Research on Machine Learning-based Prediction of Coffee Futures Prices

Yuduo Chen *

School of Mathematics, Sichuan University, Chengdu, China

* Corresponding author: chenyuduo1999@gmail.com

Abstract. Coffee is one of the major agricultural commodities in world trade, and its futures are vital tools in the global capital market. The continued vitality of the coffee market and substantial price fluctuations have increased hedging demands among market participants. Consequently, predicting future price trends of coffee futures to yield excess returns has become a focal point in the field of quantitative investment. Machine learning methods are increasingly being applied in the field of quantitative investment due to their performance advantages in complex data classification and regression. This paper analyzes the current state of the coffee futures market and the factors influencing its prices. In this study, five market indicators and one technical indicator, the bias rate, were selected as inputs. The closing price for the subsequent day, along with short-term (50 days) and long-term (200 days) price trends, were forecasted using two machine learning techniques: the linear regression model and the random forest model. The results demonstrated that, of the two predictive models utilized in this study, the random forest model performed better concerning regression prediction evaluation indices. When predicting short-term (50-day) price trends, the linear regression model exhibited superior performance. However, both models revealed significant errors in predicting long-term (200-day) price trends.

Keywords: Coffee futures, price forecast, machine learning.

1. Introduction

Coffee is a significant commodity in international trade. Currently, in the global coffee market, the financial market for coffee far exceeds the actual trade of coffee, with the annual transaction volume of coffee futures and options typically maintaining over seven times the annual total coffee production worldwide, reaching 15 to 20 times in recent years. The primary coffee futures traded globally are C-type coffee futures and Robusta coffee futures. C-type coffee futures trade Arabica coffee beans, while Robusta futures trade Robusta coffee beans. These futures are mainly traded on the Intercontinental Exchange (ICE) Futures U.S. and ICE Futures Europe.

The anticipation of future price deviations of a commodity, which is reliant on its historical pricing trends and related information, is known as price prediction. The forecasting of financial asset prices consistently attracts the attention of both researchers and investors, marking it as a critical area of interest. Firstly, using price predictions to formulate investment strategies holds both theoretical backing and practical significance. In 1970, Fama introduced the concept of EMH (Efficient Market Hypothesis), arguing that all accessible information is incorporated into asset prices, making it challenging to outperform the market by selecting undervalued stocks [1]. Nonetheless, several studies have revealed that the EMH fails to adequately explain particular financial phenomena, while certain investment strategy models can deliver superior returns [2-4]. These findings suggest that the contemporary capital market does not necessarily adhere to the EMH, implying that prices of financial commodities are indeed predictable. Future prices can be predicted by analyzing fundamental and technical indicators, facilitating the formulation of quantitative trading strategies for improved investment returns. Furthermore, advancements in computer technology have propelled machine learning algorithms as a novel research area in the domain of financial price prediction, yielding remarkable forecasting results. Contrary to the traditional time-series-based price prediction methods such as ARMA (Autoregressive Moving Average) and ARCH (Autoregressive Conditional Heteroskedasticity), machine learning techniques are adept at handling the high-dimensionality and non-stationarity characteristics of financial data, resulting in superior prediction accuracy.

This paper employs two machine learning methods, multivariate linear regression, and random forest algorithms, to build predictive models and study the prediction of price and price trends for C-type coffee futures. Firstly, linear regression, as a simple and quick modeling regression algorithm, is frequently incorporated into comparisons with other algorithms [5,6]. The random forest algorithm, due to its noise resistance, high accuracy, and less likelihood of overfitting, has shown good performance in predicting prices of financial commodities [7]. Secondly, past research on futures price prediction often centered on categories such as crude oil, gold, sugar, and cotton, with relatively less research on the price prediction of coffee futures. Thirdly, the coffee market in China continues to grow. In May 2021, the China Securities Regulatory Commission approved 16 futures varieties for development and listing by the Guangzhou Futures Exchange in China, including coffee futures. Although coffee futures have not yet been listed in China, they will become one of the key areas of focus for Chinese coffee producers and investors in the future. As C-type coffee futures have the most significant impact on the global coffee market among all coffee futures, research on them will provide references for future coffee futures trading in China.

This paper is divided into seven parts. Firstly, it introduces the fundamentals of coffee futures, reviews the research on the rationality and practical implications of price prediction, and underscores the advantages of machine learning methods in predicting prices of financial commodities. Secondly, it reviews the mainstream machine learning methods for predicting financial commodity prices. Thirdly, it elaborates on the condition of the coffee futures market. Fourthly, it analyzes main types of indicators that can reflect the information of the coffee futures market or influence the situation of the coffee futures market. Following this, it introduces the basic theories of linear regression and random forest algorithms. Then, it details the construction of the prediction model and compares the predictive performance of the two models. Lastly, this paper summarizes the construction and predictive performance of coffee futures price forecasting models, proposes possible directions for optimizing the models, and provides an outlook on the future coffee futures market. Organization of the Text

2. Literature Review

Grudnitski and Osburn applied neural network algorithms for predicting gold futures prices using historical data as far back as 1993, proving the superiority of machine learning models over conventional prediction models [8].

Ismail et al. utilized a multivariate linear regression model for gold price predictions [5], while Ciner employed various regression models such as linear regression and random forests, to evaluate the out-of-sample predictive abilities of industry returns [6]. The findings suggested the effectiveness of the random forest algorithm in assessing the predictive accuracy of financial models.

Fischer et al. leveraged LSTM (Long Short-Term Memory) networks for predicting constituents of the S&P 500 and juxtaposed the outcomes with results from random forests, DNN (Deep Neural Networks), and logistic regression models [9]. Basher and Sadorsky applied random forests to estimate the future price of Bitcoin [10]. Persio and others examined the predictive competencies of RNN (Recurrent Neural Networks), LSTM, and GRU (Gated Recurrent Units) for Google’s stock price, concluding that LSTM was best suited for predicting financial time-series data [11].

Patel et al. integrated multiple machines learning techniques, including SVM (Support Vector Machines), ANN (Artificial Neural Networks), and K-NN (K-Nearest Neighbors), to forecast the stock market index [12]. Ta et al. employed linear regression and SVM models to anticipate stock trends [13]. They observed significant improvements in prediction results after incorporating technical indicators and subsequently based quantitative trading strategies on these optimized predictions. The outcomes demonstrated the potential of strategies built on these two machine learning models to yield higher returns.

Huang et al. utilized SVM to forecast stock market volatility [14]. The findings attested to SVM's ability to efficiently handle non-linear and high-dimensional issues and its superiority over the ARIMA (Autoregressive Integrated Moving Average) model in gold price predictions.

A review of previous research reveals that linear regression, being a straightforward and fast modeling regression algorithm, is often included in comparisons with other algorithms. Neural network algorithms, such as LSTM and RNN; random forest algorithms; and SVM are all commonly used machine learning methods for price prediction. Given the characteristics of the linear regression model and the random forest algorithm, this paper selects these two methods to study the prediction of coffee futures prices.

3. Overview of the Coffee Futures Market

Accompanying the rise of the third wave of coffee in Europe around the year 2000, the global coffee industry has experienced robust growth. Major coffee enterprises have successively expanded into the global market, strategically positioning themselves to capture an ever-growing share of the consumer market. Through concerted efforts in promoting their coffee products, these companies have managed to shape consumer preferences, thus securing a stable volume of coffee product sales. As the sales volume of coffee products increases, so does the demand for raw coffee materials, making the performance of coffee futures contracts intimately linked with the global development of the coffee industry. Presented below are the annual trading volumes of C-type coffee futures contracts over a span of 20 years from 2001 to 2021.

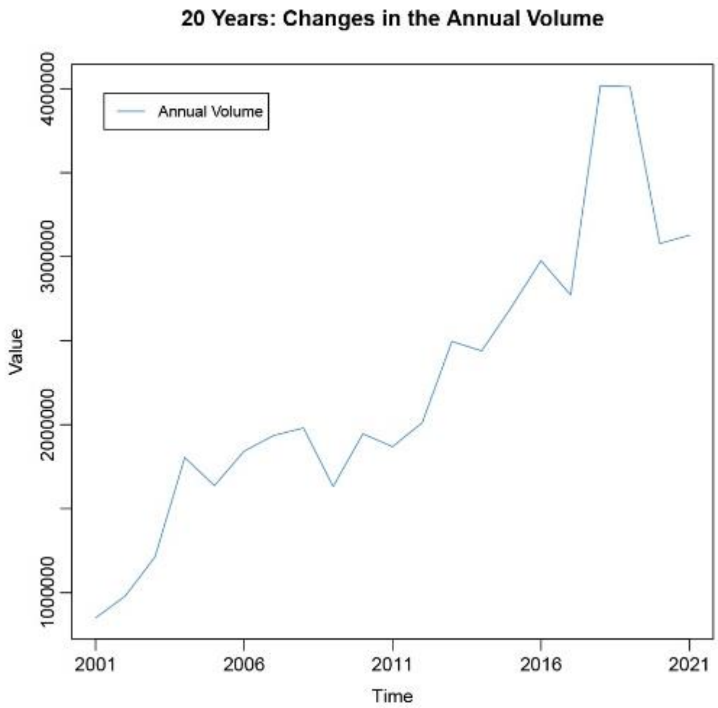

Figure 1. Annual trading volume of C-type coffee futures contracts from 2001 to 2021 (data source: Kaggle).

As can be seen from Figure 1, the overall trend in the annual transaction volume of the C-type coffee futures contracts appears to be rising, reaching a peak in 2019 before declining slightly and remaining relatively high. This implies that the demand side of the coffee industry remains strong, the overall industry development is positive, and the fundamentals of coffee futures have a basis for remaining robust.

Apart from trading volume, the closing price trend of coffee futures can also reflect market trading signals to a certain extent. The following figure shows the daily closing price trend of C-type coffee futures from November 2, 2015, to September 1, 2022.

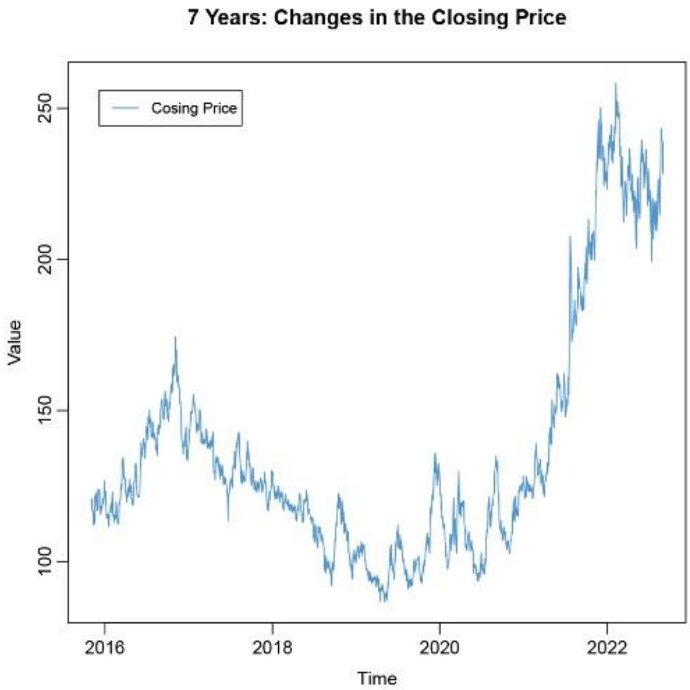

Figure 2. Daily closing price of C-type coffee futures from 2015 to 2022 (data source: Kaggle).

As can be seen from Figure \2, since 2021, the price of C-type coffee futures has been rapidly and continuously rising, reaching a historical high point over the past seven years. This round of price increases may be related to the anticipated decrease in production and the supply and demand situation in the international market. In fact, with the rapid development of the global coffee industry starting in 2020, especially the growth in sales revenue of coffee companies, coffee futures have already shown a continuous upward trend. In 2021, the demand for coffee coupled with the pressure faced by the supply side led to a rise in the price of coffee futures contracts to a new high in recent years. The market activity indicates that research on coffee futures price forecasting has positive practical implications.

4. Coffee Futures Indicators

4.1. Market Indicator

In the research of price prediction for financial commodities, market indicators are often selected as input features. As market indicators are all daily data, they can quickly and intuitively reflect market trends.

Table 1. Market indicators

Indicator type	Indicator name
	Open
	Close
	Volume
Market indicator	High
	Low
	Price change range
	Open interest

Table 1 presents the main market indicators. The opening price, as a continuation of the price fluctuations from the previous trading period and the basis for the day's price fluctuations, can intuitively reflect the market price trend and serve as a reference for investors predicting future price trends. The final price often embodies certain transaction signals. For investors, being attentive to the closing price of the underlying commodity can aid in assessing its price volatility trend. The magnitude of the trading volume signifies fund flows and investor sentiment. An influx of funds or high investor sentiment leads to increased trading volume, while fund withdrawal or low investor sentiment results in a decrease in trading volume. Thus, investors can deduce market price tendencies by scrutinizing the volume indicator. Beyond these, other frequently utilized market indicators include the highest price, lowest price, price fluctuation range, open interest, and basis.

4.2. Technical Indicators

Technical indicators reflect market conditions through the calculation of market indicators. Compared to market indicators, technical indicators can reflect market price fluctuations and trends over a period of time, containing richer market information. Therefore, technical indicators are often used as input features in futures price prediction problems.

Table 2. Technical indicator

Indicator type	Indicator name
	$MACD$ (Moving Average Convergence Divergence)
	$BIAS$ (Bias Rate)
Technical indicators	WR (Williams Overbought)
	ROC (Rate of Change)
	MTM (Momentum)

Table 2 displays some commonly used technical indicators. Technical indicators are mainly divided into two categories: those that reflect price fluctuations, such as Exponential $MACD$, WR, and $BIAS$, and those that reflect changes in the rate of price increases or decreases, such as MTM and ROC indicators.

Bias is a simple and effective technical indicator. This metric is utilized to depict the disparity and trajectory between the price at a given time t and the n-day MA. A larger positive value signifies a larger upward deviation of the security price from the MA, indicating a likely market decline; conversely, a larger negative value implies a larger downward deviation of the security price from the MA, and investors should be vigilant for potential points of upturn for transactions. The calculation formula for bias is shown in euqation (1).

$$\mathrm{BIAS} = \frac{\mathrm{C_t - MA_n}}{\mathrm{MA_n}}. \tag{1}$$

Here, C_t represents the closing price on day t, and MA_n represents the n-day moving average.

$$MA_n = \frac{\sum_{i=1}^{n} C_{t-i+1}}{n}. \tag{2}$$

4.3. Fundamental Indicators

For bulk commodity futures such as coffee, there often exists a significant connection between the futures market price and the spot market price, with no substantial deviation between the two. The price of coffee in the spot market is primarily affected by market supply, demand inventory, and climate. These impacts can cause a ripple effect, indirectly influencing the futures price. As an agricultural product, the coffee spot price is influenced by factors such as yield, consumption volume, inventory, temperature, and precipitation. In addition, national policies and seasonal factors also affect the price of coffee in the spot market, which in turn, indirectly influences the futures price.

5. The Basic Theories of Linear Regression and Random Forest

5.1. Linear Rrgression

The linear regression algorithm functions by establishing and scrutinizing the relationship between one or more independent variables and dependent variables, accomplished by minimizing the square function of the regression equation. In layman's terms, it requires finding a linear function that aptly captures the current data for use in future predictions. The appeal of the linear regression model stems from its uncomplicated nature, clarity, and rapid modeling prowess. It forms the basis for a plethora of nonlinear models and is therefore often adopted as the benchmark model in price prediction studies relative to other models. In this research, a multiple linear regression model is utilized to project the prices of future coffee trades. The core principle of this model is depicted in equation (3).

$$Y = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki} + \epsilon_i, i = 1,2, \dots, n. \tag{3}$$

Do Herein, Y is the dependent variable, k is the number of explanatory variables, n represents the sample size, and $\hat{\beta}^{ols}$ is the regression coefficient.

5.2. Random Forest

The Random Forest algorithm exhibits proficiency in addressing both regression and classification challenges. In this research, the Random Forest model is utilized to estimate coffee futures prices. It is a form of ensemble learning approach. Ensemble learning incorporates multiple learning models - referred to as "learners" - to accomplish a learning task, principally aiming to boost the precision of predictions. Within a random forest, these learners take the form of decision trees. A decision tree is a diagrammatic representation akin to a flowchart, visually demonstrating decisions and corresponding results. Each node in the tree stands for a test on a feature, each branch denotes the test's outcome, and each leaf node symbolizes a class label or a decision result.

The operational steps of the Random Forest Regression algorithm primarily include the following.

- Bootstrap sampling from the original dataset is performed to create a new sample set.
- If the number of features is m, then at each node, k features are randomly selected from these m features. The best feature and splitting criteria are then chosen from these k features to split the node. The optimization criterion for this part aims to minimize the model's MSE (Mean Square Error), expressed as (4).

$$MSE = \frac{1}{N} \sum_{i=1} N (y_i - \hat{y_i}). \tag{4}$$

Here, N is the number of samples, y_i is the actual value, and $\hat{y_i}$ is the predicted value.

- Using the steps above, a decision tree is constructed. The process is repeated to generate multiple decision trees.
- For each new input sample, the prediction result of each decision tree is calculated. The final prediction result is the average of all these prediction results.

The specific expression can be given by the equation (5).

$$y = \frac{1}{n} \sum_{i=1}^{n} T_i(x). \tag{5}$$

Here, y is the predicted value, n is the number of decision trees, and $T_i(x)$ is the prediction from the i-th decision tree.

The Random Forest model presents three notable advantages. Initially, it functions on the framework of multiple regression decision trees, with the model's regression prediction being the average of all individual decision trees - an aspect that helps to mitigate overfitting. Secondly, the Random Forest method introduces two forms of randomness - sample randomness and feature randomness. Specifically, sample randomness involves the random selection of several samples from the dataset to serve as the root nodes of regression trees, whereas feature randomness corresponds to the random selection of several potential features for the formulation of the regression decision trees. This two-fold strategy of randomness enables the model to avoid certain noise disturbances. Moreover, compared to individual algorithms, ensemble learning algorithms like the Random Forest often display enhanced prediction accuracy [7].

6. Experiments

6.1. Dataset

The data used in this paper was sourced from Kaggle. It encompasses five market indicators for C-type coffee futures on the ICE U.S. for all trading days from January 3, 2000, to September 2, 2022. The indicators include the opening, highest, lowest, closing price, and trading volume. Table 3 presents the data for the initial five days of the dataset. The unit for price is in U.S. dollars, while the trading volume is measured in the number of futures contracts.

Table 3. Data for the initial five days of the dataset (data source: Kaggle)

Date	Open	High	Low	Close	Volume
2000/1/3	122.25	124	116.1	116.5	6640
2000/1/4	116.25	120.5	115.75	116.25	5492
2000/1/5	115	121	115	118.6	6165
2000/1/6	119	121.4	116.5	116.85	5094
2000/1/7	117.25	117.75	113.8	114.15	6855

6.2. Variable Setting

This study employs five market quotation indicators, opening, highest, lowest, closing price, and volume, along with one technical indicator, the bias rate, as input features to predict the closing price and price trends of the following day. The bias rate is calculated based on the MA_5, with the formulae given in equations (1) and (2). The predicted closing price is in U.S. dollars; an anticipated increase is denoted as 1, while a prediction of a decrease or no change is denoted as 0. The predicted price trend is determined by differentiating the forecasted closing prices and assessing whether the result is positive or negative.

However, financial asset prices often exhibit non-stationary characteristics in their time series, making it challenging to handle them using linear regression models. Thus, an ADF (Augmented Dickey-Fuller) test is conducted. If the series is found to be non-stationary, a first-order differentiation is performed. Table 4 presents the variables used to construct the linear regression model.

Table 4. Variable setting for linear model

Dependent variable	Independent variables
	Open (first-order differentiation)
	High (as above)
Closing price	Low (as above)
of the next day	Close (as above)
	Volume
	$BIAS$

Given the ability of the Random Forest Regression Model to process non-stationary time series, and the fact that first-order differentiation might result in the omission of certain time series data, the model is constructed using unmodified data. Table 5 showcases the variables utilized in the assembly of the Random Forest model.

Table 5. Variable setting for the RF model

Dependent variable	Independent variables
	Open
	High
Closing price	Low
of the next day	Close
	Volume
	$BIAS$

6.3. Data Spliting

In order to achieve a better model fit, this paper selects a more extended period for model training, dividing the training and testing sets into a ratio of $7:3$. Due to the calculations of differentiation and moving averages, NA values occur. After removing data containing NA values, the final training set consists of data from January 7, 2000, to October 30, 2015; the test set contains data from November 2, 2015, to September 1, 2022. As seen in Figure 2, the closing price rapidly and continuously rises after 2021. Including this extreme situation in the training set may affect the fit of the model, while using it in the testing set can test the model's generalization ability. Therefore, this data partitioning is credible and rational.

6.4. Results

This paper presents the experimental results in terms of four aspects: regression prediction indicators, short-term (50 days) price prediction, short-term trend prediction, and long-term (200 days) trend prediction.

Concerning the aspect of goodness of fit, this paper utilizes MSE, RMSE, MAE, and R^2 to evaluate the Linear Regression model and the Random Forest model. Table 6 displays the values of different evaluation metrics for the two regression models.

Table 6. Evaluation metrics for two models

Evaluation metrics	Linear	RF
MSE	8.776703	10.59780
RMSE	2.962550	3.255426
MAE	2.106311	2.307588
R^2	0.926771	0.949412

The short-term price prediction is presented in Figure 3. This paper is concerned with short-term price prediction, which can provide references for investors' short-term investment strategies. This paper has chosen to compare the predicted and actual values from June 23, 2022 to September 1, 2022. Figure 3 depicts the comparison between the predicted values and actual values of the two prediction models.

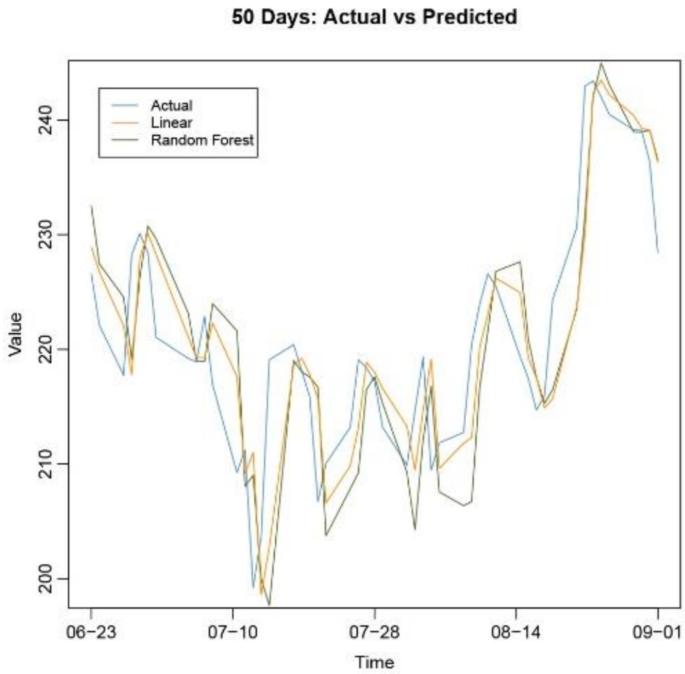

Figure 3. A comparison of the predicted and actual values yielded by the two prediction models spanning June 23, 2022, to September 1, 2022 (data sourced from Kaggle).

In addition to specific price predictions, trends in rises and falls are also important indicators of concern to investors and researchers. Investors can design investment strategies based on trend predictions and quantitative investment theory. This paper uses four metrics, Accuracy, Precision, Recall, and F1 score, to evaluate the model's prediction performance for trends in rises and falls. Table 7 and Table 8 display the metrics of prediction performance for the two predictive models during the periods from June 23, 2022, to September 1, 2022 (50 days), and from November 16, 2021, to September 1, 2022 (200 days).

Table 7. Evaluation metrics for the model's prediction performance for trends within 50 days

Evaluation metrics	Linear	RF
Accuracy	0.700000	0.600000
Precision	0.652174	0.545455
Recall	0.681818	0.545455
F1 Score	0.666667	0.545455

Table 8. Evaluation metrics for the model's prediction performance for trends within 200 days

Evaluation metrics	Linear	RF
Accuracy	0.535000	0.505000
Precision	0.505155	0.474747
Recall	0.521277	0.500000
F1 Score	0.513089	0.487047

6.5. Discussion

Concerning the aspect of model fit, as shown in Table 6, both models perform quite well in terms of the R^2 metric, which indicates a good fit of the models to the training data. The Random Forest model outperforms the Linear model in this regard.

Concerning the short-term price prediction, from Figure 3, it can be observed that the trends of the model predictions largely conform to those of the actual values, and they mostly predict the continuous up-and-down trends accurately. However, both models show a significant lag in predicting peak values, usually predicting a peak three to four days after its actual occurrence. This lag may impact the setting of investment strategies. For the Linear model, although there is a lag, the prediction of the peak value has a smaller deviation from the actual value. For the Random Forest model, in addition to the lag, the prediction of the peak value has a larger deviation from the actual value.

Regarding both the short-term and long-term trend prediction of price movements, as seen in Table 7, both models provide reasonably accurate predictions of the trend of coffee futures closing prices in the short-term, with a certain degree of credibility. The Linear model performs better in all aspects. However, as Table 8 shows, both models perform poorly in predicting the trend of coffee futures closing prices in the long- term. All metrics are close to 0.5, indicating that the predictive performance of both models in the long-term is only slightly better than a random model. On the one hand, the lag in predicting peaks, or trend changes, manifested by both predictive models, has resulted in the accumulation of errors in the long-term comparison, magnifying the errors caused by this lag. On the other hand, based on the analysis of the coffee futures market, November 16, 2021, was still in the aftermath of the sharp rise in coffee futures prices that began in 2021. In the long-term comparison, this extreme change in data made it difficult for the prediction models to make correct judgments.

7. Conclusion

This paper revisits the price prediction research logic and the application of machine learning methods in this field. It then evaluates the current state of C-type coffee futures market and the key factors influencing its prices. Using five market quote indicators (opening, highest, lowest, and closing prices, trading volume) of C-type coffee futures from ICE U.S., and one technical indicator (bias rate) as input features, it predicts the next day’s closing price and its trend. Using both raw and first-order difference processed data, Random Forest and Linear Regression models are trained and tested.

The predictive performance of the two models is compared in terms of model fit, short-term price and trend prediction, and long-term trend prediction. Both models demonstrate good fit, with the Random Forest model slightly better. They accurately predict continuous trends in short-term price prediction but lag in predicting peaks and trend changes. In short-term trend prediction, both models outperform a random model, with the Linear Regression model slightly better. However, both models perform poorly in long-term trend prediction and only slightly outperform a random model based on metric data.

Based on results and discussion, the two prediction models in this paper could benefit from further refinement. The models show strong goodness of fit and are not sensitive to peak values in the short-term price prediction. However, their performance in long-term trend predictions is subpar, possibly due to overfitting. Adding more processed technical and fundamental indicators to the input features could help alleviate overfitting and improve the models’ generalizability.

The coffee futures market, after peaking in 2021, has since declined but remains volatile. With coffee futures set to be listed on the China Guangzhou Exchange, researchers and investors will increasingly focus on coffee futures price prediction.

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