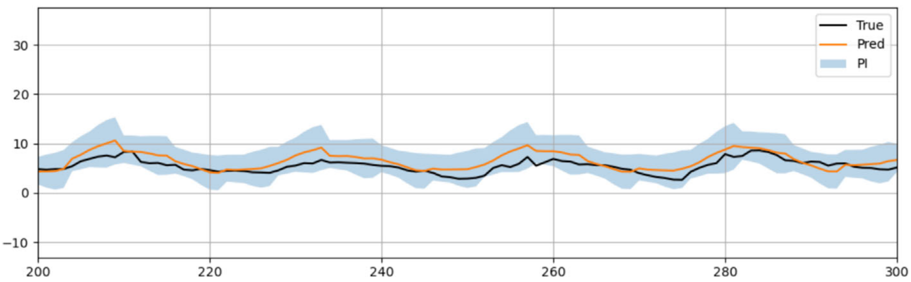


FIGURE 13 Visualization of probability forecasting results of robustness test datasets.

patterns and uncertain distributions of cotton yarn futures. Based on the self-properties of cotton yarn futures prices and a data-driven perspective, we collected 148 possible factors that may affect the target variable forecasting and extracted 18 effective features for model input using XAI techniques. Combined with existing research, our article has the following theoretical significance.

The contributions of this article are significant for forecasting in the field of operational research. Accurate forecasting is essential for making informed decisions and optimizing resources in various fields such as finance, economics, logistics, and supply chain management. The background and significance of forecasting in operational research are related to its ability to predict future outcomes based on past data and trends, helping decision-makers plan for future scenarios and minimize risks. The contributions theory of this article can be summarized in four points: (1) the data processing stage selects the LassoNet algorithm for explainable analysis. The LassoNet algorithm is based on L1 regularization and residual neural networks, which can effectively screen features and provide variable importance rankings and explanations. This modeling idea aims to screen out the variables most relevant to the dependent variable among many independent variables in the cotton yarn market data, thereby improving model interpretability. This feature selection approach also has promotional significance in practical applications. (2) Using CP-QR-LSTM to analyze the uncertainty of future cotton yarn futures price distributions. LSTM can obtain high-precision point forecasting results, but when a reliable forecasting range is required, it is difficult to support probability forecasting. Therefore, in this article, combining the CP-QR algorithm transforms the LSTM forecasting results into a probability distribution form with a confidence level. In particular, our proposed probabilistic forecasting framework can be applied not only to the LSTM point estimator built in this paper but also to point forecasting models from different domains in existing articles, which makes a small contribution to advancing the development of probabilistic forecasting methods based on deep learning models. This article also provides decision-makers with more accurate and reliable forecasting ranges, which can inform optimal resource allocation and risk management strategies. (3) The introduction of the SHAP algorithm to analyze the influence of features on forecasting results significantly improves the explainability of models. This is important in operational research because it allows decision-makers to understand how different factors contribute to forecasting results and make more informed decisions based on the insights provided by these models. (4) This paper provides a "big data-probabilistic predictive model-decision support" data-driven decision paradigm from the perspective of big data and XAI, which provides a reference for decision-making in big data scenarios. This approach is highly relevant to operational research because it enables decision-makers to leverage the huge amounts of data available to them to make more accurate and informed decisions. The integration of probabilistic forecasting and XAI methods in this paradigm offers decision-makers a transparent and reliable way to understand how different factors contribute to forecasting results and use these insights to inform their decisions.

5.2 | Practical value

We summarize the practical value of this article from three perspectives: people, organizations, and technology.

From the people's perspective, this paper provides decision support for stakeholders in the cotton textile industry. Stakeholders in the cotton textile industry and related fields can find real value in the proposed models. By providing more accurate and reliable predictions of price volatility, these models can help stakeholders, including shareholders, investors, and regulators, make informed decisions and manage risk in a volatile market environment. LassoNet, CP-QR-LSTM, and SHAP models, through their feature selection, interpretable enhancement, and explainable analysis, enable stakeholders to understand the factors that contribute to price volatility and adjust their strategies accordingly. Furthermore, the integration of big data and artificial intelligence techniques into price volatility prediction provides stakeholders with a more modern and effective approach to decision-making and risk management.

From the perspective of organizations, this article provides a more reasonable price volatility forecasting scheme for the cotton textile industry and related enterprises, helping them make decisions and plans in high-risk and high-uncertainty markets and enhancing their competitiveness. In terms of optimizing enterprise decisions, the proposed probability forecasting model can predict volatility that is more application-oriented than traditional point forecasting methods, reducing the serious consequences of incorrect decisions for enterprises. In terms of improving enterprise competitiveness, as the market competition intensifies, cotton textile industry participants need to adjust their decisions based on market volatility. Through feature selection, interpretability enhancement, and other means, the model proposed in this article enables enterprise managers to effectively understand market changes and formulate scientific and reasonable decisions, thereby enhancing the core competitiveness of enterprises. In terms of digital transformation and intelligent management of enterprises, the predicted results of the proposed model can provide important references for large-scale data analysis and management by enterprises, which is conducive to the in-depth development of digital strategies. Introducing modern computer technology into price volatility forecasting not only improves decision-making quality and direction but also responds to changes more accurately and quickly, which is beneficial to shorten enterprise response time and enhance market sensitivity.

From a technical perspective, this article combines LSTM deep networks with CP-QR algorithms to provide a new and more accurate price volatility forecasting model, utilizing new technologies such as big data and artificial intelligence to their fullest potential, possessing strong practical value. The proposed model can not only be applied to cotton yarn futures prices but can also be generalized to other datasets with time series features.

Overall, this article provides practical value not only for individuals and organizations in the cotton textile industry but also for the various stakeholders involved in the operation and development of the industry.

6 | CONCLUSION

In the context of big data, the volatility of cotton yarn futures prices exhibits characteristics such as high dimensionality, complexity, and nonlinearity. Additionally, existing machine learning prediction models often lack interpretability. Given these challenges, this study addresses two research questions: RQ1: What is the pattern of cotton yarn futures price volatility driven by data (three types of data)? RQ2: What is the relationship between XAI data empowerment and volatility in cotton yarn futures prices?

For the first research question, this study, through a review of the literature and expert experience, collected a total of 148 potential influencing factors from the perspectives of trading data, interaction data, and measurement data. The aim was to simulate the actual fluctuation environment of cotton yarn prices. Subsequently, a LassoNet network was constructed to explore the influencing factors of cotton yarn futures prices, enhancing interpretability by visualizing their importance rankings. The research integrated LSTM, CP, and QR to build a probability forecasting model, measuring the uncertainty of future cotton yarn futures price distribution. The inclusion of the CP algorithm ensured the confidence level of the model's output results. As shown in Table 7, all three experimental models, under the constraint of the CP algorithm, achieved the expected confidence levels. Notably, this study used deep learning networks as point estimators, improving the accuracy of point estimation compared to TCN and RF algorithms. This led to a reduction in the PINAW indicator value, further narrowing future uncertainty.

For the second research question, given the intrinsic lack of interpretability of the LSTM point estimator, this paper introduces the SHAP algorithm to analyze the marginal contribution of each input feature to the point estimation results. With the inclusion of the SHAP interpretability method, the model achieves a comprehensive analysis of the interaction between input features and the target variable from both a global and local perspective. This provides a high level of confidence in the predictive results. The study reveals that, in addition to historical trading data of cotton yarn futures having a significant impact on price fluctuations, factors such as CCFc1_L, FEST_O, EUR/CNY_O, and VIX_L, among others, also influence the volatility of cotton yarn prices. Their inclusion enhances the accuracy of predictions to a certain extent.

In addition, to visually compare the differences between point predictions and probability forecasts, we visualized the experimental results. As observed in Figures 8 and 9, probability forecasting demonstrates greater practical applicability. It not only provides point estimation values but also quantifies the uncertainty of their distribution, aligning more closely with human decision-making behavior.

A limitation of this study lies in the focus on the distribution of point prediction results when constructing the probability forecasting model. Consequently, a single model was utilized in constructing the point prediction model. Future research could consider further improvements on the point prediction model to enhance predictive accuracy.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

Besbes, O., & Mouchtaki, O. (2023). How big should your data really be? Data-driven newsvendor: Learning one sample at a time. *Management Science*, *4725*, 5848–5865. https://doi.org/10.1287/mnsc.2023.4725

Baştürk, N., Borowska, A., Grassi, S., Hoogerheide, L., & van Dijk, H. K. (2019). Forecast density combinations of dynamic models and data driven portfolio strategies. *Journal of Econometrics*, *210*(1), 170–186. https://doi.org/10.1016/j.jeconom.2018.11.011

Bouteska, A., Hajek, P., Fisher, B., & Abedin, M. Z. (2023). Nonlinearity in forecasting energy commodity prices: Evidence from a focused time-delayed neural network. *Research in International Business and Finance*, *64*, 101863. https://doi.org/10.1016/j.ribaf.2022.101863

Chai, S., Li, Q., Abedin, M. Z., & Lucey, B. M. (2024). Forecasting electricity prices from the state-of-the-art modeling technology and the price determinant perspectives. *Research in International Business and Finance*, *67(A)*, 102132. https://doi.org/10.1016/j.ribaf.2023.102132

Chen, Z. Y., Fan, Z. P., & Sun, M. (2023). Machine learning methods for data-driven demand estimation and assortment planning considering cross-selling and substitutions. *INFORMS Journal on Computing*, *35*(1), 158–177. https://doi.org/10.1287/ijoc.2022.1251

Chen, W., Xu, H., Jia, L., & Gao, Y. (2021). Machine learning model for Bitcoin exchange rate prediction using economic and technology determinants. *International Journal of Forecasting*, *37*(1), 28–43. https://doi.org/10.1016/j.ijforecast.2020.02.008

Du, B., Huang, S., Guo, J., Tang, H., Wang, L., & Zhou, S. (2022). Interval forecasting for urban water demand using PSO optimized KDE distribution and LSTM neural networks. *Applied Soft Computing*, *122*, 108875. https://doi.org/10.1016/j.asoc.2022.108875

Dwivedi, R., Dave, D., Naik, H., Singhal, S., Omer, R., Patel, P., … Ranjan, R. (2023). Explainable AI (XAI): Core ideas, techniques, and solutions. *ACM Computing Surveys*, *55*(9), 1–33. https://doi.org/10.1145/3561048

ElShawi, R., Sherif, Y., Al-Mallah, M., & Sakr, S. (2021). Interpretability in healthcare: A comparative study of local machine learning interpretability techniques. *Computational Intelligence*, *37*(4), 1633–1650. https://doi.org/10.1111/coin.12410

Fan, J., Fan, Y., & Barut, E. (2014). Adaptive robust variable selection. *Annals of Statistics*, *42*(1), 324–351. https://doi.org/10.1214/13-AOS1191

Fan, Y., Abedin, M. Z., & Petr, H. (2023). An explainable federated learning and blockchain-based secure credit modeling method. *European Journal of Operational Research*, *317*, 449–467. https://doi.org/10.1016/j.ejor.2023.08.040

Guo, S., Li, H., An, H., Sun, Q., Hao, X., & Liu, Y. (2019). Steel product prices transmission activities in the midstream industrial chain and global markets. *Resources Policy*, *60*, 56–71. https://doi.org/10.1016/j.resourpol.2018.11.014

Goltsos, T. E., Syntetos, A. A., Glock, C. H., & Ioannou, G. (2022). Inventory–forecasting: Mind the gap. *European Journal of Operational Research*, *299*(2), 397–419. https://doi.org/10.1016/j.ejor.2021.07.040

Hajek, P., Froelich, W., & Prochazka, O. (2020). Intuitionistic fuzzy grey cognitive maps for forecasting interval-valued time series. *Neurocomputing*, *400*, 173–185. https://doi.org/10.1016/j.neucom.2020.03.013

Hajek, P., & Abedin, M. Z. (2020). A profit function-maximizing inventory backorder prediction system using big data analytics.

IEEE Access, 8, 58982–58994. https://doi.org/10.1109/ACCESS.2020.2983118

Haffar, R., Sanchez, D., & Domingo-Ferrer, J. (2023). Explaining predictions and attacks in federated learning via random forests. *Applied Intelligence*, *53*(1), 169–185. https://doi.org/10.1007/s10489-022-03435-1

Herwartz, H. (2017). Stock return prediction under GARCH—An empirical assessment. *International Journal of Forecasting*, *33*(3), 569–580. https://doi.org/10.1016/j.ijforecast.2017.01.002

Hu, Y., Ni, J., & Wen, L. (2020). A hybrid deep learning approach by integrating LSTM-ANN networks with GARCH model for copper price volatility prediction. *Physica A:Statistical Mechanics and its Applications*, *557*, 124907. https://doi.org/10.1016/j.physa.2020.124907

Huchet, N., & Fam, P. G. (2016). The role of speculation in international futures markets on commodity prices. *Research in International Business and Finance*, *37*, 49–65. https://doi.org/10.1016/j.ribaf.2015.09.034

Hüllermeier, E., & Waegeman, W. (2021). Aleatoric and epistemic uncertainty in machine learning: An introduction to concepts and methods. *Machine Learning*, *110*, 457–506. https://doi.org/10.1007/s10994-021-05946-3

Jalota, D., Paccagnan, D., Schiffer, M., & Pavone, M. (2023). Online routing over parallel networks: Deterministic limits and data-driven enhancements. *INFORMS Journal on Computing*, *1275*, 560–577. https://doi.org/10.1287/ijoc.2023.1275

Jabeur, S. B., Mefteh-Wali, S., & Viviani, J. L. (2021). Forecasting gold price with the XGBoost algorithm and SHAP interaction values. *Annals of Operations Research*, *1-21*, 679–699. https://doi.org/10.1007/s10479-021-04187-w

Jensen, V., Bianchi, F. M., & Anfinsen, S. N. (2022). Ensemble conformalized quantile regression for probabilistic time series forecasting. *IEEE Transactions on Neural Networks and Learning Systems*, *35*, 1–12. https://doi.org/10.1109/TNNLS.2022.3217694

Jiang, H., Leng, X., & Choi, M. C. (2021). Computer prediction of cotton and sporting goods prices in e-commerce environment based on ARIMA model. *The International Journal of Electrical Engineering & Education*, *60*, 3747–3757. https://doi.org/10.1177/0020720920983706

Jiang, P., Liu, Z., Abedin, M. Z., Wang, J., Yang, W., & Dong, Q. (2024). Profit-driven weighted classifier with interpretable ability for customer churn prediction. *Omega*, *125*, 103034. https://doi.org/10.1016/j.omega.2024.103034

Johansson, U., Sönströd, C., Löfström, T., & Boström, H. (2022). Rule extraction with guarantees from regression models. *Pattern Recognition*, *126*, 108554. https://doi.org/10.1016/j.patcog.2022.108554

Kang, Y., Cao, W., Petropoulos, F., & Li, F. (2022). Forecast with forecasts: Diversity matters. *European Journal of Operational Research*, *301*(1), 180–190. https://doi.org/10.1016/j.ejor.2021.10.024

Karasu, S., Altan, A., Bekiros, S., & Ahmad, W. (2020). A new forecasting model with wrapper-based feature selection approach using multi-objective optimization technique for chaotic crude oil time series. *Energy*, *212*, 118750. https://doi.org/10.1016/j.energy.2020.118750

Karimi, M., & Zaerpour, N. (2022). Put your money where your forecast is: Supply chain collaborative forecasting with cost-function-based prediction markets. *European Journal of Operational Research*, *300*(3), 1035–1049. https://doi.org/10.1016/j.ejor.2021.09.013

Kim, H. Y., & Won, C. H. (2018). Forecasting the volatility of stock price index: A hybrid model integrating LSTM with multiple GARCH-type models. *Expert Systems with Applications*, *103*, 25–37. https://doi.org/10.1016/j.eswa.2018.03.002

Lee, J., & Ryu, D. (2019). The impacts of public news announcements on intraday implied volatility dynamics. *Journal of Futures Markets*, *39*(6), 656–685. https://doi.org/10.1002/fut.22002

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, *30*. https://www.researchgate.net/publication/317062430

Liu, G., & Ma, W. (2022). A quantum artificial neural network for stock closing price prediction. *Information Sciences*, *598*, 75–85. https://doi.org/10.1016/j.ins.2022.03.064

Li, Y., Tong, Z., Tong, S., & Westerdahl, D. (2022). A data-driven interval forecasting model for building energy prediction using attention-based LSTM and fuzzy information granulation. *Sustainable Cities and Society*, *76*, 103481. https://doi.org/10.1016/j.scs.2021.103481

Li, J., Bu, H., & Wu, J. (2017). Sentiment-aware stock market prediction: A deep learning method. In *In 2017 international conference on service systems and service management* (pp. 1–6). https://doi.org/10.1109/ICSSSM.2017.7996306

Li, X., Shang, W., & Wang, S. (2019). Text-based crude oil price forecasting: A deep learning approach. *International Journal of Forecasting*, *35*(4), 1548–1560. https://doi.org/10.1016/j.ijforecast.2018.07.006

Lemhadri, I., Ruan, F., & Tibshirani, R. (2021). LassoNet: Neural networks with feature sparsity. In *In international conference on artificial intelligence and statistics* (Vol. 130, pp. 10–18).

Lei, J., G'Sell, M., Rinaldo, A., Tibshirani, R. J., & Wasserman, L. (2018). Distribution-free predictive inference for regression. *Journal of the American Statistical Association*, *113*(523), 1094–1111. https://doi.org/10.1080/01621459.2017.1307116

Liu, B., Nowotarski, J., Hong, T., & Weron, R. (2015). Probabilistic load forecasting via quantile regression averaging on sister forecasts. *IEEE Transactions on Smart Grid*, *8*(2), 730–737. https://doi.org/10.1109/TSG.2015.2437877

Lockhart, R., Taylor, J., Tibshirani, R. J., & Tibshirani, R. (2014). A significance test for the Lasso. *Annals of Statistics*, *42*(2), 413–468. https://doi.org/10.1214/13-AOS1175

Lisboa, P. J. G., Saralajew, S., Vellido, A., Fernández-Domenech, R., & Villmann, T. (2023). The coming of age of interpretable and explainable machine learning models. *Neurocomputing*, *535*, 25–39. https://doi.org/10.1016/j.neucom.2023.02.040

Ma, Y. R., Ji, Q., & Pan, J. (2019). Oil financialization and volatility forecast: Evidence from multidimensional predictors. *Journal of Forecasting*, *38*(6), 564–581. https://doi.org/10.1002/for.2577

Mullins, J. K., & Sabherwal, R. (2022). Just enough information? The contingent curvilinear effect of information volume on decision performance in IS-enabled teams. *MIS Quarterly*, *46*(4), 2197–2227. https://doi.org/10.25300/MISQ/2022/17290

Meng, Q., Xiao, K., Shen, D., Zhu, H., & Xiong, H. (2022). Fine-grained job salary benchmarking with a non-parametric dirichlet process–based latent factor model. *INFORMS Journal on*

Computing, *34*(5), 2443–2463. https://doi.org/10.1287/ijoc.2022.1182

Muhammad, A., Smith, S. A., & Yu, T. H. E. (2021). COVID-19 and cotton import demand in China. *Agribusiness*, *37*(1), 3–24. https://doi.org/10.1002/agr.21682

Marfatia, H. A., Ji, Q., & Luo, J. (2022). Forecasting the volatility of agricultural commodity futures: The role of co-volatility and oil volatility. *Journal of Forecasting*, *41*(2), 383–404. https://doi.org/10.1002/for.2811

Panagiotelis, A., Gamakumara, P., Athanasopoulos, G., & Hyndman, R. J. (2023). Probabilistic forecast reconciliation: Properties, evaluation and score optimisation. *European Journal of Operational Research*, *306*(2), 693–706. https://doi.org/10.1016/j.ejor.2022.07.040

Pan, Y., & Stark, R. (2022). An explainable machine learning approach for engineering change management decision support in automotive industry. *Computers in*, *industry,138*, 103633. https://doi.org/10.1016/j.compind.2022.103633

Sroginis, A., Fildes, R., & Kourentzes, N. (2023). Use of contextual and model-based information in adjusting promotional forecasts. *European Journal of Operational Research*, *307*(3), 1177–1191. https://doi.org/10.1016/j.ejor.2022.10.005

Schecter, A., Nohadani, O., & Contractor, N. (2022). A robust inference method for decision making in networks. *Management Information Systems Quarterly*, *46*(2), 713–738. https://doi.org/10.25300/MISQ/2022/15992

Sun, Y., Han, A., Hong, Y., & Wang, S. (2018). Threshold autoregressive models for interval-valued time series data. *Journal of Econometrics*, *206*(2), 414–446. https://doi.org/10.1016/j.jeconom.2018.06.009

Sun, Y., Zhang, X., Wan, A. T., & Wang, S. (2022). Model averaging for interval-valued data. *European Journal of Operational Research*, *301*(2), 772–784. https://doi.org/10.1016/j.ejor.2021.11.015

Sarlo, R., Fernandes, C., & Borenstein, D. (2023). Lumpy and intermittent retail demand forecasts with score-driven models. *European Journal of Operational Research*, *307*(3), 1146–1160. https://doi.org/10.1016/j.ejor.2022.10.006

Svetunkov, I., Chen, H., & Boylan, J. E. (2023). A new taxonomy for vector exponential smoothing and its application to seasonal time series. *European Journal of Operational Research*, *304*(3), 964–980. https://doi.org/10.1016/j.ejor.2022.04.040

Tschora, L., Pierre, E., Plantevit, M., & Robardet, C. (2022). Electricity price forecasting on the day-ahead market using machine learning. *Applied Energy*, *313*, 118752. https://doi.org/10.1016/j.apenergy.2022.118752

Venkataraman, D., Vinay, N., Vardhan, T. V., Boppudi, S. P., Reddy, R. Y., & Balasubramanian, P. (2016). Yarn price prediction using advanced analytics model. In *In 016 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)* (pp. 1–8). https://doi.org/10.1109/ICCIC.2016.7919720

Vidal, A., & Kristjanpoller, W. (2020). Gold volatility prediction using a CNN-LSTM approach. *Expert Systems with Applications*, *157*, 113481. https://doi.org/10.1016/j.eswa.2020.113481

Wang, J., He, J., Feng, C., Feng, L., & Li, Y. (2021). Stock index prediction and uncertainty analysis using multi-scale nonlinear ensemble paradigm of optimal feature extraction, two-stage deep learning and Gaussian process regression. *Applied Soft Computing*, *113*, 107898. https://doi.org/10.1016/j.asoc.2021.107898

Wang, D., Wang, X., Abedin, M. Z., Wang, X., & Yin, Y. (2021). Interpretable multi-hop knowledge reasoning for gastrointestinal disease. *Annals of Operations Research*. https://doi.org/10.1007/s10479-023-05650-6

Wang, Y., Liu, W., & Liu, X. (2022). Explainable AI techniques with application to NBA gameplay prediction. *Neurocomputing*, *483*, 59–71. https://doi.org/10.1016/j.neucom.2022.01.098

Wu, Y., Liu, T., & Fang, S. (2018). Research on China's cotton price prediction based on MIV-GA-BP neural network. *Cotton Textile Technology*, (07), 77–80.

Xu, X., & Zhang, Y. (2022). Commodity price forecasting via neural networks for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat. *Intelligent Systems in Accounting, Finance and Management*, *29*(3), 169–181. https://doi.org/10.1002/isaf.1519

Yang, M., Moon, J., Yang, S., Oh, H., Lee, S., Kim, Y., & Jeong, J. (2022). Design and implementation of an explainable bidirectional lstm model based on transition system approach for cooperative ai-workers. *Applied Sciences*, *12*(13), 6390. https://doi.org/10.3390/app12136390

Yang, C., Abedin, M. Z., Zhang, H., Weng, F., & Hajek, P. (2023). An interpretable system for predicting the impact of COVID-19 government interventions on stock market sectors. *Annals of Operations Research*, 1–28. https://doi.org/10.1007/s10479-023-05311-8

Zhang, D., Li, Q., Mugera, A. W., & Ling, L. (2020). A hybrid model considering cointegration for interval-valued pork price forecasting in China. *Journal of Forecasting*, *39*(8), 1324–1341. https://doi.org/10.1002/for.2688

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