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Original Article

Improving Demand Analysis and Supply Chain Management for Hair Products During the COVID-19 Pandemic: A Machine Learning Approach

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Abstract *- This research analyzes the demand for hair care products during the COVID-19 pandemic. Two forecasting models, Arima and Sarima, based on Machine Learning technology, were proposed to improve data analysis and supply chain management. The results showed that the SARIMA model had higher mean absolute error levels than the Arima model. The study also analyzed the demand for four hair dyes using statistical models, finding that three had seasonal demand. The SARIMA model accurately predicted demand for most hair dyes except one. Errors in the predictions were measured using different indicators, and the SARIMA model had lower error levels than the Arima model. The study's results were validated and compared with previous research, showing that the SARIMA model predicted the demand for hair dyes. Overall, this study highlights the usefulness of Machine Learning models in demand analysis and supply chain management of hair care products during the COVID-19 pandemic. These findings provide a reference framework for manufacturing industries with similar characteristics that wish to optimize demand management using Machine Learning techniques.*

Keywords *- Business intelligence, Machine learning, Business analytics, Time series, Demand forecast.*

1. Introduction

In 2019, the COVID-19 pandemic started, which resulted in drastic changes in consumer behavior since more than 47 million jobs were lost [1] and affected the productivity of manufacturing companies because of raw material shortages. Under this circumstance, the difficulty of predicting customer demand was highlighted, and the lack of forecast accuracy resulted in overstocking or an increase in backorders [2]. High unsold inventory levels are a problem for companies since they do not create revenue but instead create warehousing and purchasing costs [3-5]. Therefore, demand forecasting is an indispensable and necessary process for every organization since it reduces these issues by improving decision-making and inventory management [6].

Nowadays, the amount of product variety found in modern consumer goods companies (CGC) has caused traditional forecasting methods to fail to deliver high levels of accuracy [6]. Additionally, the pressure imposed on the information technology areas to implement tools that deliver high-quality and immediate solutions has increased because companies with higher levels of digitalization deal best with uncertainty. This happens because digital tools minimize external risk by offering immediate solutions that allow the company's strategy to adapt continuously to the changing environment [7]. Under this context, machine learning has presented itself as a primary option to utilize in these situations because of its ability to adapt to highly complex scenarios [8].

This paper proposes two models based on machine learning to improve the currently traditional forecasting process for a CGC in the Peruvian market, specifically dedicated to the sales and distribution of hair care products. Due to confidentiality issues, the enterprise's name will be omitted from this article.

There is currently little research regarding using Machine Learning as a forecasting tool in the Peruvian consumer goods industry, so this research aims to find a custom machine-learning model capable of adequately forecasting the demand for a series of hair dyes. This will allow the organization to manage its supply chain more effectively and keep a competitive advantage against its local competition [9,10].

1.1. Contextual Framework: Company Under Study

The hair care industry is highly competitive. Every day, new brands are emerging with new formulations and shades, which is why efficient demand forecasting is essential. This will enable efficient use of the supply chain from the sourcing phase with input supply, production, and distribution. This avoids overproduction or product shortages [10,11]. This company arrived in Peru in 1960. Since this moment, they have improved their industry in diverse aspects such as the commercial or their process for distribution. Nowadays, they have created many new products related to kids and babies between 0 to 8 years old and hair dye (and different kinds of tint shades).

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2. Literature Review

In this research, the need to implement a suitable demand forecasting tool in the Peruvian CGC arose from improving forecast accuracy, reducing inventory levels in some products, and reducing backorders in others. Currently, the main forecasting methods employed by this organization are qualitative: Panel consensus, visionary forecasting, historical analytics, and the Delphi method. On the other hand, what is being proposed in this paper is the time series analysis, which is a quantitative method [12].

According to the literature about machine learning as a forecasting tool, the need to implement this kind of mechanism arises due to the increasing availability of information. This topic has become a research subject since it creates a need to acquire new means of data processing capable of quickly and effectively analyzing significant amounts of diverse information.

To have an idea of the growing availability of data, in 2006, all the digital information occupied an estimated 161 exabytes of storage, while in 2010, this number climbed to 40 trillion gigabytes [13,14].

2.1. The Language used in the Development of ML

It has multiple programming languages used to make artificial intelligence and machine learning applications. For our research, we will use the Python programming language, which is described below:

2.1.1. Python Language

Python is a language where your code runs in the browser when you load the page, is platform-independent and object-oriented, and is ready to perform any program, from Windows applications to network servers or web pages. It is an interpreted language that offers advantages such as the speed of development and disadvantages as a lower speed when executed. [15] cited by [16].

Here are some Python features for performing ML

- Python has an extensive library and macros, which help in coding and save time in its development.
- They have concise and readable codes, which facilitate their use
- It is fast in development and does not need to implement the algorithm to prove it.
- It is easy to interpret

Explaining concepts such as time series models, Arima, and Sarima is necessary to understand the topic better.

2.1.2. Time Series Models

A time series can be defined as the group of values that a quantitative variable can acquire during a period. Therefore, a time series model is a mathematical tool that predicts the future values a specific data set can acquire [17]. However, not all time series have the same tendency. While some can be stationary in time, others can be seasonal, cyclical, or random. Different types of models adapt better to different trends. A data scientist's job is to decide which model best fits each case [18].

For this research paper, the demand for hair dyes was forecasted through two different time series models, described in Table 1: Arima and Sarima.

Table 1. SARIMA and ARIMA models

Model	Description
ARIMA	ARIMA stands for Autoregressive Integrated Moving Average, a forecasting model that merges autoregressive and moving average processes to build a time series model (Siami-Namini et al., 2018).
SARIMA	It is a method used to analyze time series models and forecasting data with a seasonal tendency.

2.1.3. ARIMA

ARIMA stands for Autoregressive Integrated Moving Average, a forecasting model that merges autoregressive and moving average processes to build a time series model [19]. Its most essential elements consist of the following:

- Autoregression: a forecasting model that uses the relationships between observation and several past observations.
- Integration: Measuring multiple observations done in different moments of the past transforms a time series into stationary data.
- Moving average: It considers the relationship between the residual error and the observations.

By combining the moving average and the autoregressive equations, the following is obtained:

$$x_t = c + \sum_{i=1}^{p} \phi_i \, x_{t-i} + \epsilon_t + \sum_{i=0}^{q} \theta_i \, \epsilon_{t-i}$$

X*t* is the stationary variable, c is the constant, the elements in the φi are the autocorrelation coefficients, p and t are the Gausian's white noise (with mean and variance of 0), μ is the expected value of xt and θi is the weight given to the stochastic values of the time series.

2.1.4. SARIMA

It is a method utilized to analyze time series and forecast data that reflects a seasonal tendency. A Sarima model contains seasonal and stationary factors in a multiplicative model that can be understood as:

$$\Theta_p(B^S)\phi_p(B)\nabla_S^D\nabla^d X_t = \Theta_Q(B^S)\Theta_q(B)\epsilon_t$$

P is the seasonal autoregressive factors, D is the difference between seasons, and Q is the seasonal moving average.

3. Methodology

Creating an ML model is not only using the learning algorithm but also involves a process that we will detail in Figure 1 below:

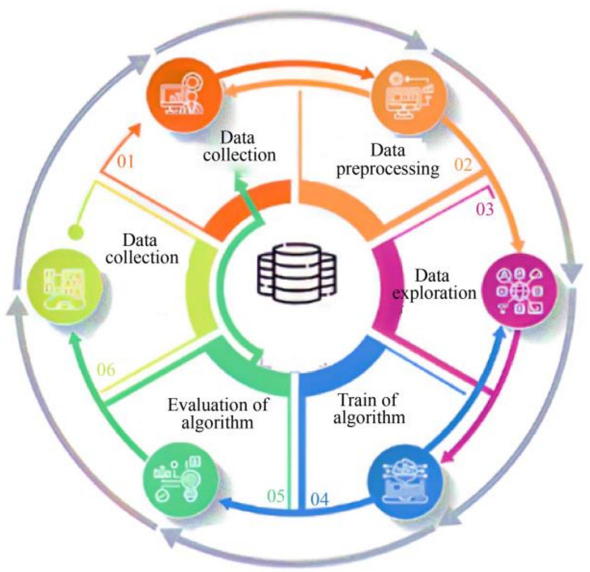

Figure 1 Process of Building a Machine Learning Model. Adapted from [14].

A description is made of each of the steps mentioned in the above image, which are described below [15], cited by [13]:

3.1. Data Collection

Data can be collected from a company or a website. This step is significant because it is the principle from which you start to achieve a successful result.

3.2. Data Preprocessing

Ensure all data is formatted to align the algorithm.

3.3. Data Exploration

An analysis is performed to correct missing values or find a pattern that facilitates the creation of the model (characteristics with more significant influence to make the prediction).

3.4. Train the Algorithm

The algorithms must be aligned with the data (those processed in the previous processes) so that the algorithms extract relevant information and make predictions.

3.5. Evaluation of Algorithms

An evaluation of the algorithm's accuracy in its predictions will be made.

3.6. Deployment of Model

Implement the model.

If you disagree with the results, you should return to the previous stage and change the parameters necessary to achieve the desired performance.

This research paper will explain terms such as time series, Arima and Sarima through a systematic literature review in indexed sources. These concepts will propose a machine learning-based model that will improve the planning capabilities of the supply chain.

Table 2. Statistical parameters

	Mean	Median	Standard Deviation
Hair Dye 1	4,583.42	3,820	3,112.20
Hair Dye 2	4,685.25	3,972	3,163.77
Hair Dye 3	2,694.93	2,108	2,409.73
Hair Dye 4	2,796.64	2,508	1,853.19

This research has an explanatory approach since it expects to find a cause-and-effect relationship between a series of variables [20]. The following null and alternative hypotheses were established:

H0: The programming language of Python will help develop the creation of a forecasting model with machine learning technology.

H1: The programming language of Python will not help develop the creation of a forecasting model with machine learning technology.

Afterward, the historical information of four different hair dyes was collected from a company that operates in the consumer goods industry. The data collected ranges from January 2017 to May 2023. It must be noted that during this period, this company employed qualitative forecasting methods, such as the opinions of the different managers or the views of the board of executives. However, this research paper proposes a quantitative forecasting model based on statistical information that assumes that past tendencies will repeat themselves in the future. More specifically, the forecasting models studied in this paper assume that the future demand is only affected by the values of the historic sales, which is why models of time series will be applied.

Once this information was collected, two different mathematical models were created with Machine Learning in the programming language of Python. This language is characterized by the fact that it can analyze large amounts of data, learn from them, and find their tendencies such that the future forecast can be predicted with the lowest error possible. These two models were Arima and Sarima.

The question now presented revolves around the viability of using machine learning technology to accurately forecast the demand for a series of hair dyes. Furthermore, this paper aims to discover which of these two models adjusts better to the given information. Another set of null and alternative hypotheses were therefore formulated:

H0: An Arima model will forecast the demand for the four hair dyes more accurately than a Sarima model.

H1: An Arima model will not forecast the demand for the four hair dyes more accurately than a Sarima model.

4. Results and Discussion

The statistical parameters for each of the four hair dyes can be found in the following table, where hair dyes 1 and 2 present the highest variance and standard deviation.

Furthermore, the seasonality was tested for each of the products through the Dickey-Fuller test. Stationarity can be attributed to a product when its mean and variance do not change throughout time.

The null hypothesis for the Dickey-Fuller test affirms that the data is not stationary, while the alternative hypothesis claims that the data is stationary.

Therefore, obtaining a p-value equal to or lesser than the significance level of 0.05 means the data is stationary. Table 3a and Table 3b show that all hair dyes, except for hair dye 4 (p-value -6.42E+00), are not stationary.

Table 3a. Results of the Dickey-Fuller test for hair dyes

	Hair Dye 1	Hair Dye 2
Test Statistic	-2.4462	-2.089485
P-value	0.1291	0.248764
# Lags used	6	4
# observations used	66	68
Critical value (1%)	-3.5336	-3.530399
Critical value (5%)	-2.9065	-2.905087
Critical value (10%)	-2.5907	-2.590001

Furthermore, the following can be understood by analyzing the critical point of 5%. Hair dyes 1, 2, and 3 are in the not-rejection zone, meaning the demand for these products is seasonal. However, hair dye 4 is the complete opposite since it is over the critical point of -2.90E, finding itself in the rejection zone with -6.42E, causing a seasonal demand [13].

Table 3b. Results of the Dickey-Fuller test for hair dyes

	Hair Dye 3	Hair Dye 4
Test Statistic	-2.400216	-6.42E+00
P-value	0.141676	1.78499E-08
# Lags used	5	0.00E+00
# observations used	67	7.20E+01
Critical value (1%)	-3.531955	-3.52E+00
Critical value (5%)	-2.905755	-2.90E+00
Critical value (10%)	-2.590357	-2.59E+00

Even though it was proven with the Dickey-Fuller that hair dyes 1, 2, and 3 were most probably seasonal, the Arima model, which is generally used for stationary information, was still analyzed and created. The predicted results of the Arima model are shown in Table 4:

Table 4. ARIMA 2023 Forecast

	HD 1	HD 2	HD 3	HD 4
apr-23	3,761	3,760	2,695	1,774
may-23	3,254	3,234	2,695	1,750
jun-23	3,373	3,339	2,695	1,718
jul-23	3,480	3,449	2,695	1,682
aug-23	3,442	3,404	2,695	1,704
sep-23	3,413	3,386	2,695	1,721
oct-23	3,418	3,340	2,695	1,719
nov-23	3,419	3,402	2,695	1,709
dic-23	3,412	3,398	2,695	1,707

Below are figures 2a, 2b, 2c, and 2d, which belong to the graphs developed by the ARIMA model. This allows us to observe the almost constant predictions and that the results will be corrected with the SARIMA model.

From everything done, it can be concluded that ARIMA models are very useful in many fields, but among the disadvantages that can be mentioned is in the applicability to time series with many observations, at least 30 data for series affected only by the regular component, and at least 50 data in seasonality series.

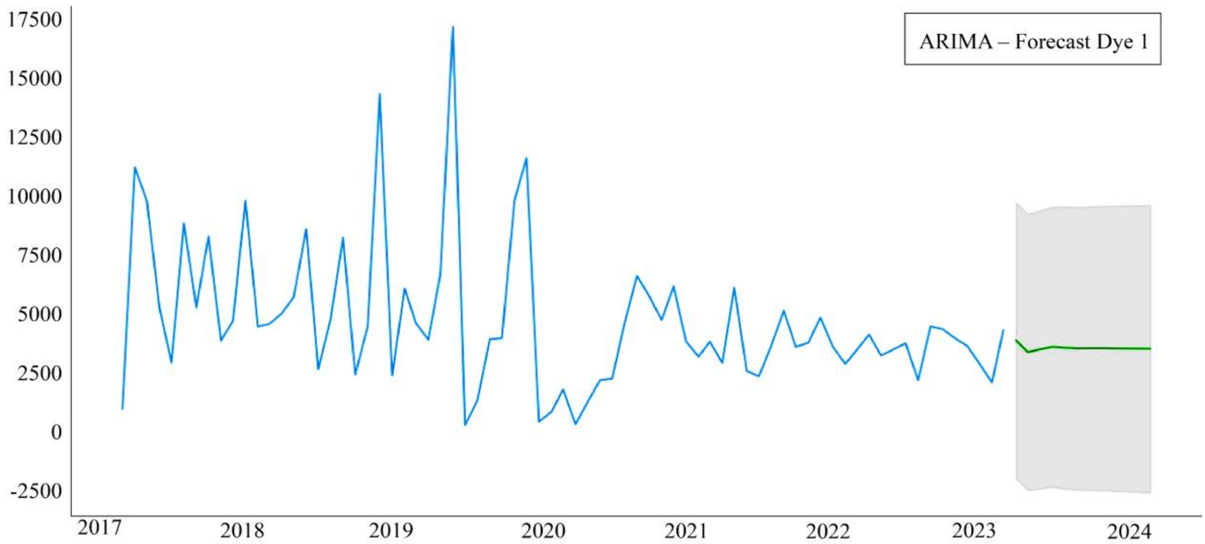

Fig. 2a Hair dye 1 prediction ARIMA

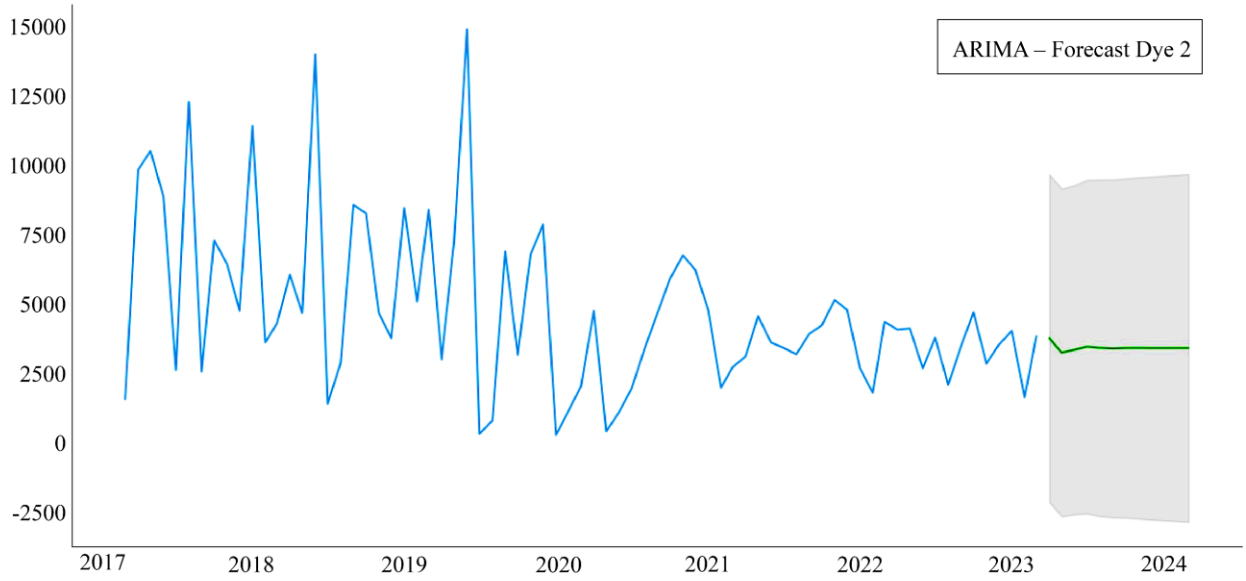

Fig. 2b Hair dye 2 prediction ARIMA

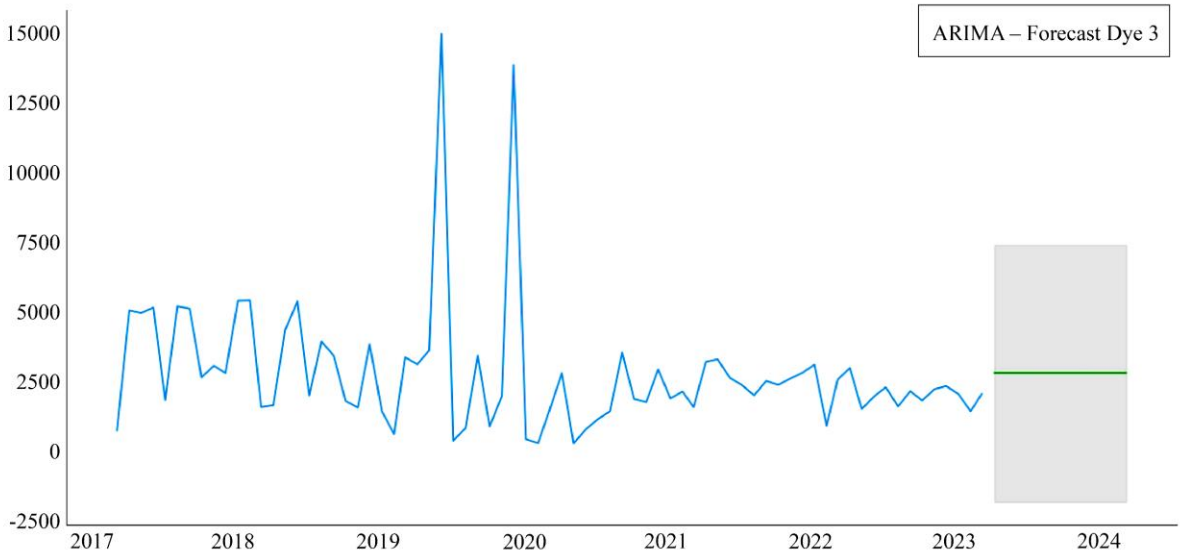

Fig. 2c Hair dye 3 prediction ARIMA

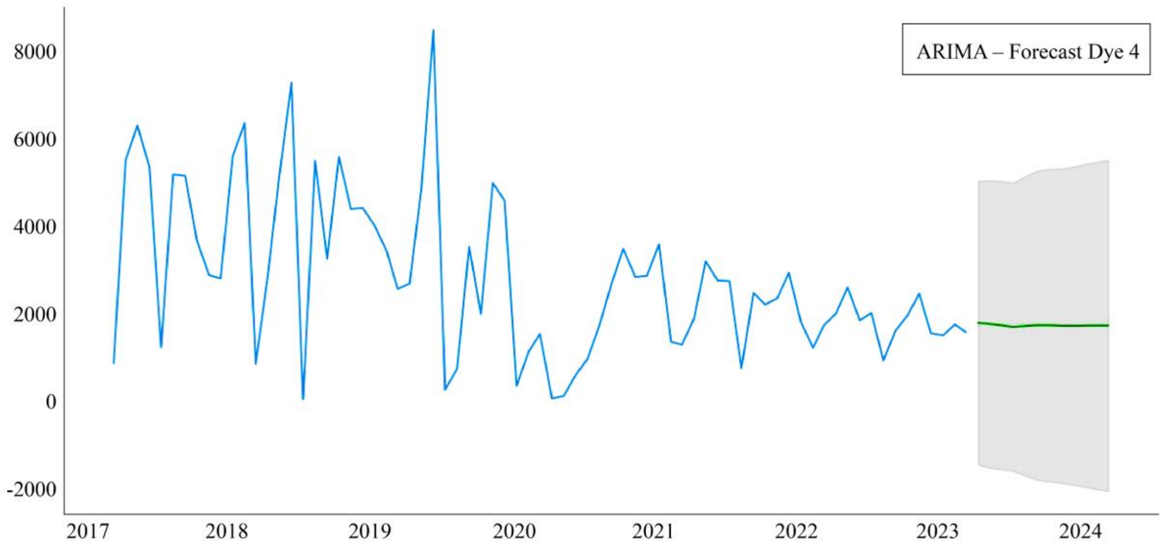

Fig. 2d Hair dye 4 prediction ARIMA

In Table 5, the different indicators that are used to measure error are summarized. MAE can be understood as the mean absolute error between the forecasted value and the actual quantity of product sold; the MSE is the mean square error, the RMSE is the root mean square error, and the MAPE is the mean average percentual error.

The MSE shown in Table 5 is significantly higher than the MAE because the historical data of the hair dye sales is full of outliers.

Table 5. Errors in the time series

	Hair			
Error	**Dye 1**	**Dye 2**	**Dye 3**	**Dye 4**
MAPE	1.83	1.35	1.35	4.68
MAE	2,224.94	2,335.83	1,429.29	1,307.02
MSE	9,756,657.51	9,648,232.67	5,647,695.35	2,969,224.32
RMSE	3,123.56	3,106.16	2,376.49	1,723.14

On the other hand, the second analyzed model is the Sarima model. This one generally adapts better to data that presents seasonal tendencies. The forecast for 2023 done with the Sarima model is presented in Table 6.

Also, you can see in Figures 3a, 3b, 3c, and 3d the graphs that represent the predictions in the Sarima model.

Table 6. SARIMA Forecast to 2023

Year	**Hair**			
2023	**Dye 1**	**Dye 2**	**Dye 3**	**Dye 4**
Apr	4,192	3,969	2,340	1,086
May	4,314	4,301	2,184	1,744
Jun	5,907	5,559	4,250	1,367
Jul	2,631	2,288	1,001	1,539
Aug	3,483	2,778	1,730	658
Sep	5,024	4,456	2,585	1,682
Oct	4,448	4,954	1,235	1,974
Nov	4,744	4,609	1,499	2,110
Dec	6,457	4,434	3,977	18,221

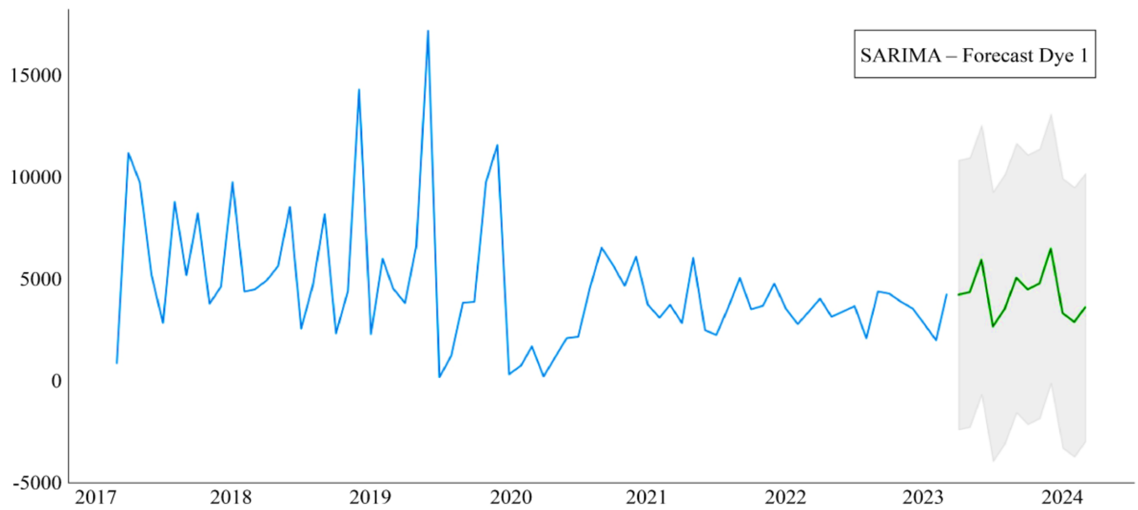

Fig. 3a Hair dye 1 prediction SARIMA

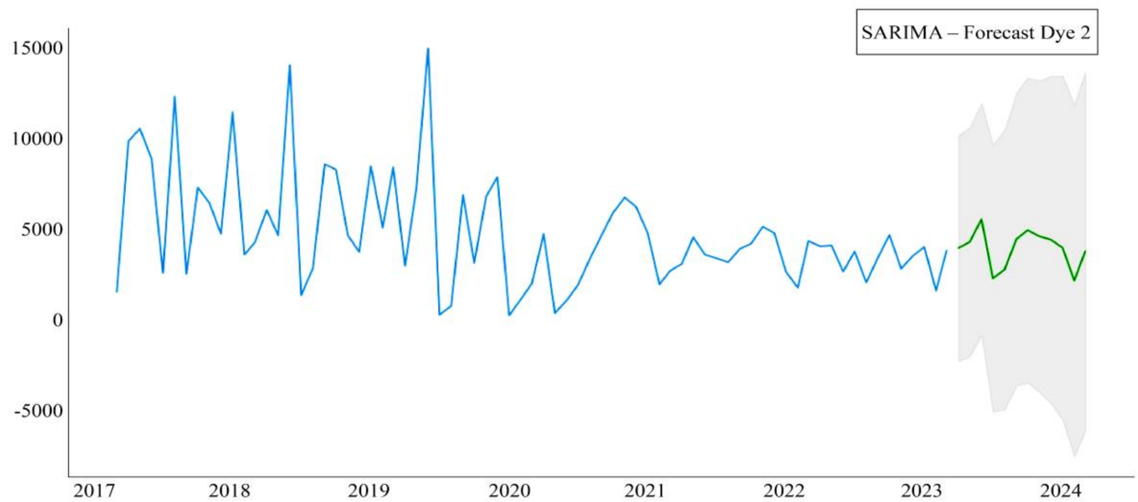

Fig. 3b Hair dye 2 prediction SARIMA

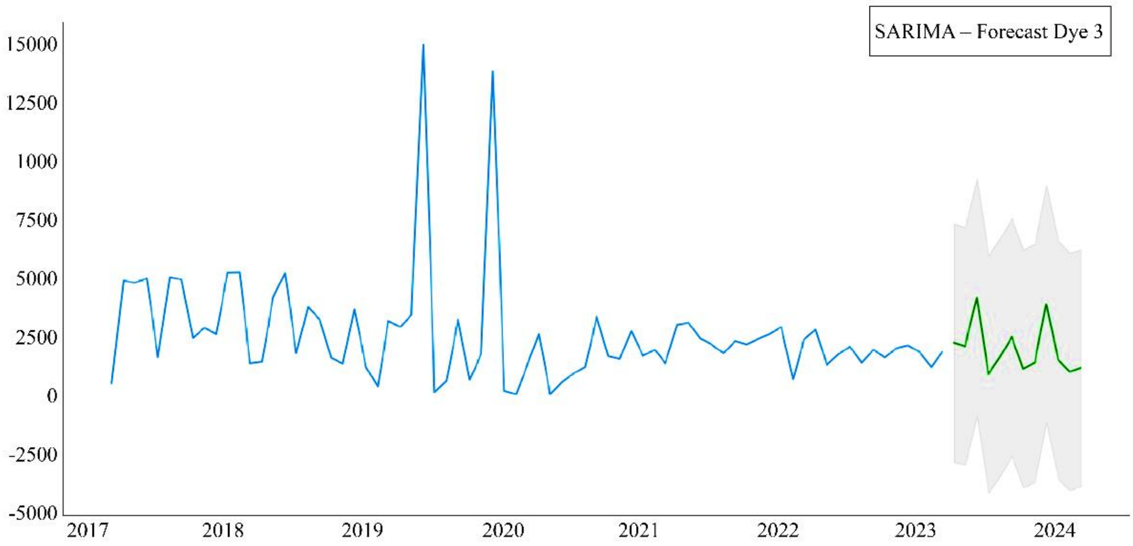

Fig. 3c Hair dye 3 prediction SARIMA

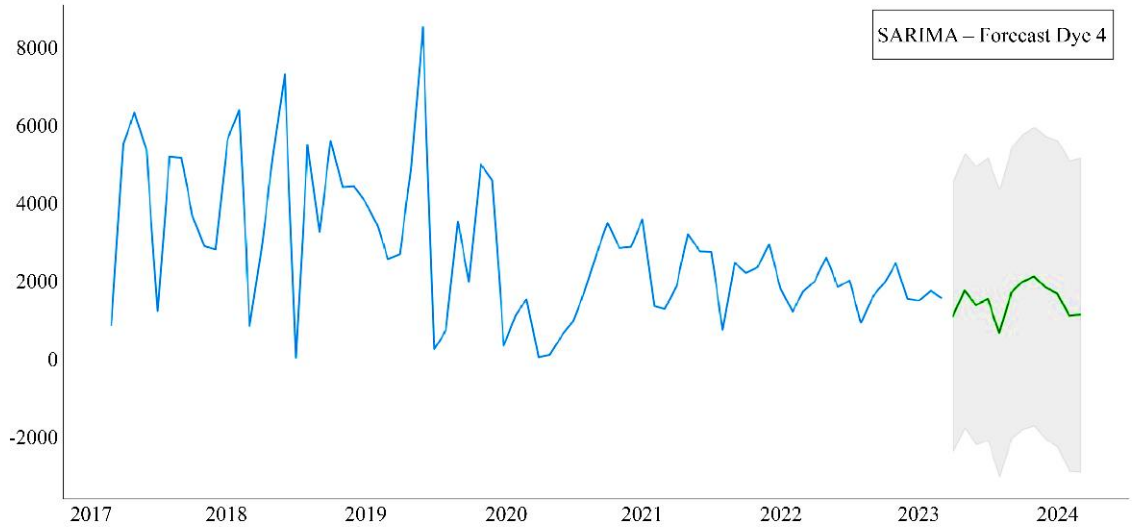

Fig. 3d Hair dye 4 prediction SARIMA

For the Sarima model, these four diagnostics must be noted: standardized residuals, KDE histogram, Normal q-q, and correlogram in Figures 4a, 4b, 4c, and 4d. There is no clear pattern for the standardized residuals for any hair dyes. However, outliers surpassing the three's absolute value for hair dye 3 can be found. On the other hand, the Kernel Density Estimation histogram must show a similar distribution to a normal distribution of N(0,1). This similarity can be found for all the hair dyes except for hair dye 3.

The following graphic shows the normal q-q, which indicates the normality of the univariate data. If the information is usually distributed, it will fall in the line of 45º. Otherwise, the distribution will not have the required regularity. This is why it can be assured that almost every sample, except hair dye three, presents a slight dispersion; this requirement is accomplished. Lastly, the ACF Correlogram indicates a correlation between different periods. In this case, five years. The first correlation is significant, while the rest, 95%, are insignificant except for hair dyes 1 and 3.

As the previous image shows, the Sarima model in Python accomplishes most of the established parameters for hair dye 1, 2, and 3 since it does not present standardized residuals. The KDE curve is like the normal distribution; the normal Q-Q has most of the data gathered in the curve, and, lastly, the correlogram indicates that there may be a need to add more predictors to make the model more precise. However, the only case that does not fit the established parameters is hair dye three because it shows standardized residuals in 2019 and 202, and a dispersed normal distribution and Normal Q-Q.

4.1. Validation

The result of the average RMSE was contrasted against the existing literature in similar scenarios, obtaining a better result than previous investigations; this result is shown in Table 7.

Table 7a shows a summary of the Arima and Sarima results. Figures 5a, 5b, 5c, and 5d present the actual demand versus the Arima and Sarima models evaluated in this investigation. Furthermore, these results are compared with the actual demand experienced for April and May through the MAE indicator.

It can be observed how, despite the Dickey-Fuller test proving that the historic data for hair dyes 1, 2, and 3 are seasonal, the Sarima model is the one that presents the highest levels of error (31.33%, 102.54%, 25.76%, 79.21%, 34.48%, 40%, 44. 82%, 13.25%) when it is compared against the results of the Arima model (17.83%, 52.77%, 19.14%, 34.75%, 54.89%, 72.76%, 9.86%, 13.64%). This is an unexpected result because the standard Arima model is generally more adapted to stationary data.

The only exception is the hair dye 3, for which the Sarima model presents better forecasts for April and May (34.48% vs. 54.89% and 40% vs. 72.76%). It can also be noted that the error levels tend to be lower in April and higher in May. For example, for hair dye 1, the Arima and Sarima values are 17.83% and 31.33% in April, while the MAE rises to 34.75% and 79.21% in May. This happened because these hair dyes are only sold in the traditional distribution channel (small businesses), a sector that experienced an unexpected fall in the sell-out department.

According to Cabrera et al. [23], an MAE lower than 30% is acceptable for a company in the consumer goods industry in Peru. Arima surpasses this value on four occasions, mainly in May, a month that experienced circumstances in the Peruvian market that no one could have foreseen that heavily impacted the demand.

Furthermore, when comparing the results of the Arima model presented in this paper with previous research conducted in the Peruvian market for CGCs [22-24], a lower averaged RMSE is found in one case, while a slightly higher one in another, as demonstrated in Table 7. This signifies that the current model reaches expectations.

Table 7. Averaged RMSE comparison to others' research

	Research work	[20]	[19]
RMSE	9.21	31.71	2.84

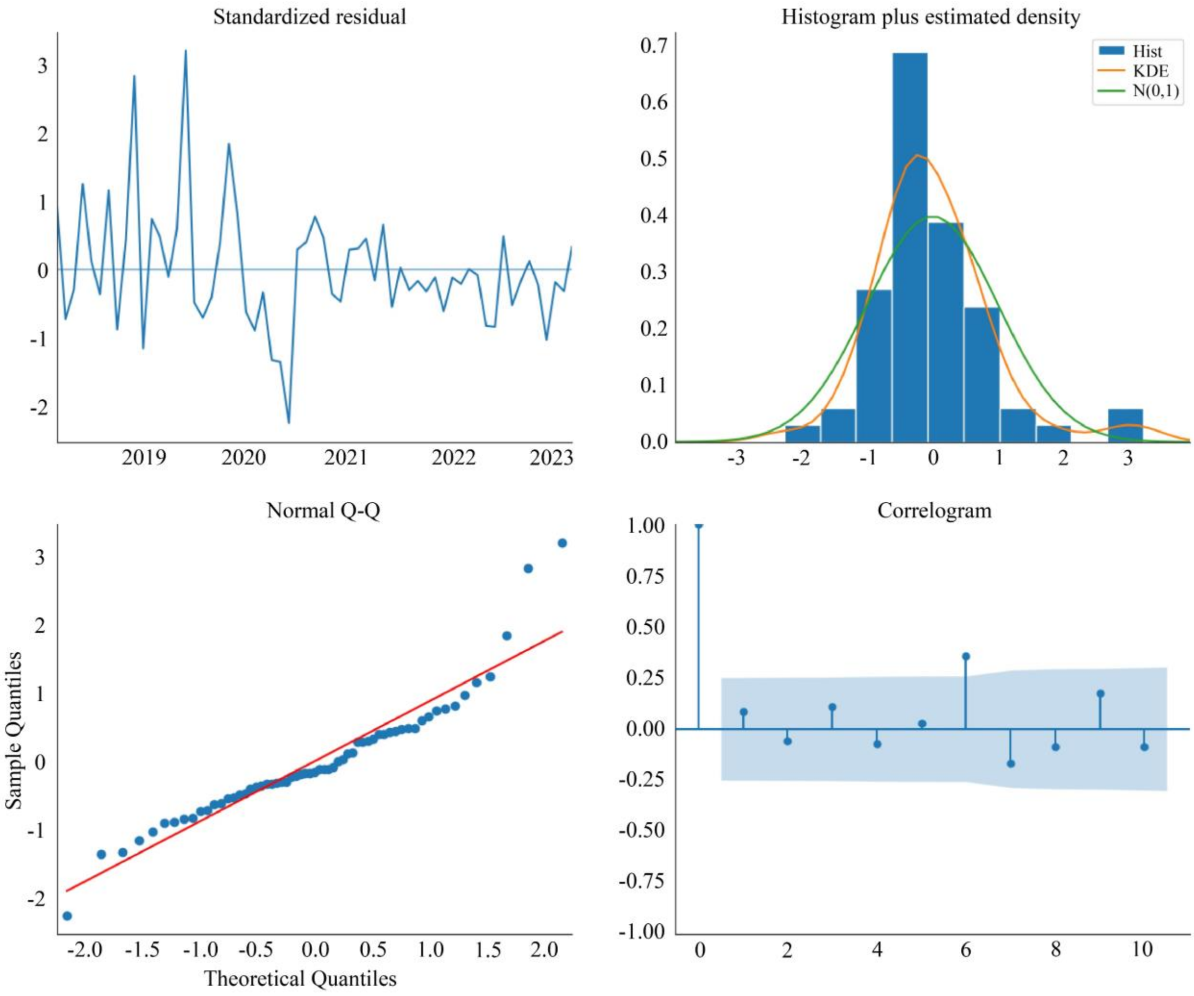

Fig. 4a hair dye 1 of the parameters of SARIMA

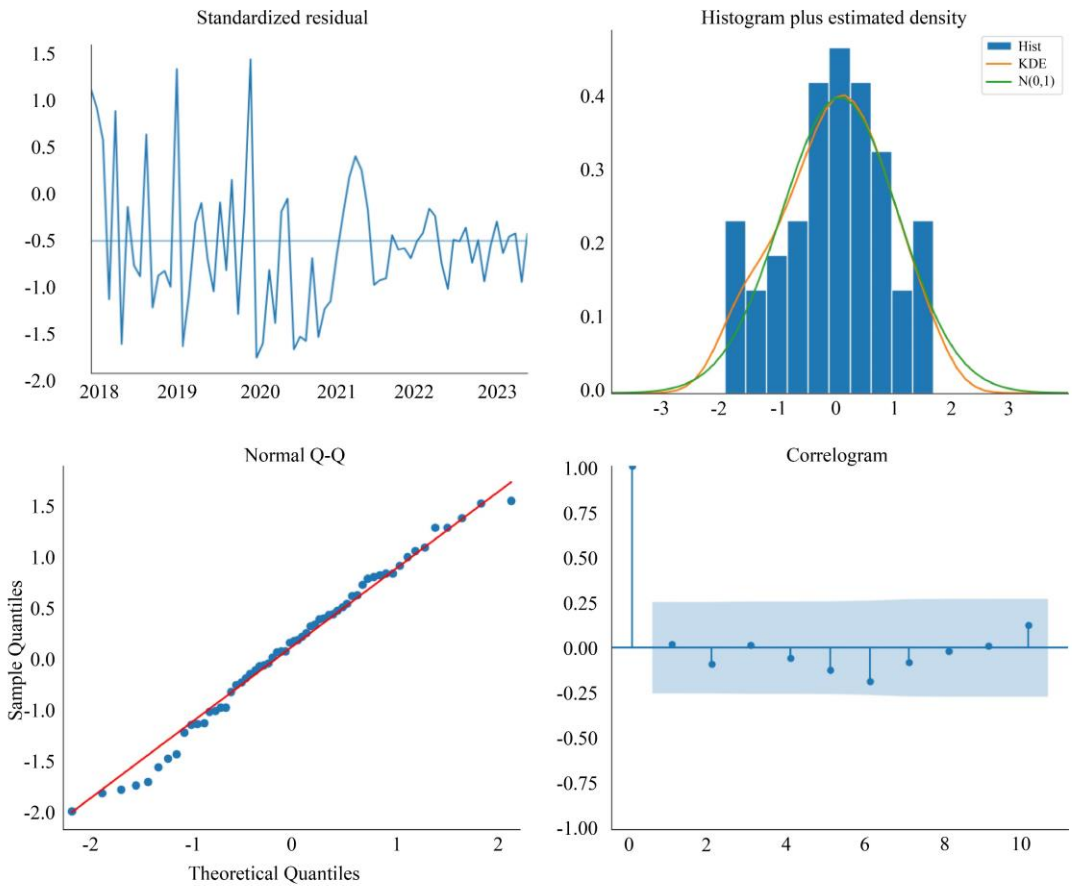

Fig. 4b Hair dye 2 of the Parameters of SARIMA

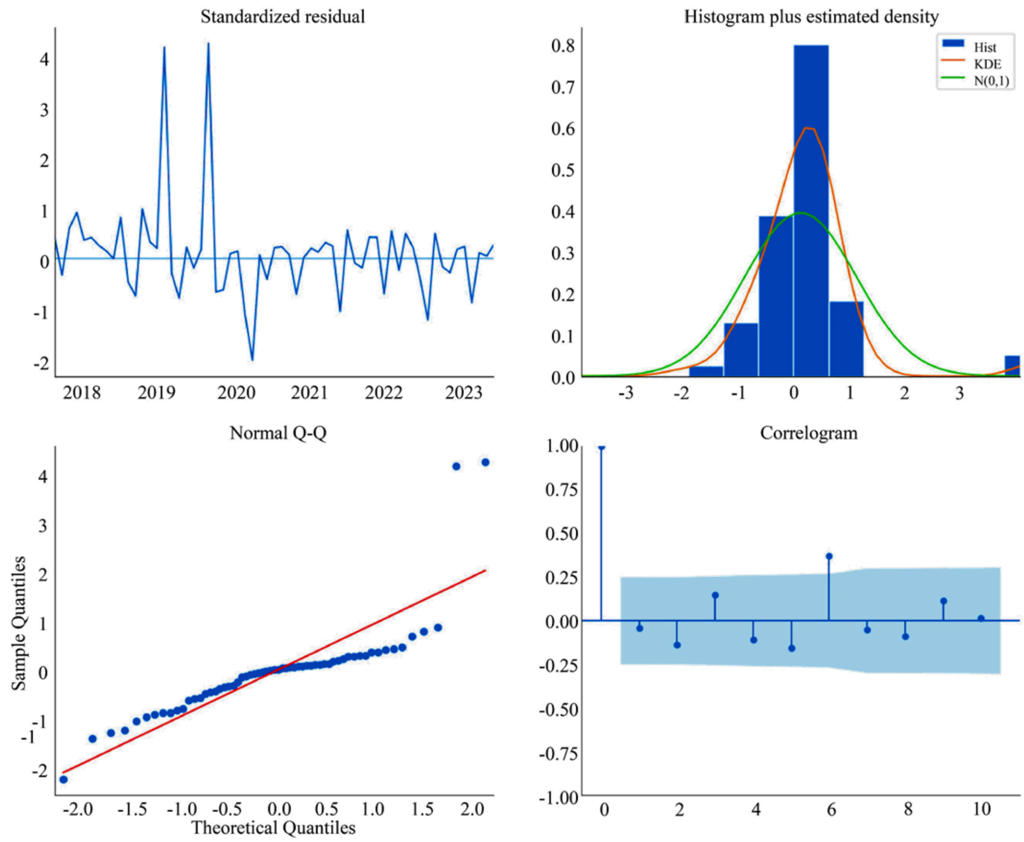

Fig. 4c hair dye3 of the Parameters of SARIMA

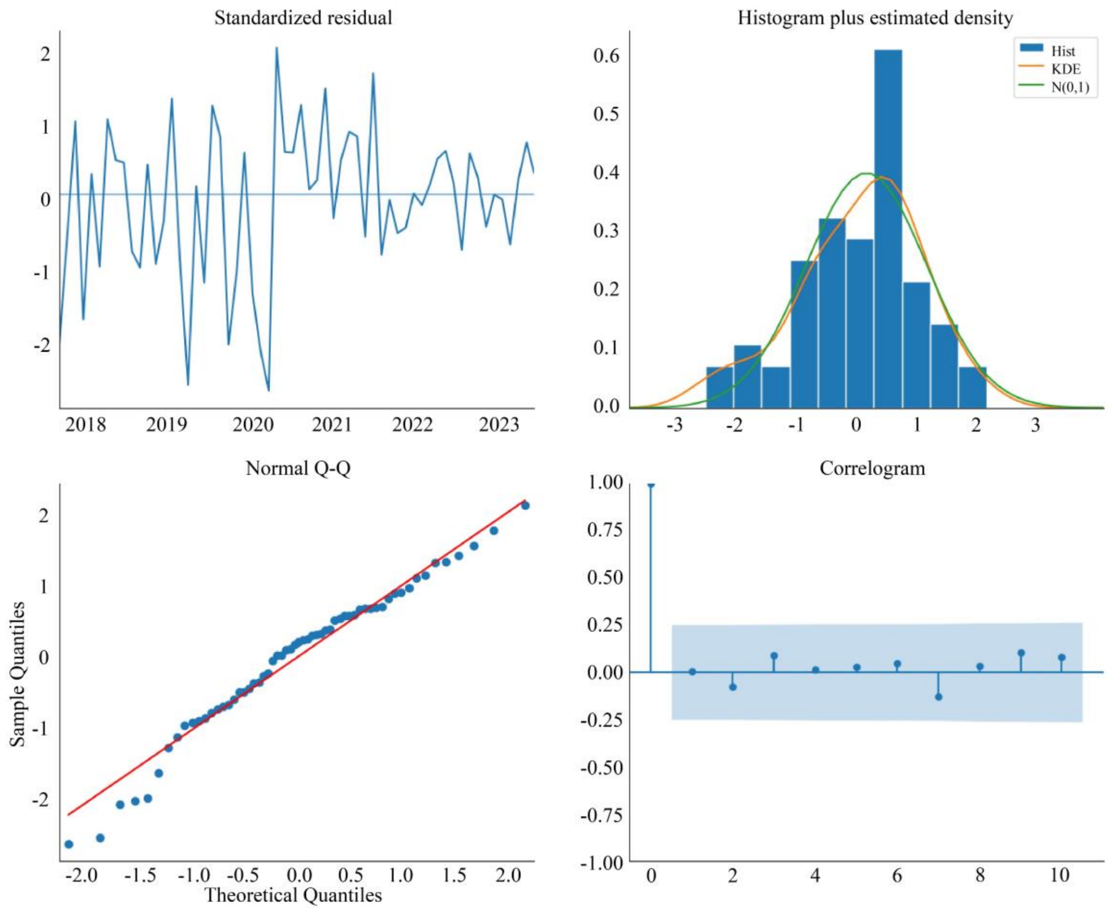

Fig. 4d hair dye 4 of the Parameters of SARIMA

Table 7a. Model selection

Product	Month	Models			Forecast MAE	
		Actual Demand	Arima Forecast	Sarima Forecast	Arima	Sarima
Hair Dye 1	abr-23	3192	3761	4192	17,83%	31,33%
	may-23	2130	3254	4314	52,77%	102,54%
Hair Dye 2	apr-23	3156	3760	3969	19,14%	25,76%
	may-23	2400	3234	4301	34,75%	79,21%
Hair Dye 3	apr-23	1740	2695	2340	54,89%	34,48%
	may-23	1560	2695	2184	72,76%	40,00%
Hair Dye 4	apr-23	1968	1774	1086	9,86%	44,82%
	may-23	1540	1750	1744	13,64%	13,25%

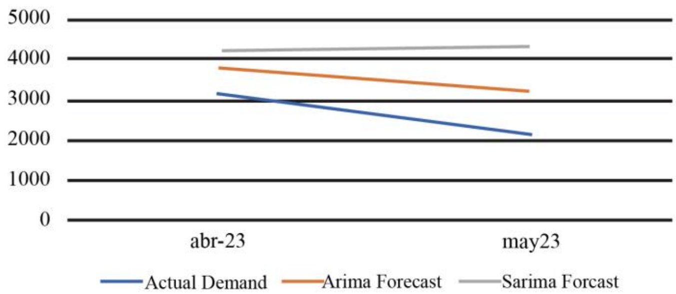

Fig. 5a Real demand hair dye 1 vs. ML Models

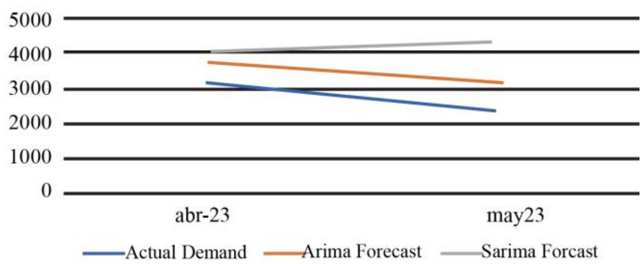

Fig. 5b Real demand hair dye 2 vs ML Models

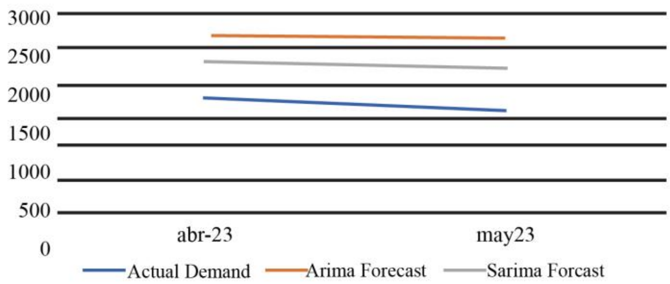

Fig. 5c Real demand hair dye 3 vs. ML Models

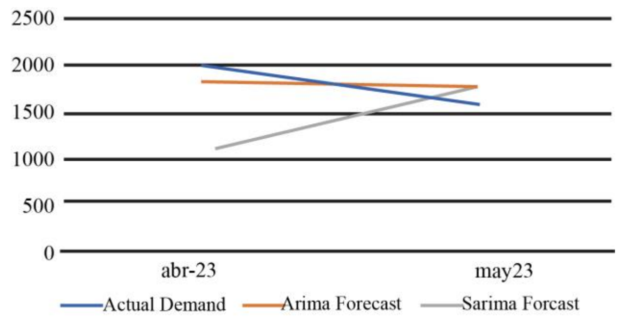

Fig. 5d Real demand hair dye 4 vs. ML Models

4.2. Limitations

Limitations of this research include:

Lack of data: The research relies on historical product demand data availability to perform the time series analysis. If sufficient or quality data is unavailable, this may affect the accuracy of the predictions.

Focus on a specific sector: The research focuses on the hair care products industry in the Peruvian market. This limits the generalizability of the results to other sectors or countries.

Lack of previous research: There is a lack of previous research on using Machine Learning as a forecasting tool in the consumer goods industry in Peru. This may limit the availability of relevant literature and comparisons with other studies.

Limitations of the Machine Learning model: The proposed Machine Learning model may have its own limitations, such as the need for high-quality training data, proper selection of algorithms and interpretation of results.

4.3. Future Work

Some possible future work for this research could include:

Improving the Machine Learning model: Explore and evaluate different Machine Learning algorithms to improve the accuracy and performance of the forecasting model.

Incorporation of additional variables: Consider including additional variables, such as economic data or market information, to improve forecast accuracy.

Analysis of other sectors or markets: Extend the research to other sectors or consumer goods markets to assess the applicability and generalizability of the proposed model.

Evaluation of practical implementation: Conduct a feasibility study and cost evaluation to implement the forecasting model in the studied company and measure its impact on supply chain management.

5. Conclusion

In conclusion, it was discovered that the historical sales data for hair dyes 1, 2, and 3 present seasonal tendencies. In contrast, hair dye 4 has a stationary tendency, meaning the Sarima model should have forecasted data with lower error levels. However, this was not the case since the Sarima model presented higher levels of error (31.33%, 102.54%, 25.76%, 79.21%, 34.48%, 40%, 44. 82%, 13.25%) when compared to the MAE values calculated with the Arima model (17.83%, 52.77%, 19.14%, 34.75%, 54.89%, 72.76%, 9.86%, 13.64%).

Additionally, it was determined that both the Sarima and the Arima models tend to overestimate the demand. For hair dye 1, in April and May, 569 and 1124 units were overestimated; for hair dye 2, it was 2604 and 834 units; for hair dye 3, it was 3955 and 1135 units; and, finally, hair dye 4 was the only exception to this tendency since 194 units underestimated the demand in April. This is caused by the fact that the demand in the past tended to grow at higher rates.

The study's findings demonstrated that the SARIMA model predicted the demand for hair dyes and was verified and compared with earlier studies. In conclusion, this research emphasizes the value of machine learning models for supply chain management and demand analysis of hair care items during the COVID-19 epidemic. These results provide a foundation for comparison for comparable manufacturing businesses looking to use machine learning to improve demand management.

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