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Original Article

Application of Financial Prediction for Share Price Improvement in the Business Sector by means of Artificial Neural Network

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Abstract - *The use of artificial neural networks has an important role; nowadays, they represent an advantage for solving complex problems with different constraints in comparison with traditional methods. The research presents the theory and model; addresses the analysis of corporate financial statements, using the research tool to apply financial forecasting to improve the corporate stock price. The objective is to determine the results of the application of financial prediction for the improvement of stock prices in the corporate sector by means of artificial neural networks. Also, to build different models to evaluate the behavior of networks in different numbers of input variables or neurons in the hidden layer and the probabilities of success by means of the prediction results in the input variables. The predictive capacity in the methods used is based on perceptron-type layers and a strategy that allows alternative system modelling in the predictive control of financial statements.*

Keywords - *Artificial Neural Network, Business, Prediction, Financial, Neurons, Model.*

1. Introduction

The business sector experiences difficulty in financial profitability that characterizes the lapses through the indicators of technical analysis and systematic analysis; based on the conceptions that correspond to performing a detailed study to make a proper investment in corporate financial management. The model allows us to evaluate actions' performance to examine a sound economy for decision-making. It is related to inspecting the finances of the business sector, which are the main criteria for investment decisions (Cumming and Hornuf, 2021).

Opportunities in digital transformation to create new business models and a new scheme on algorithmic financial trading applied to neural networks highlight that computational wisdom techniques for financial business systems continuously were quite famous. In the last decade, deep learning models have started to receive more attention. Especially in the image processing society, a new algorithmic business model using a 2-D convolutional neural network based on image processing features thus transforms financial time series into 2-D images, applying to fifteen different technical indicators, each with different boundary selections. As a result, each indicator instance produces data for a span of 15 days (Sezer, 2018).

Volatility related to financial danger and its predictive accuracy by neural networks is paramount in portfolio improvement. A gigantic proportion of literature to date indicates that support vector machines are the superior algorithms for financial data regression. The new deep Learning, short-term and extensive memory ordinary neural networks outperformed SVM in categorization drawbacks. The new unbiased evaluation of these two modeling techniques for regression drawbacks and, in comparison, a model that succeeds in predicting regression will be conditional autoregressive generalized in financial volatility and danger prediction. In conclusion, research will help investors triumph in the competition to maximize their returns (Liu, 2019).

Prediction in the stock market sector employing LSTM neural networks highlights that investing in a group of assets is not straightforward. The irregularity of the financial market allows the primary model to forecast future asset values more accurately. Based on making CSPs perform tasks that commonly need human wisdom, machine learning is currently the dominant trend in scientific research. A model using ordinary neural networks, especially the short- and long-term memory model, predicts the stock market's future values, is to accurately visualize a machine learning algorithm and the time to improve our model (Moghar and Hamiche, 2020).

2. Literature Review

Zhao and Li (2022) detailed the use of experimental neural networks applied to financial development. Furthermore, productivity and growth remain interconnected, and the feasibility of the relevance of such linkages is distinct for developing economies. Digital executions based on a neural network approach indicate that central bank digital currency could represent a profound structural change in the financial area, especially in banking. An intensive neural network design to model the introduction and its potential effect on commercial bank deposits, the postulated model predicts the possibility of bank runs' occurrence in system properties' functionality (Richmond, 2019).

Gu et al. (2020) indicated that the compression of the behavior of recurrent neural networks in the micro-segmentation of consumers in the financial area is not a trivial task and was an atypical omission of the current scientific literature. On the other hand, learning such components influences and allows us to give recurrent scientific recommendations for improving the model's predictive accuracy. Artificial intelligence and representation learning offer a unique possibility to solve the problem of micro-segmentation, although pervasive in many industries (Bose et al., 2022).

Ottati(2017) details a model of business adaptation in the global economy, the proliferation of artificial intelligence in susceptible industries, and finance has become dependent on the applicability of deep models. Reallocating properties in state space with high fidelity was used for the description. In the face of increasing default and limited studies on predicting financial problems, a related financial prediction model among neural networks aimed to establish the most important predictors of financial problems and detect their optimal prediction models in an economic environment (Zizi et al., 2021).

Belfrage and Kallifatides (2018) mentioned that the market economy comprises organizations, high credit risks and financial risks. It is quite difficult to obtain financial backing. Based on the important concepts of the supply budget model, he investigates the backpropagation of errors committed and explores the primary influencing of the financial effect. Error back propagation algorithm neural network is an algorithm that considers the financial elements of an elementary and theoretical introduction to the current model, allowing the use of supervised algorithm neural network algorithms to be trained and tested in establishing the authorized risk assessment rules (Bianchi e, 2021).

Yu and Yan (2020) mentioned that stock market prediction employed with neural networks and understanding financial analysis allows prophesying its development and changes in critical aspects of inquiry in academic and financial circles. Financial data has complex, inconclusive and chaotic information. Foreshadowing its development trends is a drastically difficult challenge, which is why the fluctuations of financial data are subject to an infinity of correlated components that change repeatedly (Bade, 2021).

Munoz et al. (2016) proposed establishing decisions, prophesying and examining financial and time-dependent data. Deep neural networks combine the benefits of Learning and have the possibility to use to solve drawbacks more successfully. The conventional machine learning algorithm allows for treating financial product cost data as a one-dimensional series generated by the projection of a system (Bianchi et al., 2021).

Corvalán (2018) details the implementation of artificial intelligence in a prediction model design based on a deep neural network based on the procedure and short- and long-term memory networks used to prophesize costs. The proposed prediction model is applied to guess various stock indexes for different periods. A comparison of the results shows that the proposed prediction model has higher prediction accuracy. It allows for designing machine learning types using the prediction model that establishes higher prediction accuracy (Brunnermeier et al., 2021).

2.1. Change in Methodology for Stock Price Flow Forecasting

Hosaka et al. (2019) emphasized convolutional neural networks and the identification of a plurality of accuracy fields. The application of convolutional neural networks to financial studies, studies on the prediction of cost movements. This seems to be because convolutional neural networks are more correct for image application and less for numerical data in general. Integrating financial statements from a convolutional neural network exercise to business investment prediction is treated as a class categorization problem (Buraschi, Piatti and Whelan, 2021).

Venegas (2021) establishes automated processes that decrease risk, the financial statements of Japan allow to obtain the image generated by this process to practice and test a convolutional neural network, and the magnitude of the data set is increased using weighted averages to generate synthetic data aspects, a large number of images were applied for the classes of organizations, and successive to practice convolutional neural network based on GoogleNet allows to establish the diagnosis and organizational change for sustainable development (Li, et al., 2019).

Figure 1 shows the progress of artificial intelligence neural networks for exploration in the stock market field, which still requires much research. The capability and advantage of the investment risk and variability prediction model using an automated methodology based on neural networks. The application of a risk quantification model for an investment portfolio allows organized processing for design and fault location with immediate responsiveness (Baron et al., 2021).

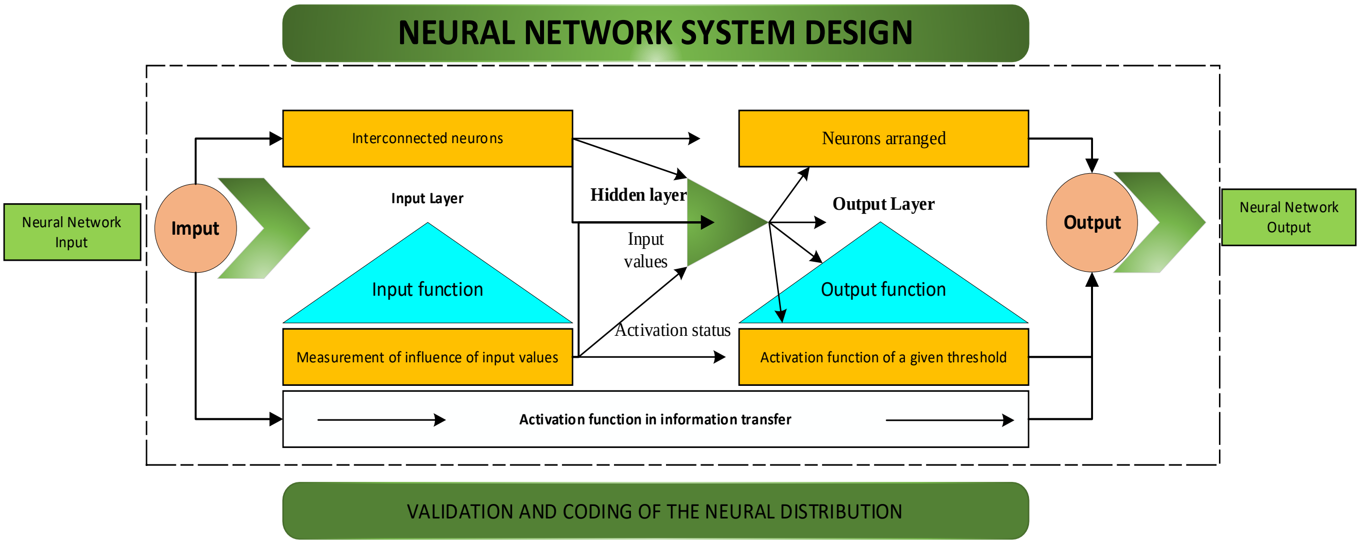


Fig. 1 System Design

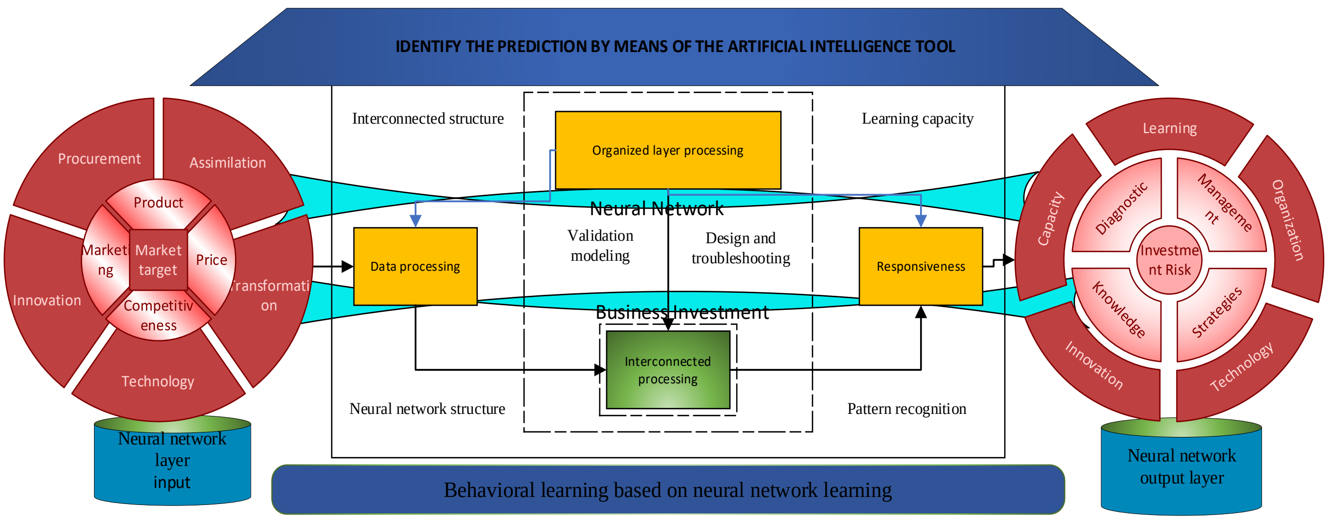


Fig. 2 Behavioral learning based on neural network learning

Yan et al. (2021) mention the financial transaction prediction model based on neural networks, the advancement of monumental data and deep learning technology in various fields. Deep Learning by model training process, training sample selection, model composition and improvement procedures are used to be subjective. The term strong neural output is used to model and forecast financial transaction data, the types of components affecting the model's prediction accuracy. High accuracy is based on strong or recurrent neural networks (Howell, 2019).

Duan (2019) relates to deep financial system modeling, as the danger of default in peer-to-peer lending is notoriously difficult to assess. The research offers a deep neural network approach to assess lending risks positively. The neural network enables the transformation of numerical data through coding capability across safe loans, risky loans and bad loans. The TensorFlow program enables the implementation of machine learning processes. The test sets consist of visualizations, which belong to the class of low-risk loans, synthetic minority sampling techniques to improve the prediction accuracy of deep neural networks, and the importance of analysis and synthesis for business development (Tami and Lugovskyy, 2019).

Sezer (2018) mentions algorithmic financial trading applied to neural networks and computational wisdom techniques for financial business systems that generate a competitive advantage. Deep learning models are gaining more importance, especially in the image-processing society. A new algorithmic business model using a convolutional neural network based on image processing features transform financial time series, applying in technical indicators, resulting in each instance of indicator data for a time span, allowing to establish business intelligence and the degree of impact on organizations (Gurkey and Lugovskyy, 2019).

Figure 2 details the model's development with the necessary elements to distribute processing adequately. The strategy of classifying adequately to mitigate the expected risks, given that it can estimate the probability density of the development and classification vectors. Predicting the behavior of financial markets has always attracted the attention of investors in the stock market to obtain the highest possible return and lower risk (Chinco et al., 2022).

Liu (2019) emphasizes volatility related to financial danger and its prediction accuracy by neural networks, which is paramount in portfolio improvement. To date, a gigantic proportion of literature indicates that support vector machines are the superior algorithms for financial data regression. New deep Learning enables ordinary neural networks to establish support vectors for categorizing and evaluating successful regression modeling techniques that allow generalizing financial volatility or risk forecasting. The research will help investors win the competition to maximize their returns (Grennan, 2022).

2.2. Predictive Analytics for Improved Enterprise Financial Planning

Moghar (2020), who mentions prediction in the stock market sector using long-term memory neural networks (LSTM), specifies that it has never been easy to invest in a group of assets; the abnormality of the financial market does not allow primary models to predict future asset values more accurately. Machine learning is based on having computers perform tasks that usually require human wisdom, the dominant trend in scientific research. A model that uses ordinary neural networks, particularly the short- and long-term memory model, to predict future stock market values. The main objective is to see how accurately it can predict and improve our model using a machine-learning algorithm. Conduct detailed research based on different varieties of products, and make sales forecasts using artificial intelligence (Guven and Sinsir, 2020).

Sun and Lei (2021) emphasized financial research for mining enterprises employed with a neural network model base. The goal is to build an early warning financial indicator system. Cluster analysis methods are combined with a set value method in which strategies are applied to obtain accurate predictions. The design of the early warning model applied to the financial issues of the neural network, a high accuracy in the predictions to be used in listed mining companies. The financial situation of companies with a good status requires an early warning format in reduced time. Guidelines on employing a flowchart to apply the artificial neural network were developed (Hollow, 2020).

Benedict (2019) mentions the credit risk analysis of public companies based on analytics, logistics and neural networks. The power to identify the various characteristics through financial indicators by granting credit. The high recorded values make obtaining the profit margin through the set of sales volumes in the period possible. The recommended model based on neural networks is given using logistic regression, with satisfactory results. It is worth mentioning that one of the limitations identified in the present study is to generate models in the established sector. The indicators allow contribute to the forecasting of the insolvency of the entities through the methodology to be able to have a constant evolution in the liquidity of the business and in such a way to be able to avoid losses (Obstfeld et al., 2020).

Xu and Yang (2022) detailed financial risk control based on neural networks to provide insight into the different risks. Economic integration arises globally. Commercial banks face a business environment and liquidity risk that can reflect the level of security. A neural network model allows the improvement of qualitative and quantitative data. A risk control system requires to be able to creating of a model that can control risks. The research focused on commercial banks where a neural network was implemented; the method can overcome deficiencies for better risk control. It allows for improving operational performance for better bank performance. The neural model allows us to improve computational accuracy by applying the method to increase the amount of data in a hidden layer (Wang, 2020).

3. Methodology

The research allows us to understand a descriptive design study. This methodological approach collects data on different aspects of the application of financial prediction for the improvement in the price of shares in the business sector through the artificial neural network, allowing a predictive analysis to implement and describe the behavior of the study variable. Applying financial prediction to improve the price of shares in the business sector through artificial neural networks allows for analysis and development for the advancement of research and decision-making. to build elements that help to identify characteristics to reduce the investment risk. The approach is quantitative and non-experimental to collect information and data from companies in Lima's stock exchanges, which allowed analysis and diagnosis performance, thus focusing on factors and variables that allow research and innovation to improve the investment grade (Walas and Redchuck, 2021).

Muhammad (2022) established optimization based on harmonic selective Learning in the multilevel inverter; neural networks are classified by the type of connections based on an algorithm and various developments; between input and output connections, different layers of neurons make intermediary or hidden that can be connected. The connections help classify the types of networks that are convenient to develop for a given task, allowing us to assimilate the brain's functioning with the functioning of artificial intelligence software. The classification and use of the algorithm allow the optimization of the neural network method based on reaching the minimum point of an error.

4. Results

The proposed neural network model showed the counts and percentages of all cases of the active data set and the cases of each counterpart group to statistically summarize the variable subgroups within the category of one or more of each grouping. By which all levels of the variable are crossed to show the order of the statistics confirmed with 1510 training elements with a percentage of 60.2%, 719 test elements with 28.7% and 279 reserve elements with 11.1%, as indicated in Table 1.

Table 1. Summary of case processing analysis

		N	Percentage
Sample	Training	1510	60,2%
	Test	719	28,7%
	Reserve	279	11,1%
Valid		2508	100,0%
Excluded		0	
Total		2508	

4.1. Evaluation of Statistical Indicators Neural Network

The network mainly shows the transmission of a data packet. It works according to the connection model of the systems established during the process to identify the neural network in collecting information. On the object of the network parameters presented in groups and subgroups, the network information set 4 input variables with the standardized covariate, 3 hidden layer variables, and 1 action mean variable, as shown in Table 2.

The artificial intelligence method, through neural networks, allows data processing through the monolayer or simple perceptron, multilayer or convolutional perceptron. They are connected to each other and work together, consisting of data processing and information exchange by recognizing patterns of financial trends with the ability to learn and improve performance. It allows independent and dependent variables. The activation parameters of the neural network model through the neural network diagram. Displays each predictor and categorical node with targets in the diagram of the category measurement scale with predictive method 4 layers of inputs, 3 hidden layers and 1 layer of output following.

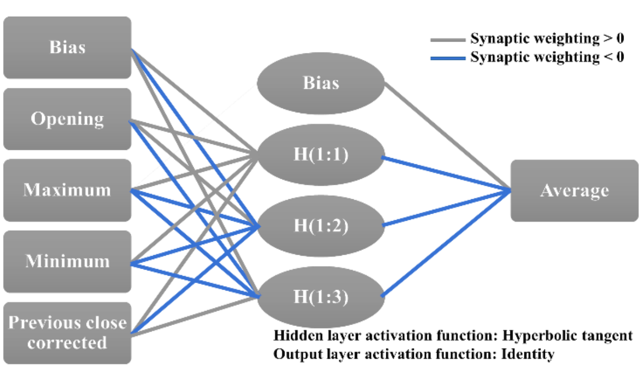


Fig. 3 Diagram of neural networks, data taken from RStudio 4.1.0.

Table 2. Network information analysis

Network information			
Input layer	Covariable	1	Opening
		2	Maximum
		3	Minimum
		4	Previous closing Corrected
	Number of units		4
	Method of change of scale for covariate		Standardized
Hidden Layer	Number of hidden layers		1
	Number of units in hidden layer 1[a]		3
	Activation function		Hyperbolic tangent
Output layer	Dependent variable	1	Average
	Number of units		1
	Scaling method for scale dependence		Standardized
	Activation function		Identity
	Error function		Sum of squares
a. Exclude unit of bias			

Table 3. General analysis of the model

Model detail		
Training	Sum of square error	,647
	Relative error	,001
	Stopping rule used	Allows to achieve a training error ratio criterion (.001).
	Training time	0:00:00.04
Test	Sum of squares error	2,696
	Relative error	,007
Reserve	Relative error	,001
Dependent variable: Average		

Table 4. Parameter estimation

Estimates parameter					
Predictor		Prognostic			
		Hidden layer 1			Output layer
		H(1:1)	Average	H(1:3)	Average
Input layer	(Bias)	,144	-,718	,766	
	Opening	1,201	,066	-,171	
	Maximum	1,201	-,116	-,335	
	Minimum	,712	-,482	-,088	
	Previous close corrected	,812	-,436	,117	
Hidden layer 1	(Bias)				,933
	H(1:1)				-,034
	H(1:2)				-,734
	H(1:3)				-2,130

The method assigns the value to the parameter that characterizes the field under study. It accurately determines the model from a sample drawn from the population. It serves to know and attribute a distribution of the data; the intervals between which these values are estimated with a certain degree of confidence are greater the larger the interval. Therefore, the smaller the error of the initial estimate, the narrower the confidence interval to improve finance and investments according to indicators of the ratio of the mean of the shares. The hidden layers are formed by neurons whose input comes from that corresponds to output which allows determining the characteristics of the environment that it tries to model. In the input layer predictor, the corrected prior closure has greater relevance in H(1:1) with a value of 0.812, H(1:2) with a value of -0.436 and H(1:3) with a value of 0.117, as indicated in table 4.

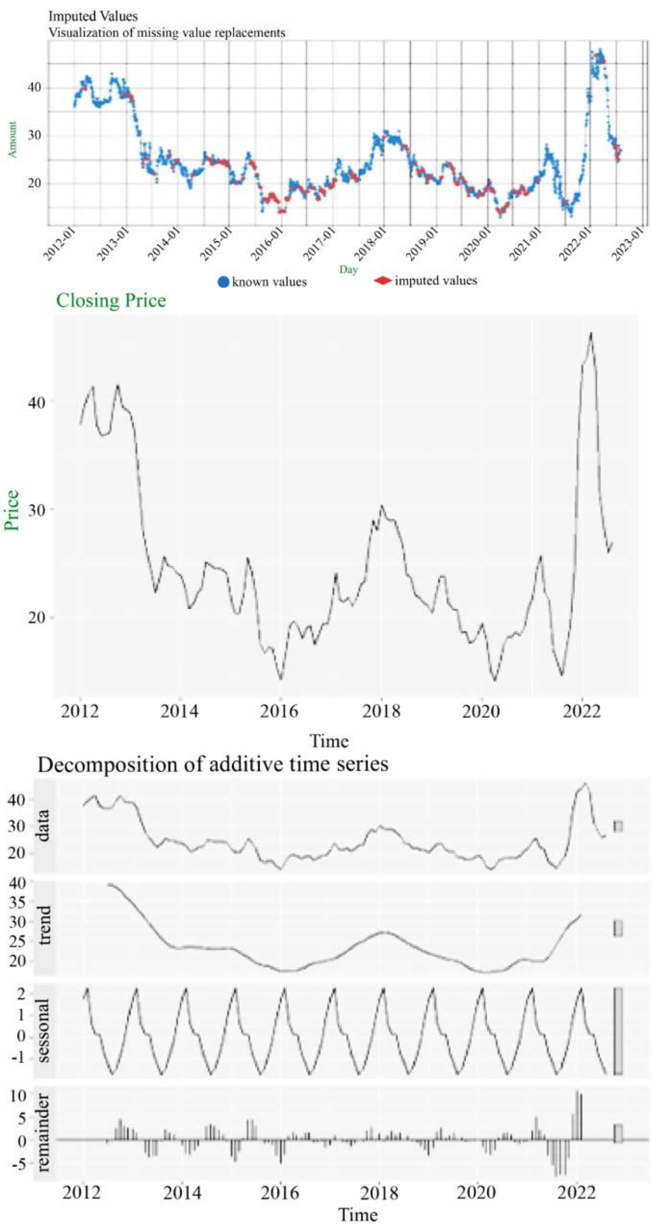


Fig. 4 Imputation by interpolation, data taken by RStudio 4.1.0.

Table 5. Importance of input variable

The importance of the independent variable		
	Importance	Standardized importance
Opening	,179	36,5%
Maximum	,491	100,0%
Minimum	,234	47,7%
Previous close corrected	,096	19,5%

The use of neural networks in the neural layer allows for highlighting the importance of the input of the neural layer, hidden layers and the output layer. In the importance ranking Opening stock price at the beginning of the day is 36.5%, a maximum of 100%, a minimum of 47.7% and the corrected previous close of 19.5%, as shown in Table 5.

Analyzing the stock price variable will allow imputing of the values by interpolation to establish the data type appropriate for the research. It is advisable to perform the transformations within the data set in the corresponding share price date field to separate the month and the year and then add the forecast target variable. This way, it is possible to perform a transport flow that establishes a time series of seasonality and trend, as indicated in Figure 4.

We can appreciate the seasonality data, taking into account. On the other hand, the trend is higher representative of the previous periods.

It is observed in Table 6 that the p-value is higher than 5% (p-value = 0.8187>0.05), so the null hypothesis is fulfilled, and the series is not stationary. It allows looking for the changes so that the series will become stationary to apply the ARIMA model.

Table 6. Dickey-Fuller test

Augmented Dickey-Fuller Test
data: Y
Dickey-Fuller = -1.4173, Lag order = 5, p-value = 0.8187
alternative hypothesis: stationary

Table 7. Sensory neuron test

Adf.test (DY)
warning in adf.test (DY): p-value smaller tan printed p-value
Augmented Dickey-Fuller Test
data: DY
Dickey-Fuller = -6.5371, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

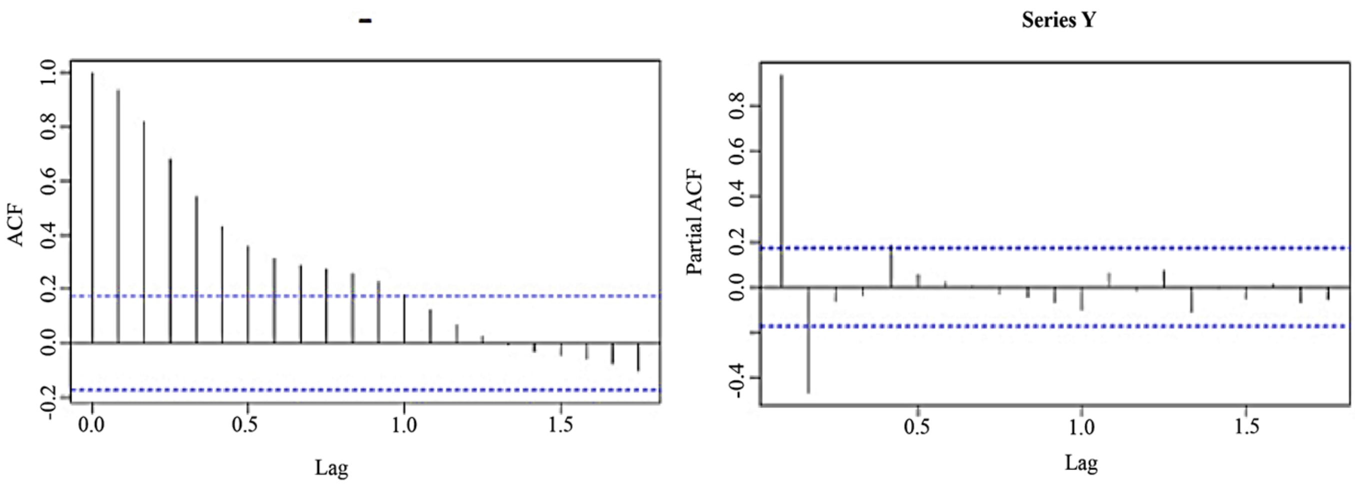


Fig. 5 Series behavior data were taken by RStudio 4.1.0.

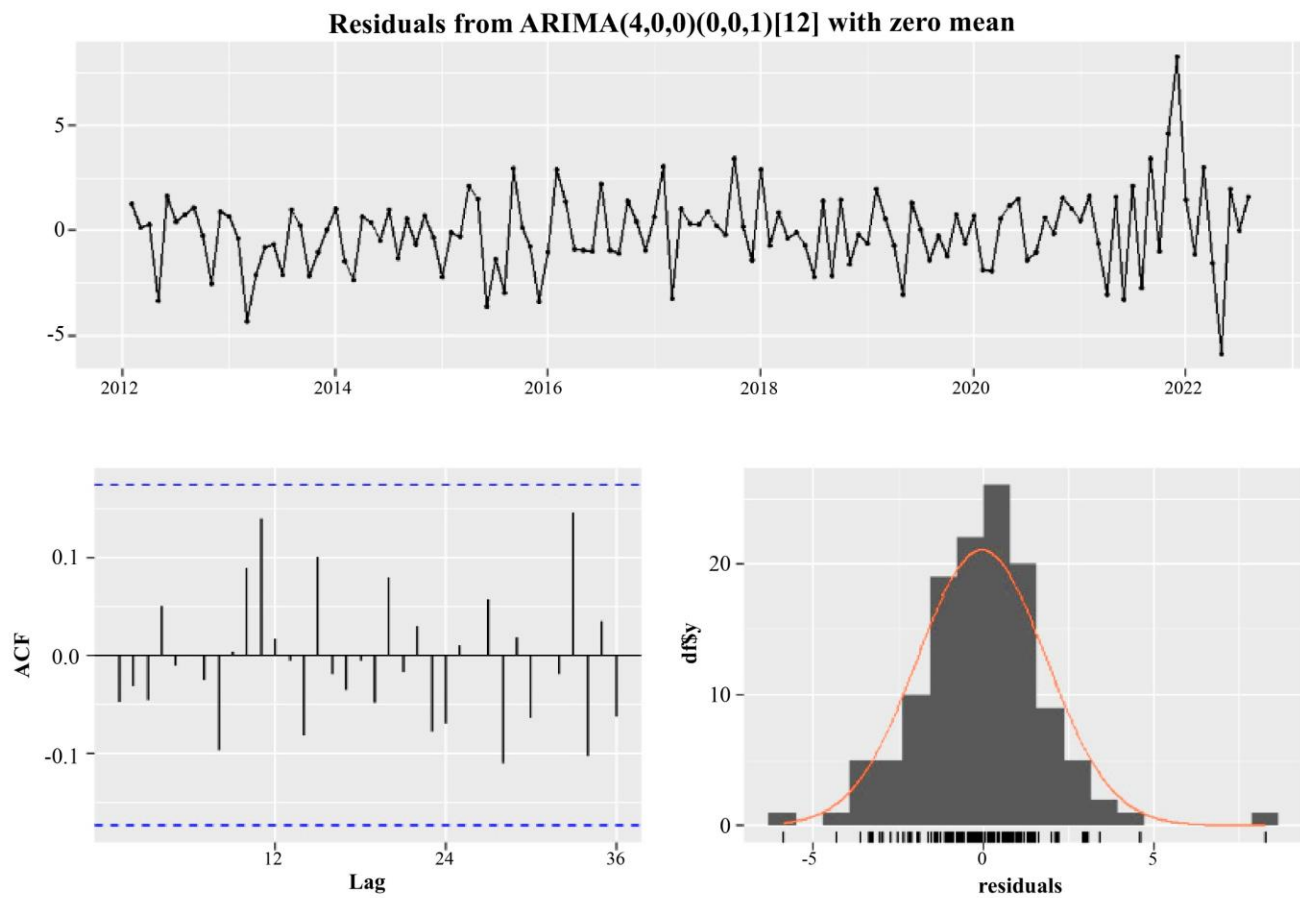


Fig. 6 Model a check of the results, data taken by RStudio 4.1.0.

As shown in Figure 5, the significance level is approximately 2%. Both cases have a decreasing peak towards 0, where the ACF function case can be observed to identify the moving average process. The residuals are well above the significance levels. In the PACF function that allows identifying the autoregressive process values, it is observed in some of its levels above 0 that exceed the significance levels of 2%. A simple differentiation of order one is applied to the series. The difference has been applied to the series, which is, on average, around 0.

As shown in Table 7, when applying the Dickey-Fuller test after differentiation, we obtain a result with p-value = 0.01 < 0.05, confirming that the series is currently stationary. We now apply the ARIMA model, as shown in Table 8.

Table 8. ARIMA Forecasting Model

Modelo de pronóstico ARIMA
model <- auto.arima(DY, trace = T, stepwise = F, approximation =F, max.d = 0)
print(model)
Series: DY
ARIMA (4, 0,0) (0, 0, 1) [12] with zero mean
Coefficients:
ar1 ar2 ar3 ar4 sma1
0.5715 -0.1273 0.160 -0.4225 -0.2445
s.e. 0.0833 0.0955 0.097 0.0938 0.1371
sigma^2 = 3.71: log-likelihood = -261.83
AIC=535.67 AICc=536.37 BIC=552.73
checkresiduals(model)

It is shown in Fig. 6 that the missing value residuals allow us to find generally within the significance limits of the ACF function to identify the moving average process using the model checking results.

The residual distribution is centered at 0, and a normal distribution is obtained. It allows an estimation of the model to be performed. Next, an estimation of this model will be performed. The forecasting estimation process, in which we will predict the value of the closing price in the next eight months with a significance level of 95%, using Ljung's box test.

The prediction result allows us to see the result of the prediction that corresponds to the differentiating series. To create a new ts object, we must define the data types to be used using the graph composition, as shown in Figure 7.

4.2. Neural Networks (nntear)

Neural networks determine the best outcome with only one hidden input layer for forecasting in a univariate time series set. Seed (2022) /red_neuronal <- nnetar(Y) We proceed to check the residuals presented in the model: heck residuals (neural_network).

Figure 8 shows the levels of residuals that exceed the blue 2% significance line according to the ACF plot, usually centered at 0 and maintaining a normal distribution on the residual plot. The data prediction is performed at eight months, with a significance of 95% of the data.

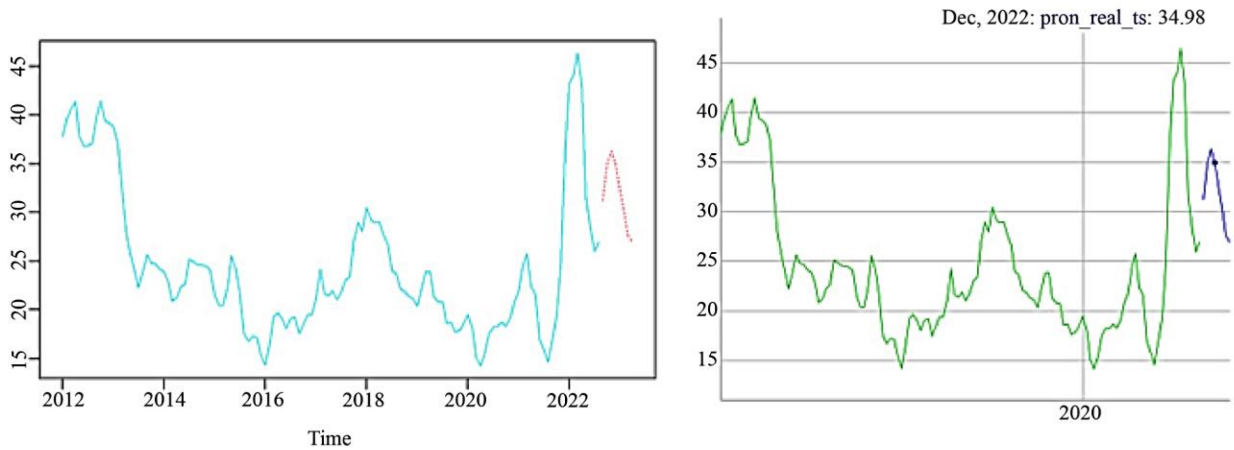
mod4 <- prediction (red_neural, h=8, level = 95)

The fitting data representation in the series of the model prediction plotted in the graph allows using the residual model's fitted function, allowing obtaining a fit with the historical data.

Figure 9 shows the residual value that would be the difference between the bold text formatting model line and the red text formatting line through prediction. It allows us to determine the model's results by grouping it in a data frame assigned in the prediction variable for further execution.

It can be observed that the best prediction is obtained with the neural network model. When analyzing the variable amount, values were found to proceed to impute these values through interpolation because, in the research, it was found that it is adequate for this type of data. Then we proceed to perform the transformations within the data set in the field.

The corresponding Quotation Date field is used to separate the month and year and then add the target variables of the forecast. Since it is a time series, the original data can be transformed into the "ts" format.



	Jan <chr>	Jan <chr>	Mar <chr>	Apr <chr>	May <chr>	Jun <chr>	Jul <chr>	Aug <chr>	Sep <chr>	Oct <chr>	Nov <chr>	Dec <chr>
2022									26.85814	26.20966	25.35001	24.45926
2023	23.56489	22.78430	22.13727	21.67110								

2 row | 1-10 of 13 columns

Fig. 7 Imputation by interpolation, data taken by RStudio 4.1.0.

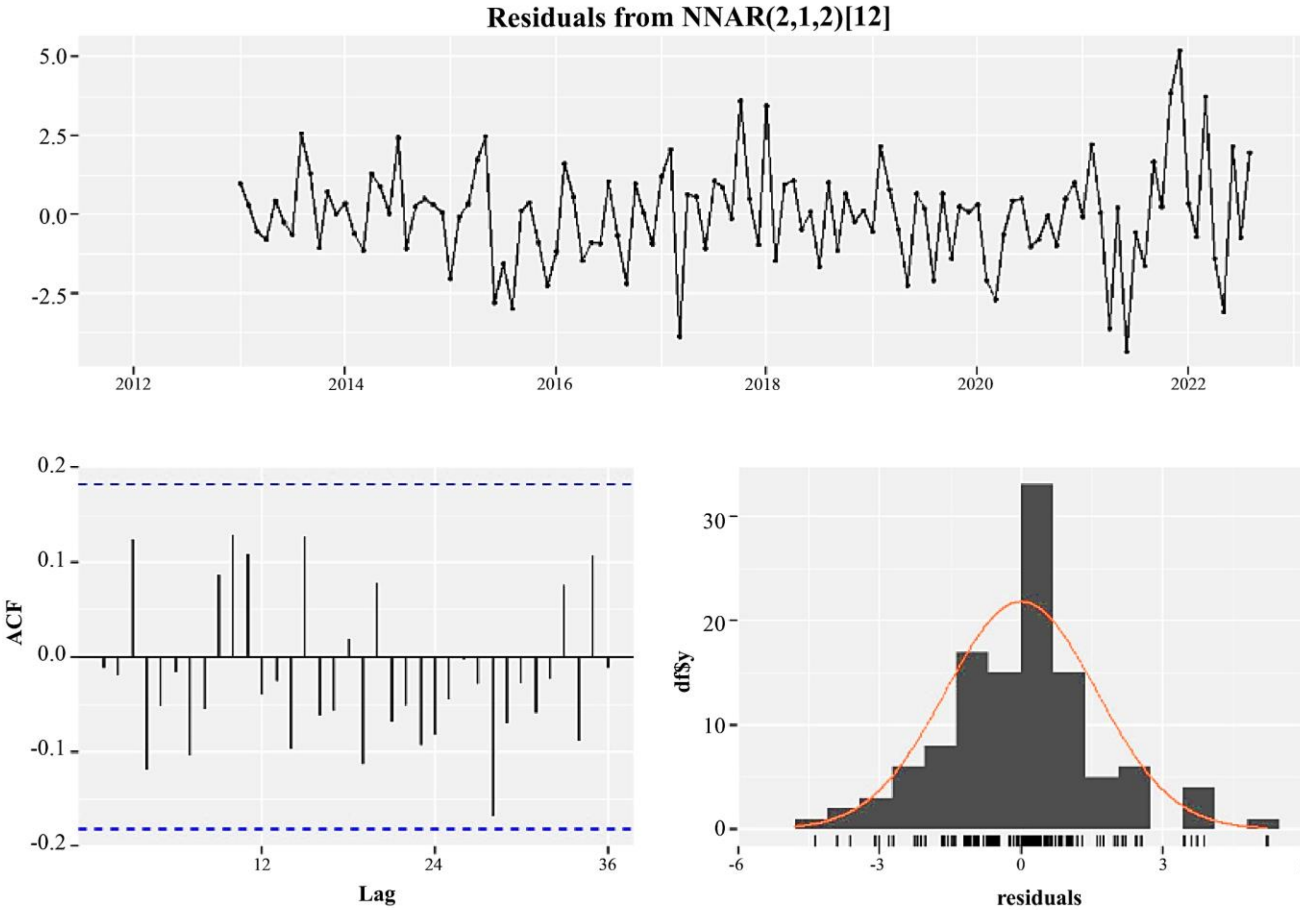


Fig. 8 Residue check in the model, data taken by RStudio 4.1.0.

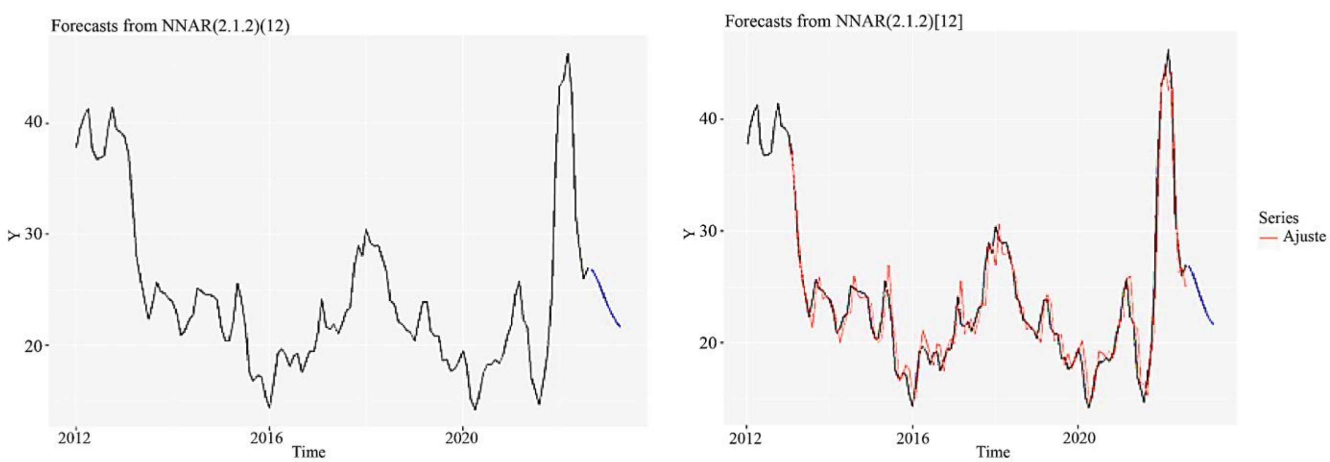


Fig. 9 Residual model of the fitted function, data taken from RStudio 4.1.0.

Table 9. Ljung's Box Test

Ljung-Box test
data: Residuals from ARIMA (4, 0,0) (0, 0, 1) [12] with zero mean
Q* = 12.294, df = 19, p-value = 0.8727
Model df: 5. Total lags used: 24
mod1 <- forecast(model, 8, level = 95)

Table 10. Developing Ljung's Box Test

Y <- ts(data_mes[,3], start = c(2012,1), end = c(2022,8), frequency = 12)
Grafico de la serie
autoplot(Y) +
ggtitle("Rentabilidad") +
ylab("Monto")

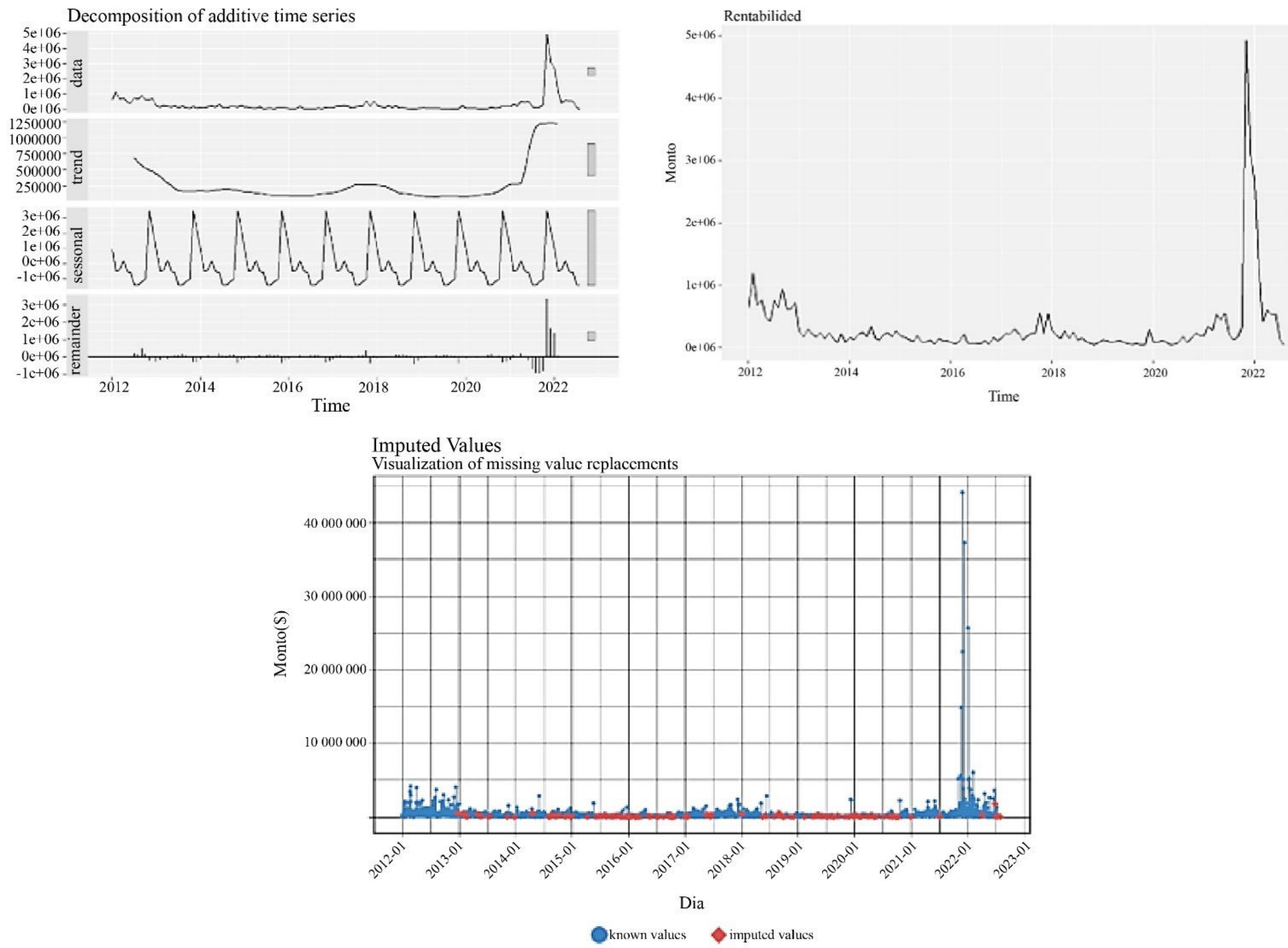


Fig. 10 Seasonality graph, data were taken by RStudio 4.1.0.

Table 11. Improved Dickey Fuller's Test

Augmented Dickey-Fuller Test
data: Y
Dickey-Fuller = -3.469, Lag order = 5, p-value = 0.04795
alternative hypothesis: stationary

Table 10 shows the criteria for developing the Ljung box test. The graph of the series decomposition is shown, which is decomposed into three graphs: seasonality, trend and the graph where the residuals are represented.

Figure 10 shows the seasonality data, whereby the data pattern is repeated every year. On the other hand, it can be observed that the trend represents first a small decrease and then a respective increase.

It is observed in Table 11 that the p-value = 0.04795<0.05 is less than 5%, so the null hypothesis is not fulfilled, and it can be decided that it is a stationary series. So, the ARIMA model can be applied.

It can be observed in Figure 11 that the significance level is approximately 2%; in both graphs, there is a decreasing lag peak towards 0. It is observed in the case of the simple autocorrelation function. The only residual that exceeds the significance level is the partial autocorrelation function. The levels are above 0, exceeding the 2% significance levels. The improved ARIMA forecasting model is developed.

```
model <- auto.arima(Y, trace = T, stepwise = F,
approximation =F, max.d = 0) print(model)
```

Table 12. Improved ARIMA forecasting model

Series: Y
ARIMA(0,0,3) with non-zero mean
Coefficients:
ma1 ma2 ma3 mean
0.6371 0.5719 0.2473 312938.09
s.e. 0.0876 0.0901 0.0922 91883.19
sigma^2 = 1.878e+11: log-likelihood = -1841.33
AIC=3692.65 AICc=3693.15 BIC=3706.91

Table 12 shows the variability using the residual model for the period 2012 to 2022. A check of the model results is performed: check residuals (model). As can be seen in Figure 12, the residuals of the missing values are generally within the significance limit of the simple autocorrelation function.

Table 13. Improved Ljung ARIMA Box Test

Ljung-Box test
data: Residuals from ARIMA(0,0,3) with non-zero mean
Q* = 2.8921, df = 21, p-value = 1
Model df: 3. Total lags used: 24
mod1 <- forecast(model, 8, level = 95)

The distribution of residuals tends to center at 0. Therefore, it has a tendency to a normal distribution.

Nevertheless, an estimation of this model will be performed. For the trend that will predict the closing price value in the next 8 months, with a significance level of 95%, we use the Ljung ARIMA enhanced box test, as shown in Table 13.

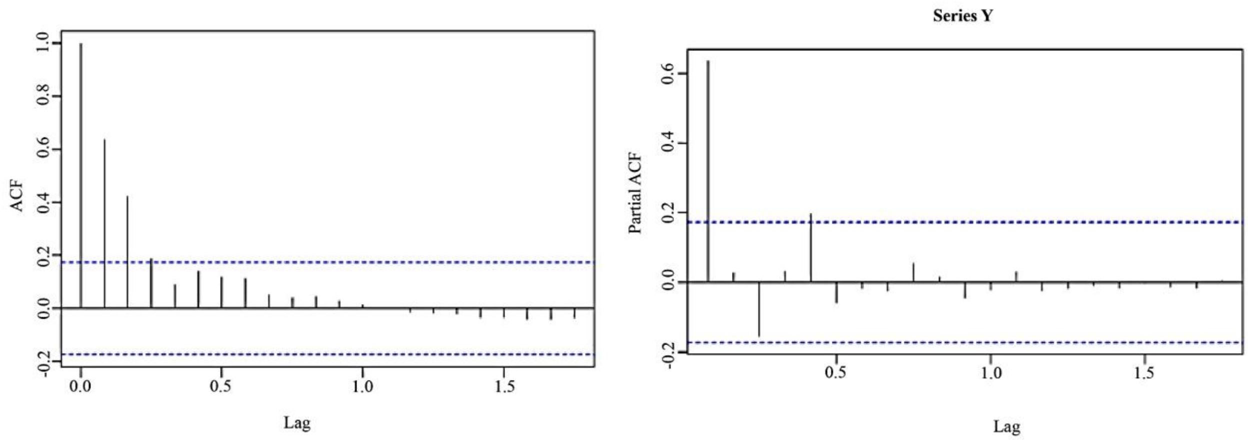


Fig. 11 Residual plot of significance levels, data taken by RStudio 4.1.0.

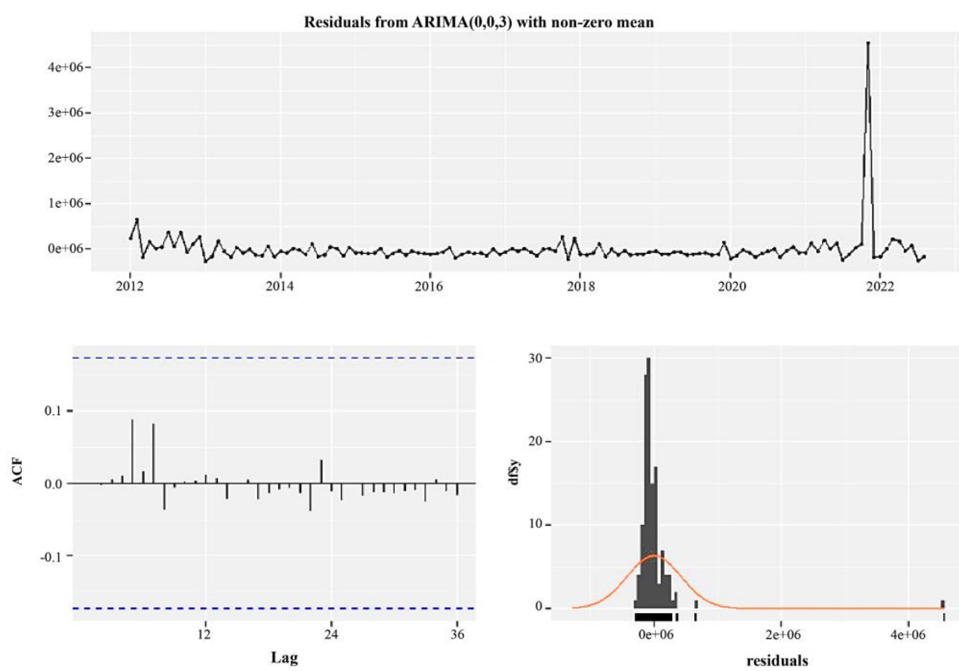


Fig. 12 ARIMA Prediction Model, data taken by RStudio 4.1.0.

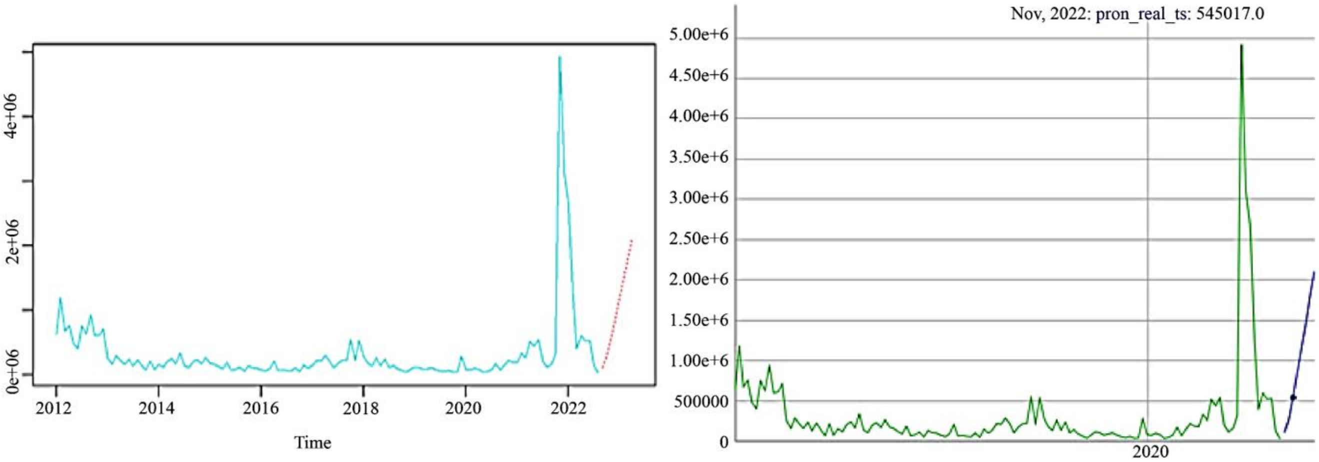


Fig. 13 Prediction by differentiated series, data taken by RStudio 4.1.0.

Figure 13 shows the results obtained using artificial neural networks for financial prediction in stock market improvement, using the differentiated series and transforming the data to real data. The application of the ts object allows the best prediction in the neural network model.

5. Conclusion

The study concerning the analysis of financial prediction utilizing artificial neural networks constitutes the development of a key transcendental model to predict the improvement of stock prices, identify variables, and evaluate indicators that allow measuring investment risk levels.

The research allows for identifying and establishing objective aspects for the investor to evaluate, analyze and synthesize the prediction of stock prices in making investment decisions in different business sectors.

The business sector allows identifying aspects of vital importance for the financial performance found in the behavior of the share price in the business sector by means of artificial neural networks in the short and long term.

The investor detects volatility in the share price; the application allows the analysis and interpretation of the application of financial prediction in improving the share price in the business sector through an artificial neural network.

6. Recommendations

Define the use and application within the structure of modeling that allows identifying the recovery of the share price to manage the most effective working capital through neural networks.

Analyze the data from a retrospective and prospective view of the stock price in order to create specific conditions to provide a mechanism for recovery and establish financial predictions.

Implement models and strategic indicators through neural networks in order to predict the financial investment environment to reduce business risks. Conduct training to perform financial analysis to improve results in the economic and financial environment of the business sector to make better decisions and implement corrective actions.

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