International Journal of

Modern Statistics

(IJMS)

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CARI Journals

International Journal of Modern Statistics
ISSN: 2958-8340 (Online)
Vol. 5, Issue No. 1, pp 14 - 28, 2025
www.carijournals.org

An Algorithm for Predicting Coffee Prices Using ARIMA Model

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Accepted: 14th July 2025 Received in Revised Form: 9th August 2025 Published: 13th August 2025

ABSTRACT

Purpose: In this study, an algorithm for predicting coffee prices was developed incorporating the ARIMA model. The Algorithm simplifies the process of finding the optimal parameter values (p,d,q) for the ARIMA model.

Methodology: Secondary data from the Uganda Coffee Development Authority monthly reports was used. The data involved monthly coffee prices of Arabica and Robusta coffee for the years 2014-2021. CRISP-DM methodology and Python programming language were used. Arabica and Robusta coffee prices for the years 2019-2022 were predicted.

Findings: The study showed seasonality in the prices.

Unique Contribution to Theory, Practice and Policy: The study recommends that coffee farmers, traders, cooperatives, and the Uganda Coffee Development Authority use the forecasting tool, link it to market information platforms for easy access to regular price updates, and enhance it to track seasonal price changes.

Keywords: *Coffee Prices, ARIMA, Algorithm, Predicting, Arabica, Robusta*

Introduction

Globally, coffee is one of the most important trade commodities and it substantially contributes to the livelihoods of millions of smallholders worldwide [1]. From the information provided by the International Coffee Organization, consumption of coffee from April 2019 to March 2020 was 164.2 million 60 kg bags globally, and an increase of 1.3% for the year 2022 was projected [2]. In Africa, coffee is one of the most valuable commodities, and is a primary source of income in some countries [3]. One of the top coffee producers in Africa is Uganda, which contributes approximately 2.5% of the global coffee [4]. In Uganda, coffee is known to be the most important export crop [5][6]. Coffee contributes 20% of the Uganda's foreign exchange earnings [3]. Coffee plays a big role in the livelihoods and economy of Uganda's population.

Coffee in Uganda is sold in different forms depending on the availability of labor and financial needs [8]. In Uganda, 90% of coffee farmers have an average farm size less than 0.5ha to 2.5ha [9]. Small scale farmers intercrop their coffee trees with other food crops [4]. It is known that 85% of the coffee grown in Uganda is Robusta and the rest being Arabica [7]. There are factors that affect the two coffee types including supply, demand, climate and commodity market. Climate as a factor affects supply. The prices of green coffee are mainly determined by supply and demand [10].

Coffee producing countries earned $30 billion in a decade (2010-2020) and currently, retail sales exceed $70 billion as of 2021, but coffee producing countries receive less than $6 billion. Farmers who produce coffee on average receive less than 1 per cent of what a consumer pays for a cup in a coffee shop [11] and this affects farmers who depend on coffee growing. The exports are subject to price fluctuations that are known of bringing risks to farmers, marketing institutions, importers and consumers [12]. In 2014, Robusta monthly prices increased from 3350shs in January [13] to 3650shs in February [14] then to 3900shs in March [15], 4000shs in April [16], and decreased to 3700shs in May [17]. In 2014 Arabica coffee monthly prices increased from 3350shs in January [13] to 4450shs in February [14], then to 6250shs in March [15], 6450shs in April [16], and decreased to 6300shs in May [17]. Many stakeholders face these price fluctuations in the coffee market [18] due to world market price trends.

Price fluctuations affect decision-making and improvement of coffee in the international market. The government of Uganda introduced a coffee stabilization tax in 1990s when the world prices of coffee, doubled between 1992/93 and 1994/95 and this was due to the abolishment of minimum prices, and removal of the export tax [5]. In 2020 the government of Uganda together with the Uganda Coffee Development Authority, encouraged coffee farmers to embrace value addition in order to attract the international market [19]. Uganda Coffee Development Authority suggested that with good quality of coffee and value addition, there will be an improvement in Uganda's coffee market [19].

Several authors have used models to assess the impact of coffee price changes on Ugandan household groups. One of the models used was a standard Computable General Equilibrium model

[5]. Some coffee prediction models have been developed to help improve the accuracy of price policy decision and forecasting, however, in Uganda, price fluctuations continue to get worse requiring concerted efforts. There is need for more accurate models to predict coffee prices [12]. In this study, an algorithm for predicting coffee prices is designed incorporating the Auto Regressive Integrated Moving Average (ARIMA) Model. The Algorithm is to simplify the process of finding the optimal parameter values (p,d,q) for the ARIMA Model.

Literature Review

Predicting is used in providing assistance to decision making for the future [2]. According to the study carried out by Abreham, comparison of different machine learning algorithms for predicting coffee prices was done and one with high performance to predict the unforeseen data was selected [12]. Historical data was used to predict the future market direction. After feeding in data to the different algorithms, different results were obtained. Linear regression and Support vector regression were considered as the worst models for predicting coffee prices because their results were below zero whereas KNN and decision tree were better. The study conducted in Indonesia used backpropagation neural networks algorithm to determine the prediction of coffee prices [25]. The importance of the study was to help farmers to get more leverage. Data used in training ranged from 2010-2014, the one for testing was from 2015- 2017. The best model was 3-15-1 because the minimum mean square error of 0.00904753. The study suggested conjugate gradient to be used in the next study when predicting coffee prices [2].

Moving Average (MA) model are used in creating a smooth stock price curve and filtering out noise data. The disadvantage of Moving averages is that they draw trends from past information and they don't take into account changes that may affect a security's future performance [27]. Novanda *et al.* [28] aimed at analyzing and comparing the different forecasting techniques for selecting the best to predict the volatility of coffee commodity prices. The study used secondary data at both world and domestic markets. From the study, Moving Average and decomposition did not qualify to predict the volatility of coffee commodity prices. Also factors that affect coffee prices were not identified.

Autoregressive Integrated and Moving Average (ARIMA) models produce predictions based on the synthesis of historical data patterns [28]. The formula of ARIMA model takes the form:

X_t=$\mu^1 + \varphi_1 \sum_{i=1}^{i=p} X_{t-p}$ +$\theta_1 k = 1k = qet - k$, where t = 1, 2, 3 ... T, εt is a process that is not correlated with mean zero, φ_i and θ_i are coefficient values and μ^1 is the intercept, X_t is the data on which the ARIMA model is to be applied. In ARIMA model, AR is Auto Regression representing p, which explains the partial correlation between the series and lags of itself, while MA is Moving Average representing q, which explains the number of lags to be used as predictors [29]. ARIMA model of Mung'atu [29] was used to forecast the unit price of coffee export in Rwanda using mathematical and statistical knowledge. Secondary data was collected from January 2010-December 2017 from National institute of statistics of Rwanda. The best ARIMA model was selected using Mean Square Error, Akaike's Information Criterion and Schwart's Bayesian Criterion. The study recommended ARIMA as a powerful model used in analyzing time series data. Other ARIMA models are seen in the works of Novanda *et al.* [28], Bandyopadhyay [30], and Vijayakumar and N. Chilamkurti [31].

Methodology

CRISP-DM (Cross Industry Standard Process for Data Mining) approach [40] was used. It ensures that the data selected can meet the objective of the study and modeling objectives. It consists of 6 stages which include, Study definition, Data Understanding, Data Preparation, Modelling, Evaluation and Deployment as seen in Figure 1 below.

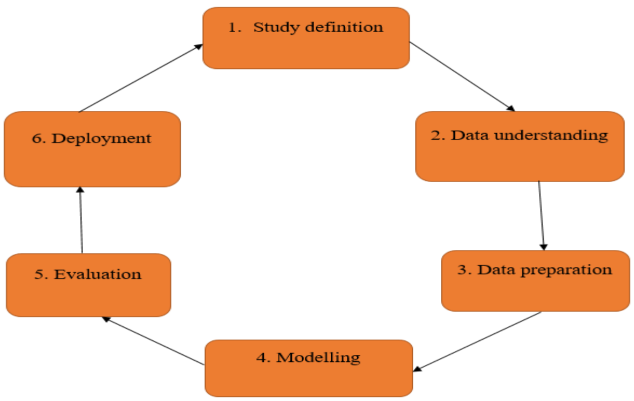

Figure 1: CRISPM methodology diagram

Secondary data from Uganda Coffee Development Authority monthly report used to train and test the model. Data involved monthly coffee prices of Arabica and Robusta coffee for the years 2014-2021. Microsoft excel used in collecting, organizing and analyzing data. Python software was used to find the parameter values (p,d,q) of the ARIMA model using Partial autocorrelation function and Auto correlation function graphs. The algorithm designed was evaluated to check if the aim of the study was achieved. This was done by predicting future coffee prices of 2019-2023 for the two types of coffee. Root Mean Square Error was computed to analyze the performance of the ARIMA model.

Results

4.1 Data Analysis and Modelling

Data was first cleaned to ensure that it was comma separated since python uses comma-separated files. The data included prices for the two coffee types, Robusta and Arabica, for 84 months as shown in Figure 2. Figure 3 shows the summaries of the prices of the two coffee types.

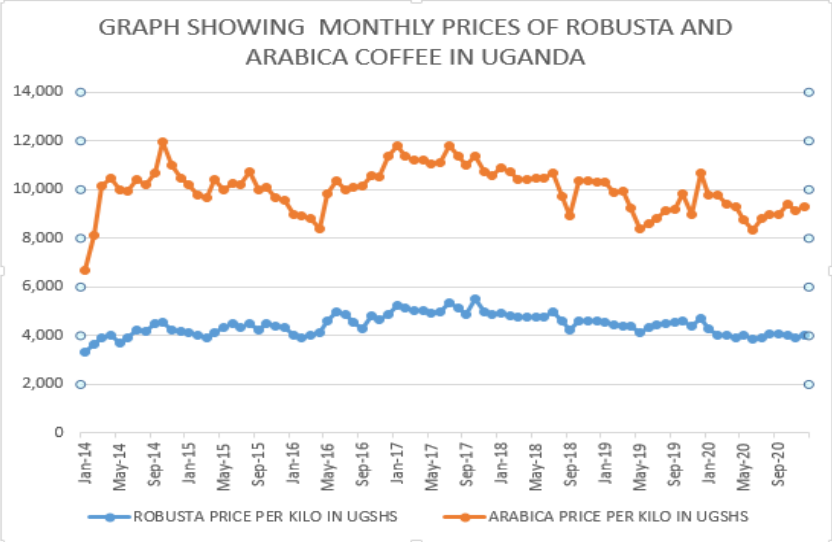

Figure 2: Monthly Prices of Robusta and Arabica coffee from 2014 to 2020.

#Read Data

```
df=pd.read_csv('trialPrice.csv',index_col='MONTHS',parse_dates=True)
df=df.dropna()
print('Shape of data',df.shape)
df.head()
```

```
Shape of data (84, 2)
```

	ROBUSTA	ARABICA
MONTHS		
2014-01-01	3350	3350
2014-02-01	3650	4450
2014-03-01	3900	6250
2014-04-01	4000	6450
2014-05-01	3700	6300

Figure 2 : Sample data on Arabica and Robusta coffee prices.

International Journal of Modern Statistics

ISSN: 2958-8340 (Online)

Vol. 5, Issue No. 1, pp 14 - 28, 2025

	ROBUSTA	ARABICA
count	84.000000	84.000000
mean	4435.119048	5565.476190
std	426.937805	678.365159
min	3350.000000	3350.000000
25%	4100.000000	5187.500000
50%	4425.000000	5700.000000
75%	4750.000000	6050.000000
max	5500.000000	7400.000000

Figure 3: Data summaries for both Arabica and Robusta coffee prices.

Figure 5 shows that Robusta coffee prices had seasonality, with peaks in the middle of each year except for the years 2018, 2019 and 2020.Figure 6 shows that Arabica coffee prices had very little seasonality, with the peak in the year 2014 and reducing prices in the years of 2015, 2016, 2017, 2018, 2019, 2020

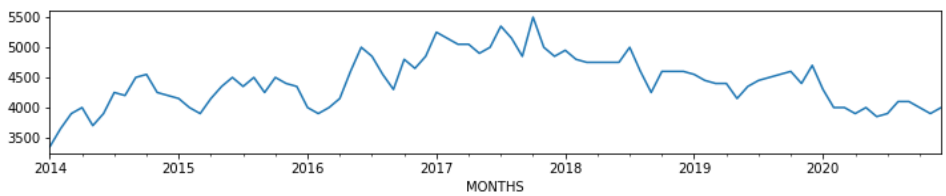

Figure 5: Robusta coffee prices with seasonality

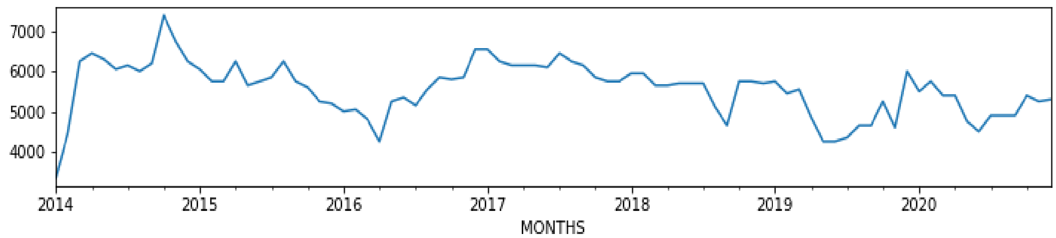

Figure 6: Arabica coffee prices with very little seasonality

The parameters p,d,q were found by using partial auto correlation function, Augmented Dickey Fuller test and the auto correlation function, respectively. To find the value of d of the ARIMA model for Robusta Coffee prices, the Augmented Dickey Fuller (ADF) test was used. The ADF test is a statistical test used to ascertain whether a given time series is stationary or not [30]. In this case, if the P-value is less than the significant value of 0.05, then the time series is stationary. The ADF test on Robusta coffee prices gave the P-value of 0.07. This showed that Robusta coffee prices were not stationary, and differencing was done once, making the value of d to be 1.

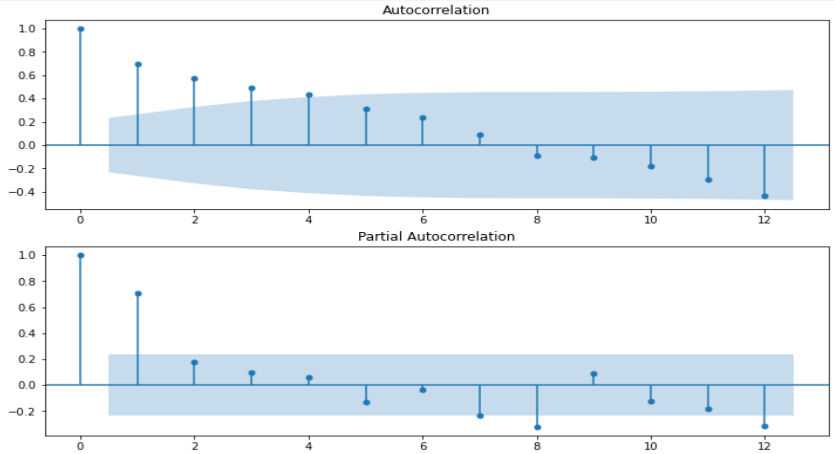

Figure 7: PACF and ACF graphs for Robusta prices

To find the value of p of the ARIMA model for Robusta coffee, the partial auto correlation graph was used, and the auto correlation graph was used to find the value of q as shown in Figure 7.

In the process of finding the value of p, the Auto Correlation Function (ACF) plot gradually decreases and the Partial Auto Correlation Function (PACF) plot shows a sharp drop immediately after the first lag. Thus the graphs suggest that an AR (1) model would be appropriate for the time series, making the value of p to be 1.The values of q were {1, 2, 3} since these were the lags above the significant line as shown in the auto correlation graph of Figure 6. Therefore, three ARIMA models for Robusta coffee prices were obtained as ARIMA(1,1,1), ARIMA(1,1,2) and ARIMA(1,1,3). The best model was obtained after calculating the Root Mean Square Error (RMSE) for the three models, and the one with the least RMSE was found to be ARIMA (1,1,2) as shown in Table 2.

Table 1: RMSE results of ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (1,1,3) for Robusta

ARIMA model for Robusta coffee	**RMSE**
ARIMA(1,1,1)	461
ARIMA(1,1,2)	449
ARIMA(1,1,3)	452

The process for finding the parameter values p,d,q was repeated for Arabica coffee prices, and it was found out that the P-value was 0.0775, above the significant value of 0.05, hence Arabica coffee prices were not stationary. To make the prices stationary, differencing was done once, making the value of d to be 1. The partial auto correlation graph of Figure 8 suggests that an AR (1) model would be appropriate for the time series, making the value of p to be 1. The values of q were also found to be {1, 2, 3} as shown in the auto correlation graph of Figure 7. The resulting ARIMA models for Arabica coffee prices were ARIMA(1,1,1), ARIMA(1,1,2) and ARIMA(1,1,3), and the best model was found to be ARIMA (1,1,1) with the least RMSE as shown in Table 3.

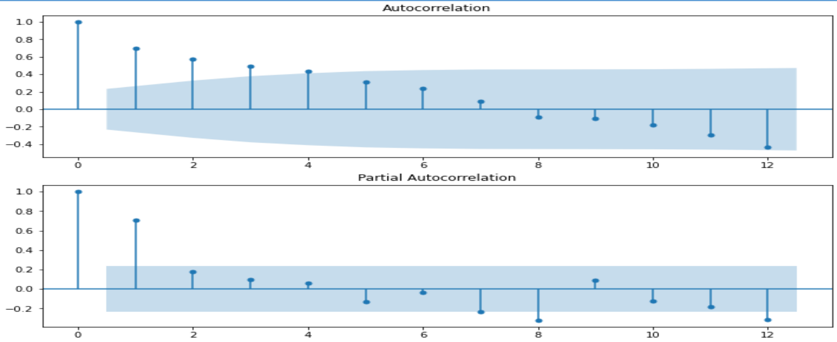

Figure 8: ACF and PACF graphs for Arabica prices.

Table 2: RMSE results of ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (1,1,3) for Arabica.

ARIMA model for Arabica coffee	RMSE
ARIMA(1,1,1)	477
ARIMA(1,1,2)	565
ARIMA(1,1,3)	536

4.2 Algorithm Formulation

The algorithm is formulated as follows:

Step 1: Read the data using the read method (pd.read_csv)

Step 2: Describe the data using the describe function (df.describe())

Step 3: Plot the graph of the dataset

Step 4: Check for stationarity using adfuller

If (p-value <0.05), d= 0

Else, find the differencing using the plot.acf method

Step 5: Find the value of p using plot pacf

Step 6: Find the value of q using plot acf

Step 7: Fit the ARIMA model using the (model.fit) method.

Step 8: Split the data into testing and training data

Step 9: Train the model using the ARIMA parameter values

Step 10: Test the model by predicting the future values

Step 11: Find the root mean square error of the series.

4.3 Prediction of Coffee Prices

Data is split into two sets, for training and testing. Training data is from January 2014 to December 2018 and testing data is from January 2019 to December 2020. ARIMA predictions are made and compared with the testing data for both Robusta and Arabica. The models are run to predict future prices for the years 2021-2023 as shown in Figure 9 for Robusta and Figure 10 for Arabica.

International Journal of Modern Statistics
ISSN: 2958-8340 (Online)
Vol. 5, Issue No. 1, pp 14 - 28, 2025

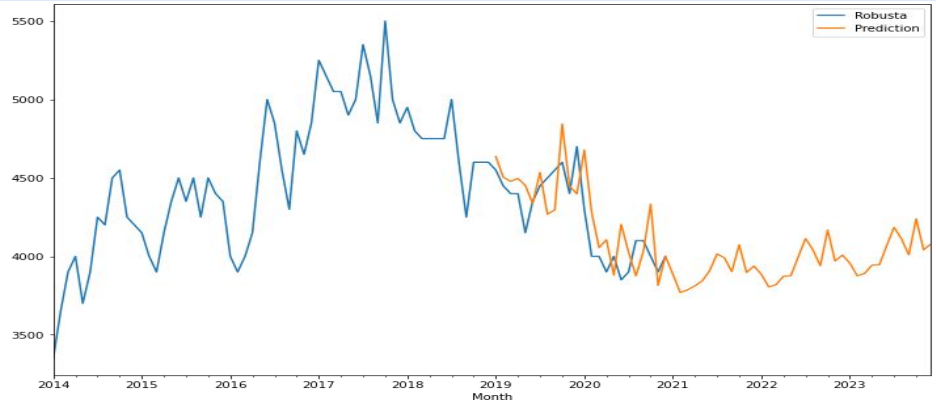

Figure 9: ARIMA (1,1,2) predictions for the years 2019-2023 for Robusta.

The ARIMA predictions were close to the actual prices of Robusta coffee for the years 2019 and 2021. The results of ARIMA (1,1,2) were tabulated as shown in Table 4 for comparison.

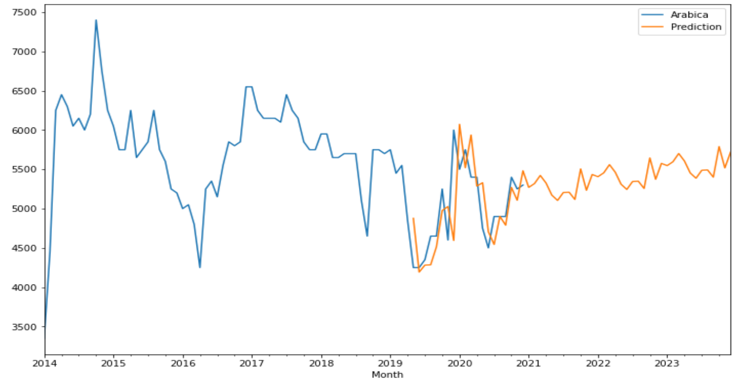

Figure 10: ARIMA (1,1,1) predictions for the years 2019-2023 for Arabica

Figure 10 shows coffee price predictions obtained using ARIMA (1,1,1) for Arabica for the years 2019-2023 of which 2019 and 2020 are for testing. It is clear that the ARIMA predictions are close to the actual prices of Arabica coffee for the years 2019 and 2020 as shown in Table 5.

Table 6 shows the Arabica and Robusta coffee price predictions for the year 2023 respectively that are obtained using ARIMA (1,1,1) and ARIMA (1,1,2) respectively.

Table 3: Comparison of monthly prices of Robusta and ARIMA predictions for 2019 and 2020.

Month, Year	Actual monthly prices for	ARIMA predicted prices
Jan 2019	4550	4636
Feb 2019	4450	4504
March 2019	4400	4477
April 2019	4400	4496
May 2019	4150	4452
June 2019	4350	4337
July 2019	4450	4535
August 2019	4500	4268
September 2019	4550	4297
October 2019	4600	4843
November 2019	4400	4447
December 2019	4700	4397
January 2020	4300	4677
February 2020	4000	4278
March 2020	4000	4055
April 2020	3900	4106
May 2020	4000	3879
June 2020	3850	4203
July 2020	3900	4026
August 2020	4100	3874
September 2020	4100	4029
October 2020	4000	4332
November 2020	3900	3814
December 2020	4000	4001

Table 4: Comparison of monthly prices for Arabica and ARIMA(1,1,1) predictions for 2019 and 2020

Month, Year	**Actual monthly prices for Arabica**	**ARIMA predicted prices**
May 2019	4250	4876
June 2019	4250	4192
July 2019	4350	4281
August 2019	4650	4285
September 2019	4650	4514
October 2019	5250	4975
November 2019	4600	5026
December 2019	6000	6073
January 2020	5500	5520
February 2020	5750	5737
March 2020	5400	5329
April 2020	5400	5286
May 2020	4750	5329
June 2020	4500	4706
July 2020	4900	4543
August 2020	4900	4901
September 2020	4900	4788
October 2020	5400	5267
November 2020	5250	5106
December 2020	5300	5483

Table 5: Predicted prices for Arabica and Robusta for the year 2023

Year , Month,	**Coffee price predictions (Ushs) for Arabica using ARIMA (1,1,1)**	**Coffee price predictions (Ushs) for Robusta using ARIMA (1,1,2)**
2023-01-01	5547	3956
2023-02-01	5596	3876
2023-03-01	5701	3890
2023-04-01	5605	3943
2023-05-01	5453	3946
2023-06-01	5386	4067
2023-07-01	5488	4181
2023-08-01	5492	4111
2023-09-01	5400	4009
2023-10-01	5789	4239
2023-11-01	5517	4041
2023-12-01	5720	4078

Conclusion

In this study, different existing price prediction models were reviewed. CRISP-DM approach was used in formulating the algorithm to predict coffee prices. Data for training and testing was obtained from the Uganda Coffee Development Authority for the years 2014-2020 for both Robusta and Arabica. The results suggest that Uganda's coffee prices have an aspect of seasonality.

ARIMA models were obtained for the two types of coffee. The best ARIMA models for Arabica and Robusta coffee prices were found to be ARIMA(1,1,1) and ARIMA(1,1,2) respectively, and they were used to predict coffee prices for the years 2019 and 2020 taken as testing data, and the extension was made to cover the years 2021-2023. ARIMA prediction results were found to be close to the actual prices of the two coffee types. The study that predicted future prices of gold [30] found out that the accurate model for predicting gold prices was ARIMA (1,1,1). However, after testing the Root Mean Square Error on the model using gold prices, the RMSE was 711 which was high compared to the RMSE values in Table 2 and Table 3, that is, 449 for ARIMA (1,1,2) for the case of Robusta and 477 for ARIMA (1,1,1) for Arabica. This implies that there is improvement in the accuracy of the models.

Recommendations

The designed algorithm is able to determine the ARIMA parameter values of different coffee types and also to predict future prices. The algorithm is recommended for use even when predicting prices of other commodities. There is need to deploy the developed algorithm, and future ARIMA models could incorporate a factor of seasonality for example SARIMA for better comparisons of degrees of accuracy. This research is recommended to coffee farmers, traders, cooperatives and the Uganda Coffee Development to use it. It should be connected to platforms that share market information so that traders can easily access regular prices forecasts to avoid losses. This prediction tool can be to also track seasonal changes in prices.

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