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Forecasting Stellar XLM Prices: Insights from ARIMA Analysis

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Abstract

The given research is aimed at solving the urgent problem of verifiable methods of forecasting cryptocurrency trading, with a preset focus on Stellar (XLM). Nevertheless, cryptocurrency forecasting is becoming more and more popular and it is still the case that there is a deficiency of research devoted to the use of the most advanced models to Stellar XLM price data. In many instances, the existing studies may pay less attention to the specific features of this cryptocurrency, hence creating a gap between our knowledge and understanding of how its prices fluctuate. Our experimental approach will investigate what accuracy forecasting models, especially the ARIMA model, can come up with by predicting the price of Stellar XLM. The purpose of this research is to experiment with a dataset for several years to know the workability of theoretical results on the forecasting models of Stellar XLM cryptocurrency. Our experimental research evidenced the acceptable price accuracy when forecasting Stellar XLM prices. Regarding the volume data, our metrics are a MAPE (Mean Absolute Percentage Error) of 16.82% and MSE (Mean Squared Error) of 7.41.10 -15 and Accuracyman (Accuracy) of 83.18%. On the other hand, the data with very high data recorded the best performance, with a MAPE of 4. 26%, MSE = 0.00025, and Accuracy of 95.74%. This finding again evinces that applying the more advanced models of forecasting and choosing appropriate data sources is key in a good Stellar XLM forecast. Thereby this study contributes to filling the research gaps and by administrative tools providing insights into the practical use of forecasting models, it guides stakeholders having to cope with the difficulties of crypto-currency markets.

Keywords: *Cryptocurrency, ARIMA analysis, Stellar XLM, Exploratory Data Analysis, Interquartile Range*

INTRODUCTION

Crypto assets have upended financial studies' long-serving tradition, and where once there was only opportunity for a few, it is now given to all. Besides the mentioned digital assets, Stellar is one of the crypto coins that continues to have a stunning impact as it provides a platform that is made to help speed up transactions carried out across borders. On the other hand, the hyper-instability of cryptocurrency markets usually becomes a key obstacle for any person who wants to approach those markets with a sense of understanding. Within the scope of crypto-prediction forecasting, there are more and more publications that focus on these issues and are engaged in uncovering the cryptocurrencies' price moves, permits, and trends. Nevertheless, the bulk of research mainly applies to the leading cryptocurrencies, especially Bitcoin and Ethereum, and disregards viewpoints of newly emerging currencies such as Stellar XLM. Hence, the aforementioned research agendas include a large unaddressed area in the matter of using computational forecasting models involving Stellar XLM data.

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Table 1: Summary of Comparable Works Related to Stellar XLM

Authors	Year	Study Title	Focus
Minjeong Kim, Yujin Kwon, Yongdae Kim [1]	2019	Is Stellar As Secure As You Think	Security of Stellar as a cryptocurrency adopting federated Byzantine agreement (FBA)
Nida Khan, Tabrez Ahmad, Radu State [2]	2019	Feasibility of Stellar as a Blockchain-Based Micropayment System	Feasibility of Stellar as a micropayment system compared to other platforms
Stephen Boyer, Oliver Dain, Robert K. Cunningham [3]	2005	Stellar: A Fusion System for Scenario Construction and Security Risk Assessment	Fusion system for scenario construction and security risk assessment of Stellar
Zewen Chi, Shaohan Huang, Li Dong, Shuming Ma, Saksham Singhal, Payal Bajaj, Xia Song, Furu Wei [4]	2021	XLM-E: Cross-Lingual Language Model Pre-training via ELECTRA	Technical aspects of Stellar, potentially touching upon consensus mechanism and structure
Yingjia Zhao, Xin Tao[5]	2021	ZYJ@LT-EDI-EACL2021: XLM-RoBERTa-Based Model with Attention for Hope Speech Detection	Potential vulnerabilities or limitations of Stellar's centralized structure and consensus protocol

Table 1 details the significant works relevant to the Stellar XLM coin, the author or co-writers, the year of publication, study title and the aim and focus of each study. These researches all fell under different subject matters of Stellar, including, its security, how feasible it is for micropayments, the fusion system is used for scenario construction, and the risks that are involved in its consensus protocol.

To address this gap in research, our study aims to investigate the following research questions:

1. How effective are advanced forecasting models, particularly the ARIMA model, in predicting trading data for Stellar XLM cryptocurrency?

2. What are the key factors influencing Stellar XLM price movements, and how do they differ from those of other cryptocurrencies?

3. How does the performance of forecasting models vary when applied to Stellar XLM trading data compared to more mainstream cryptocurrencies?

This research is directed to discovering the suitability of the advanced forecasting models, the ARIMA model in particular, for forecasting Stellar XLM trading data as cryptocurrency. Furthermore, try to find out the major drivers affecting Stellar XLM rate dynamics and compare forecasting results of Stellar XLM to the performance of models considering the price change of more familiar cryptocurrencies. The research is devoted to supplementing the currently available body of knowledge about cryptocurrency forecasting by concentrating on one of the altcoins of the Stellar XLM. Aligning the advanced forecasting models to the data of trading Stellar XLM, I can give precious insights into the shifting mechanism and in the end, allow the understanding of cryptocurrency behaviour in the market to be deeper. In addition, this one-of-a-kind model is designed to expand the cryptocurrency research scope through a comparison with other literature that already exists in the field. Show how this can be helpful in decision-making for investors, traders, and financial analysts who constantly face the challenges of cryptocurrency markets. In the following paragraph, the author will summarize the literature review, proceed by how the gathered and analyzed datasets will be explained, and the methodology described in Section III. As shown in Section III analysis of the study findings applying various machine learning models are described. Subsection IV, correspondingly, provides the summation of our major findings and points out the possible research areas for future study.

LITERATURE REVIEW

The rise of cryptocurrencies has caught everyone's attention in the last couple of years as a replacement for traditional financial vehicles and a type of alternative medium for exchanging funds. Within this bunch of contenders, Stellar (XLM) has recently come to the forefront and now is one of those that enables faster and more trustworthy cross-border transactions through its blockchain network [2]. Studies of Stellar Blockchain feasibility as a blockchain micropayment system showed that it has great capability not only to expedite transaction time but also reduce transaction costs [2]. Challenges on the contrary have been raised regarding the security and operation protocol of the Stellar network and it has been proved in several researches that the protocols and network are not wide enough and are vulnerable towards attacks [7] [12]. The examination of cryptocurrency markets has given more than just an educational view. Analysis of leading and behavioural patterns within digital currency systems has additionally been a crucial component. Corresponding to this, Cagli (2019) suggests an elevated level of prices regarding Bitcoin and other coins, a phenomenon that is a clear indication of the high volatility and speculative trading activity [3]. This reality has been suggested by Canh et. al. (2019), who relied on DCC-MGARCH model of systemic risks, and unpacked the existence of correlations and interdependencies among different cryptocurrencies [5]. Chowdhury et al. (2022) opined that the bubble and crash phenomena is a feature of the cryptocurrency market which also influences the contagion effect among the investors (6). Besides, researchers have not only found ways that blockchain technology could be applied in the real world but also focused on practical applications beyond the trading of cryptocurrency. Mokdad and Hewahi (2022) conducted an activity to evaluate Blockchain smart contracts, assessing Ethereum, EOSIo, Stellar and other blockchains to see their functionality and performance [8]. In one paper (Afandi, 2019), the researcher looked into how the inclusion of cryptocurrency investments in portfolio construction affects returns and the diversification benefits, suggesting that digital assets may be useful as well as profitable in financial decision-making [9]. Research projects have used Stellar to look into cases where Stellar was actively the catalyst of how financial inclusion and DLT technology were used in cross-border payment and the ability to access financial services [14]. Also, a buildup of sound and equitable ways for sharing collective resources of the Stellar blockchain community has been taken into consideration which resolves issues of transparency and governance among others [10] [12]. Varieties of publications on Stellar and cryptocurrency markets have developed but the fields of safety, scalability, and implementations in practice have still some space to fill. This study is meant to fill the gaps in the literature by applying the advanced forecasting models on the Stellar XLM trading data and becoming a source line into the price dynamics and market behaviour. Through the use of machine learning tools and analyzing the historical data of Stellers trading, it is possible to augment our knowledge about the behaviour of Stellers assets and the implications for investors, traders and financial analysts.

METHODOLOGY

In this section, the methodology used in the following steps: the gathering of data, its pre-processing, the analysis of data and finally the interpretation of data. The methodology has four (or several as appropriate) consecutive steps including data collection, cleaning, preprocessing, selection of a model and evaluation.

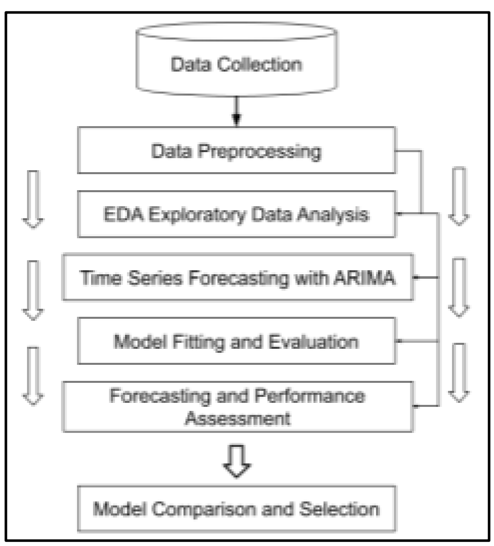


Figure 1: The flow of the proposed methodology

The visualization on see Fig. 1 explains how the proposed strategy operates from the start: data collection, data preprocessing, exploratory data analysis, forecasting time series applying ARIMA model, model tuning, forecasting & performance evaluation, model comparison and selection. This way every step is based on the previous step until the model that is the one most applicable to Stellar XLM crypto coins forecasting is chosen.

1. Data Collection: The composing of three CBV datasets (CSV files) containing trading data for Stellar XLM digital currency started on September 17, 2014, and closes by November 29, 2021. These datasets are composed of trading data of a daily, weekly, and monthly nature, and they comprise trading characteristics, which are, for example, date, open price, high price, low price, close price, adjusted close price, and so on. The data comes from Yahoo Finance.

2. Data Preprocessing: The preprocessing step, nonetheless, included detecting missing data, handling duplicates, and getting rid of the outlier issues. If a dataset had missing data, it was imputed with corresponding means and observations that were duplicated were removed to ensure that data were intact. We used the IQR technique for outliers detection and then dropped these off the data set so the model accuracy could increase.

3. Exploratory Data Analysis (EDA): EDA is performed as a final step. Its main purpose is to get additional information about the distribution, trends and relationships in the dataset. Representing data with approaches like histograms, line charts, and correlation matrices was used to provide visualized analysis and highlight specific patterns in the data.

4. Time Series Forecasting with ARIMA: Autoregressive Integrated Moving Average (ARIMA) models were determined as the most suitable approach for time series modelling and forecasting of the Stellar XLM trading data. The parameters of the ARIMA model as well as p, q, and d, used the method like Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) which are the methods of discovering the correct specification of autoregressive, moving average, and mixed models of time series.

5. Model Fitting and Evaluation: ARIMA models were fitted to the dataset and the model's performance was evaluated using different performance metrics such as MAPE, MSE, RMSE and correlation coefficients. Residual analysis was conducted to check the model's adequacy and to find any patterns or anomalies.

6. Forecasting and Performance Assessment: The ARIMA models developed were applied in forecasting the future values of the Stellar XLM trading data obtained. The evaluation metrics used in the previous part were also employed to assess the forecasts, consequently, revealing the reliability and performance of the forecasting models.

7. Model Comparison and Selection: In the end, the ARIMA models performed using various parts of the dataset (e.g. daily and weekly trade data) were compared to understand the best model suitable for predicting Stellar XLM cryptocurrency prices.

This systematic methodology helped do deeper analysis as well as forecast future price movements and assess the accuracy of the forecasting models. The findings from this analysis will contribute to the rationale of Stellar XLM cryptocurrency dynamics and will offer essential facts for the stakeholders in the financial sector.

Propose Model

The proposed procedure protocol in diagram 2 below systematically guides a model of forecasting Stellar XLM prices by time series analysis. The model starts with data exploration at which time basic observation of dataset information and its structure is performed to know the dataset more clearly. Then, preprocessing the data takes place, for instance, transforming the column names to lowercase, with Pearson correlation being used to calculate correlations between variables, and identifying outliers. There is the precedence of outlier identification and their elimination to uphold the purity of the data. After the data is preprocessed, EDA technique is used to get the information about the distributions of the variables and find out any trends. Finally, datasets are analyzed after the removal of outliers to check the influence on the distribution of data. Further, the model utilizes the Auto Regressive Integrated Moving Average method (ARIMA) for forecasting time series. The choice of differencing is made through calculating the P-value, and identifying the order of AR.

Calculating forecast accuracy is done in several ways, including mean absolute percentage error (MAPE), mean error (ME), mean absolute error (MAE) and root mean squared error (RMSE), among others. Predicted results along with actual high data and volume data are plotted to see if the model could perform well. Eventually, the model being presented gives the structure that is capable of forecasting Stellar XLM cryptocurrency price and the model incorporates data exploration, preprocessing, EDA, and ARIMA modelling techniques. This approach will provide stakeholders with the ability to make informed judgment calls based on accurate data about XLM market price fluctuation prediction.

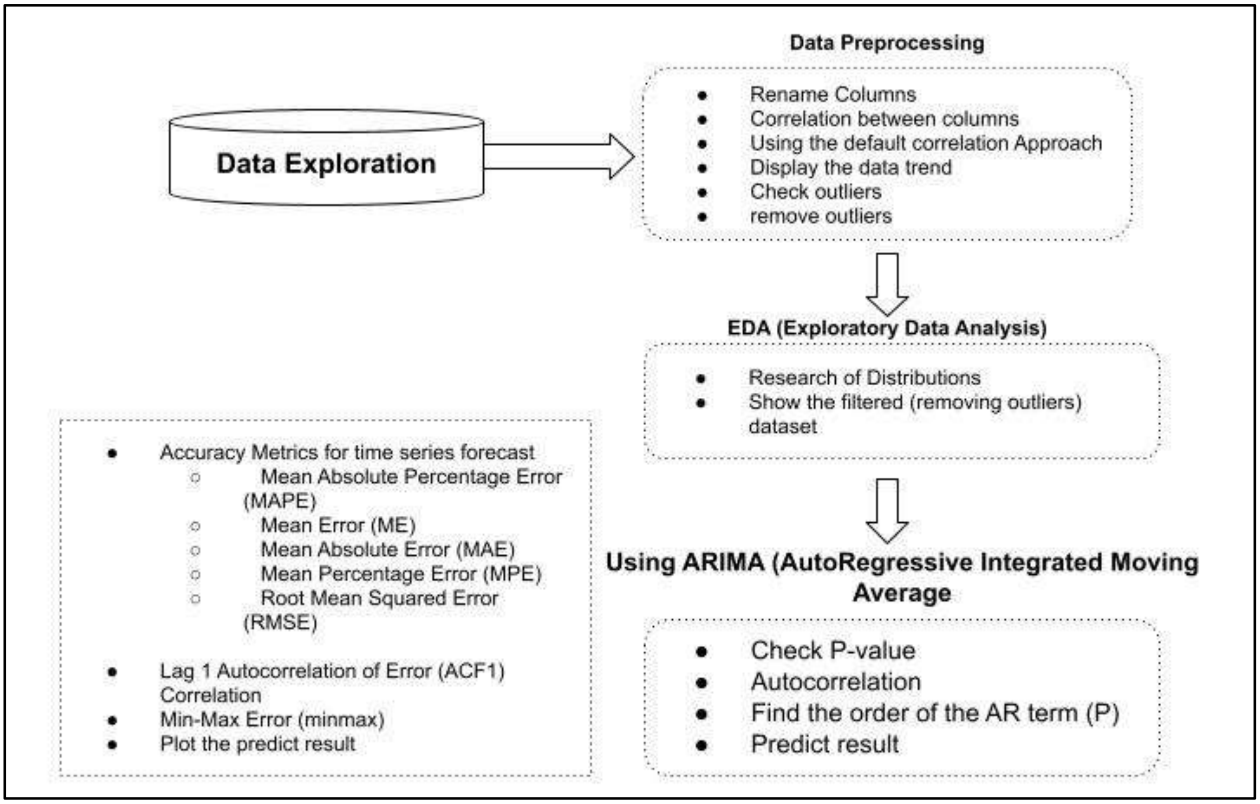


Figure 2: Proposed ARIMA Forecasting Model for Stellar XLM Cryptocurrency Prices

RESULTS AND DISCUSSION

The section on results and discussion empowers the presented model as the forecasting tool of Stellar XLM cryptocurrency prices. It includes the result of data exploration, preprocessing, exploratory data analysis (EDA), time series forecasting via the ARIMA model and the assessment of forecast accuracy. The main objective of this part is to do an interpretation of the results, draw conclusions from them, and offer insights into the effectiveness of the forecasting model.

Data Exploration and Preprocessing

The Dataset Quality and Suitability Assessment stage, in which key steps were carried out to ensure that the dataset was ready for analysis, was among the most important ones during the Data Exploration and Preprocessing phase. Exploration revealed that 24 feeler data values were not available within the "Daily data" section. An additional examination revised this affirmation that all the given items did not duplicate, as was the case reflected in Figure 3. Next, we performed data reprocessing to reinforce the accuracy of the presented data. These sets consisted of the lowerword of the names of the columns, which promoted consistency and clarity and helped in understanding the dataset by the users. Furthermore, the origin of a Pearson correlation coefficient was discovered to reveal possible linkages between the different columns, which in turn provided insight into the possible dependencies. The identification and subsequent deletion of the outliers additionally strengthened the data reliability it was watching being unstable and blocked it from distorting the analysis outcomes. As such, those preprocessing tasks served as a platform on which all the analytical works would be built and hence the model development was not a problem.

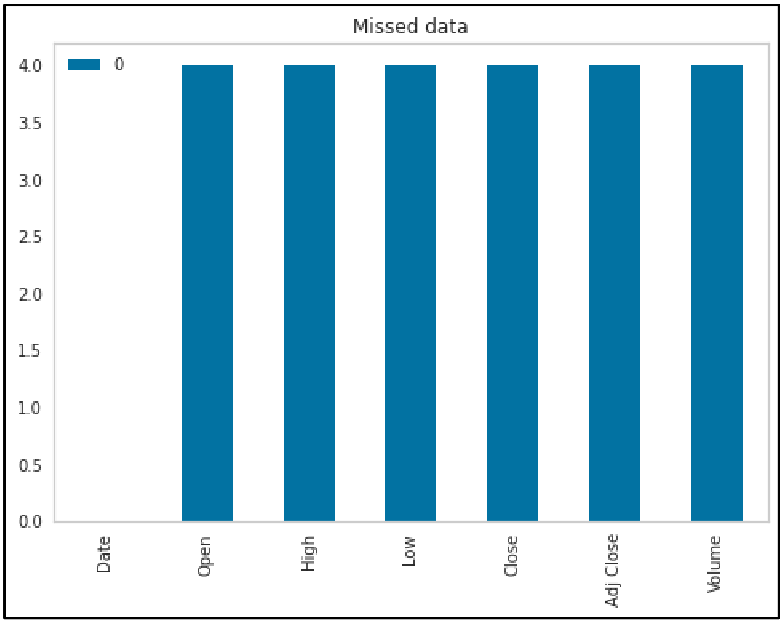


Figure 3: Visualization of Missing Data Entries

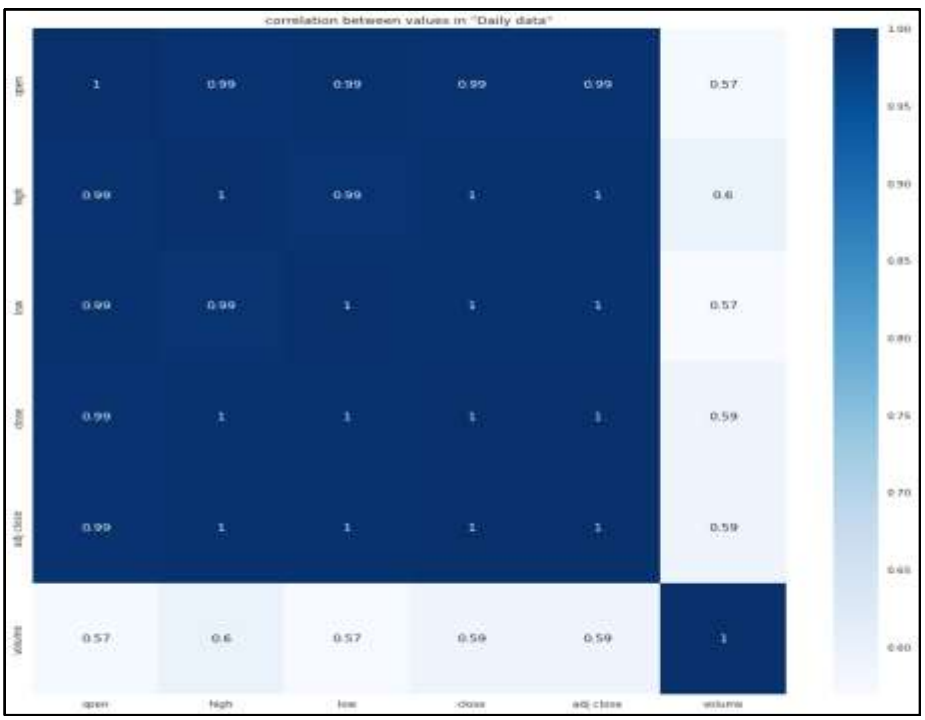


Figure 4: Heatmap of Pearson Correlation Coefficients for Dataset Attributes

Figure 4 shows that there is a relatively notable correlation coefficient of 0.6 between the "high" and "volume" attributes which are depicted in this correlation analysis The correlation demonstrates a moderate positive linear relationship whenever Stellar XLM Digital Currency's high price gets involved and trading volume increases. Utilizing this interdependence approach, one can deduce that those shifts in the bitcoin trading volume can generate some effects on Stellar XLM's high price as well. Such recognition is useful when dealing with NaN (missing value) in the "high" bar using interpolation that is based on the related data in the "volume" bar. Through the use of the relationship of these attributes, one can significantly enrich the dataset and help analysts and researchers perform a more reliable analysis and modelling. The Skewness values before and after filling NAs in the dataset reveal not much difference. For the first column, a little bit of the increase in skewness from 1.667 to 1.668 can be seen, meaning that a small change to the right part of the skewness happened. A different observation is that the skewness of the second column is higher than the first but remains rising slightly from 5.748 to 5.753 due to NaN filling, which means that the data distribution is biased to the positive side. Such changes provide information about the characteristics of the distribution of the dataset after the data that failed to fill the NaN based on distribution type.

Data Trends: The various metrics of the Stellar XLM cryptocurrency trading dataset against the date. Each metric is represented by a different line color for clarity as shown in Figure 5 , and a legend is included for easy identification. Here's a breakdown of the plotted metrics:

Opening Price (red line)

Closing Price (green line)

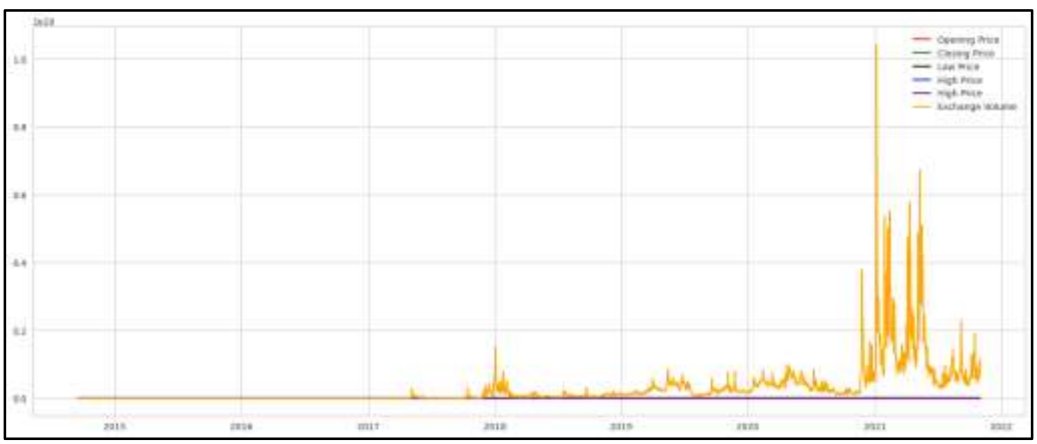
Low Price (black line)

High Price (blue line)

Adjusted Close Price (purple line)

Exchange Volume (orange line)

Such a visualization lets us comprehensively analyze the way these indicators are changing over time, which helps detect trends, patterns and relationships between the most common indicators. Also, it facilitates the planning of strategies for the trade as well as risk management. The green line demonstrates how the volume is always in motion, peaking just towards the end of 2021 and the beginning of 2022, this is evidence that within the Stellar XLM market, there are periods of great trading activities. This kind of behaviour pattern implies that the market at that moment is up to the mind of the traders and investors as they could be interested, and influenced by the market liquidity which is as well as a key factor in this current situation.



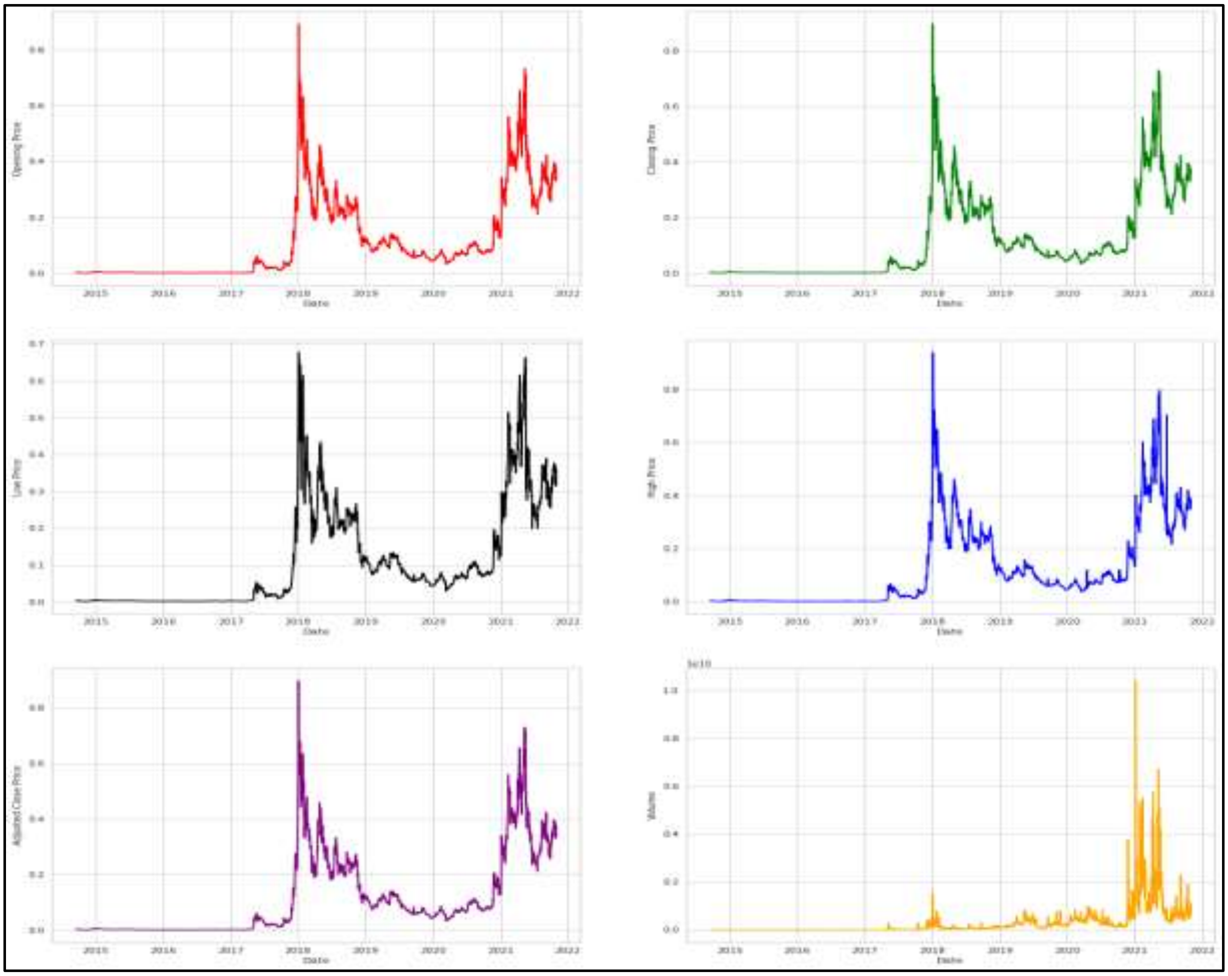
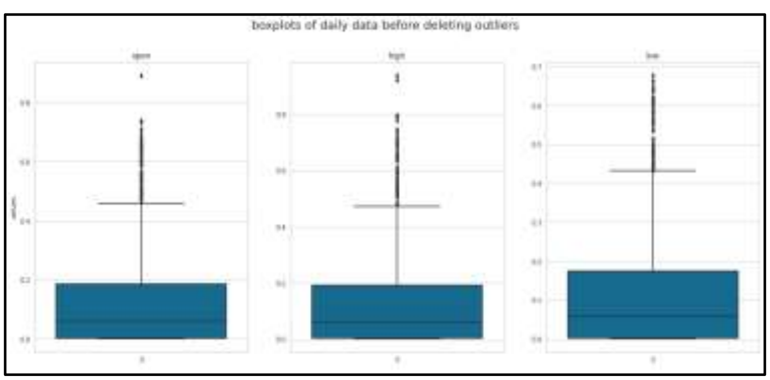


Figure 5: Stellar XLM Cryptocurrency Trading Metrics Over Time

Check Outliers: Before deleting the outliers from the daily data of the Stellar XLM cryptocurrency trading dataset, box plot graphs can be used to map the data distribution and look for any excessive values in the dataset. Boxplot is a visualization of the distribution structure and shows the occurrence of outliers from the regular range. This figure shows boxplots for all the columns of daily data for easy inspection of the distribution of values and identification of any outliers in the dataset.



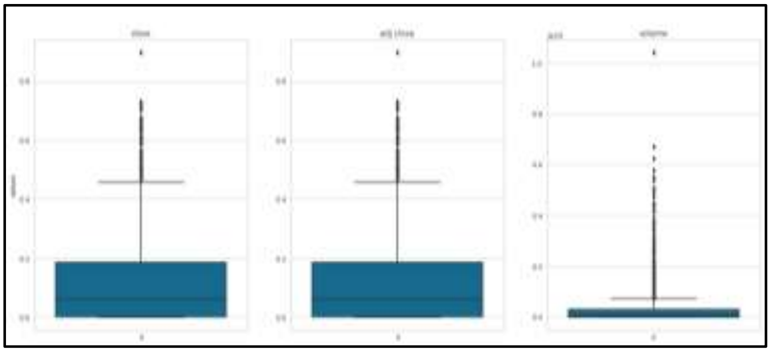


Figure 7: Daily Data before deleting outliers

Interquartile Range (IQR) to Remove Outliers: The Interquartile Range (IQR) has been calculated for each column in the "Daily data" dataset. Here are the IQR values for each column:

- Open: 0.1838528
- High: 0.19066
- Low: 0.1732605
- Close: 0.184524
- Adj Close: 0.184524
- Volume:291,684,700

After removing outliers based on these IQR values, the dataset size has changed from (2602, 7) to (2328, 7), indicating that some rows containing outliers have been removed. This process helps to ensure that the dataset is free from extreme values that could skew analysis results.

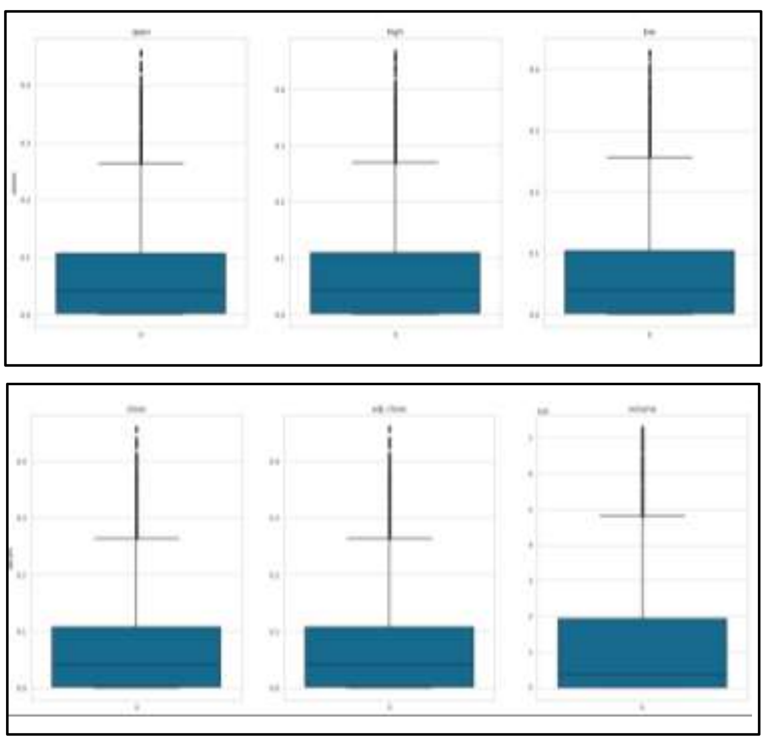


Figure 8: Daily Data after removing outliers using Inter quartile Range (IQR)

Exploratory Data Analysis (EDA): Exploratory Data Analysis (EDA) aided greatly in the detection of trends and features in the dataset. This implies investigating distributions of some significant variables like Open, High, Low, Close, Adj Close, and Volume to uncover patterns and deviations. The respective skewness values were computed in Figure 9 displaying deviations of these variables from a normal distribution. The skewness values of Open, High, Low, Close, Adj Close, and Volume were 1.47, 1.47, 1.45, 1.46, 1.46, and 1.51 each. Figure 9 portrays these variables in the mean, represented in red and in the median, green. Such analysis provides valuable clues to the data's intrinsic features and helps to find the appropriate methods of modelling and decision processes.

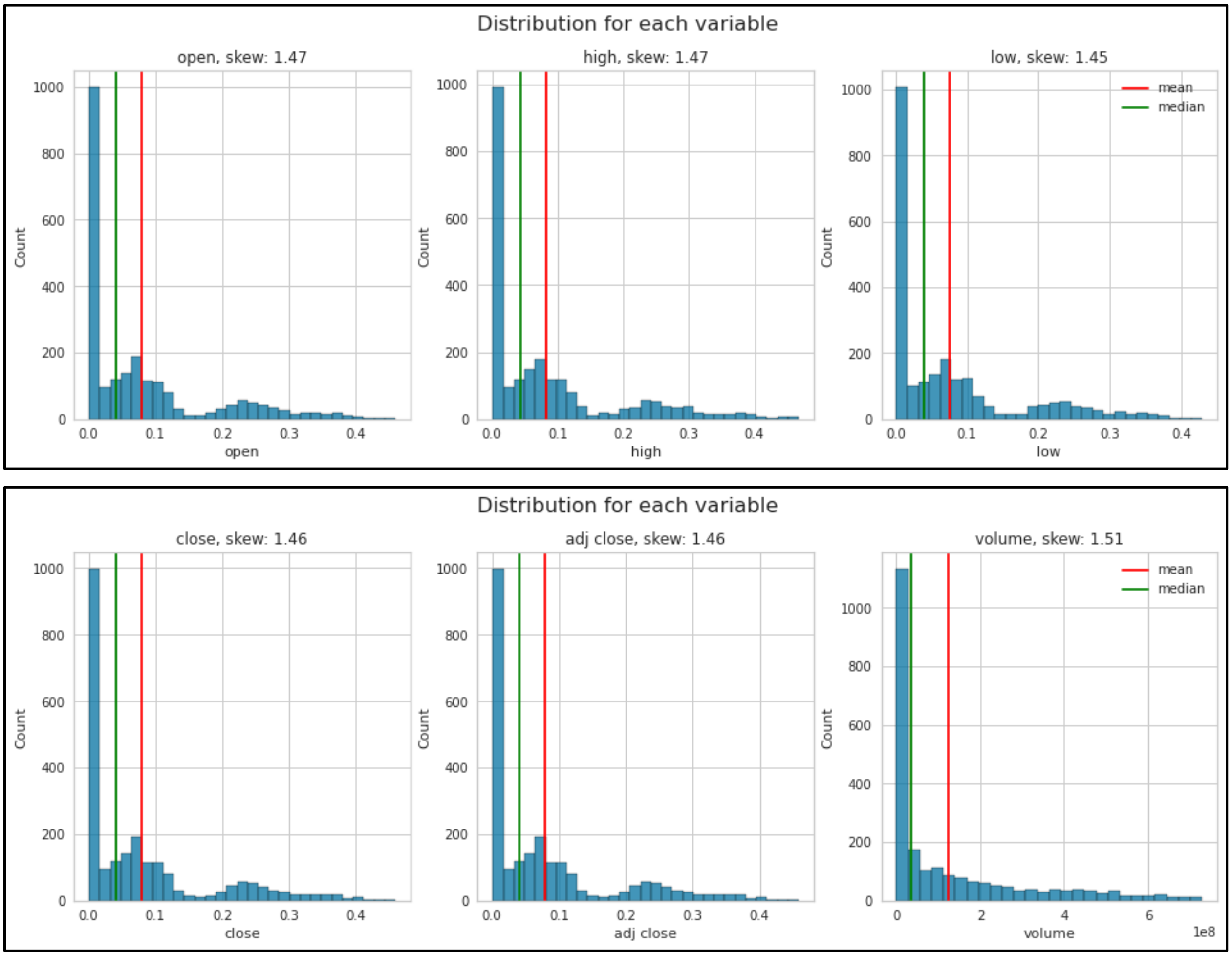


Figure 9: Distribution of Key Variables with Mean and Median

Data Trends After Filtered Dataset: Now is the time to verify if outliers were eliminated and to check how it affected the data's distribution pattern and trends after this. Looking at the cleaned dataset in Figure 10 assists in confirming if the method used for removal works to get rid of outliers, and, simultaneously, it does not alter the data representation. It will be possible to observe smoother distributions, and the variance will be considerably smaller than before the data was filtered, indicating that the data are much more normalized. Holding consistently with the original data set in the areas of statistics representing key indicators aka means, medians, and standard deviations, the filtered data set affirms the absence of outliers. Such analysis ensures the quality of the response data for the model's coming tasks.

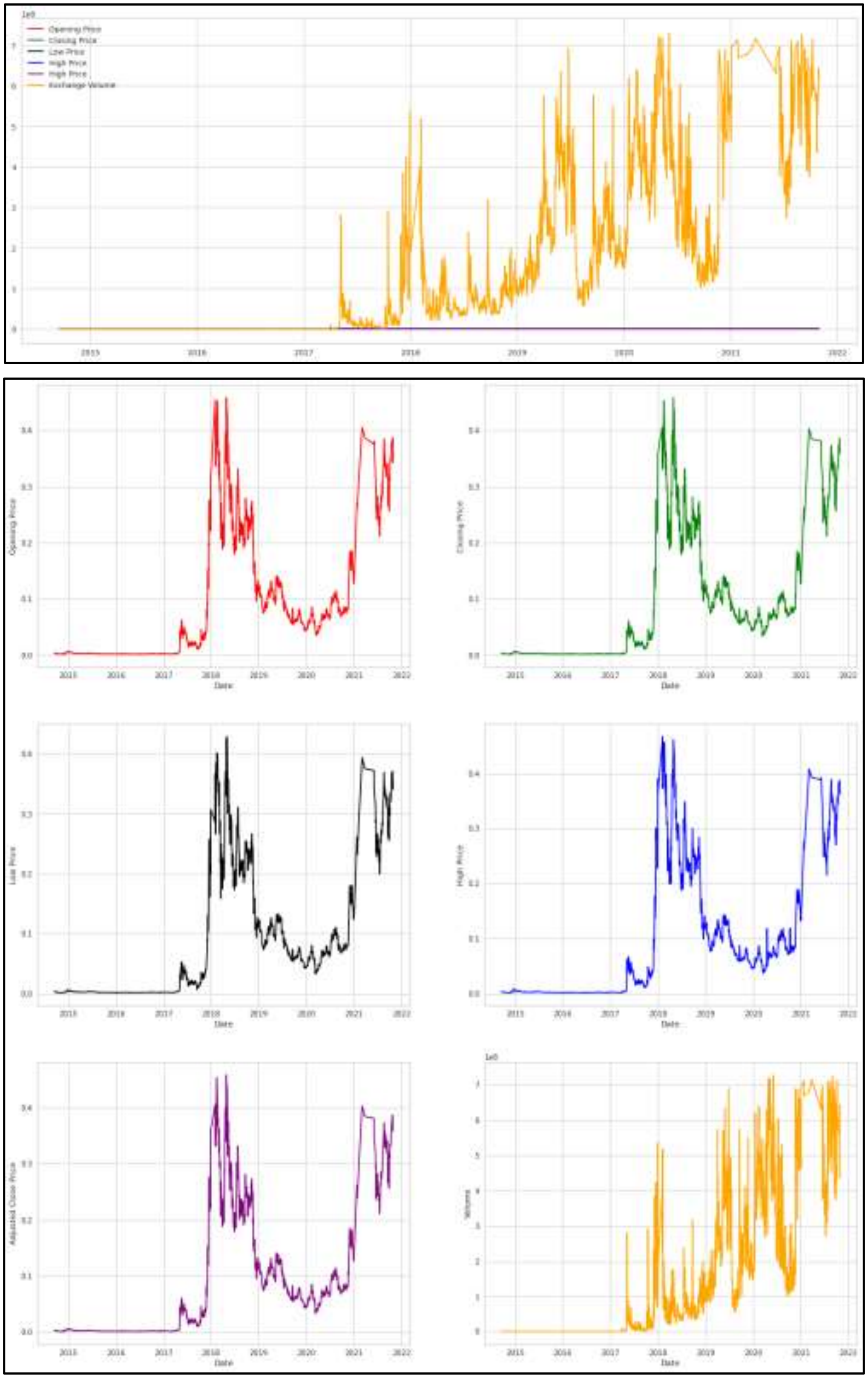


Figure 10 : Filtered dataset - after removal of outliers

Time Series Forecasting with ARIMA: First, in the time series forecasting process by ARIMA model, the orders of differencing that can anchor stationarity were deducted. Even though the issue was resolved by performing Augmented Dickey-Fuller (ADF) tests on critical indicators like Open, High, Close, and Volume. The ADF statistics and the p-values attached were calculated for every single variable. P-Value more than its significance level (commonly 0.05) indicates Nonstationarity. From the outcomes, it was noticed that all variables presented a non-stationary feature since their p-values were above 0.05. Since the process was non-stationary, differencing was carried out to attain stationarity which is a prerequisite for future modelling. The strategy applied means the differencing to be undertaken iteratively until stationarity is obtained, as tested by the ADF test. The model involves the study of the autocorrelation function (ACF) and partial autocorrelation function (PACF) for finding the suitable AR and MA terms of the model. The performance of the diagnostic tests marked the beginning of the ARIMA model's calibration process as the model was set based on the best possible values for the forecast to be closest to the actual Stellar XLM cryptocurrency prices.

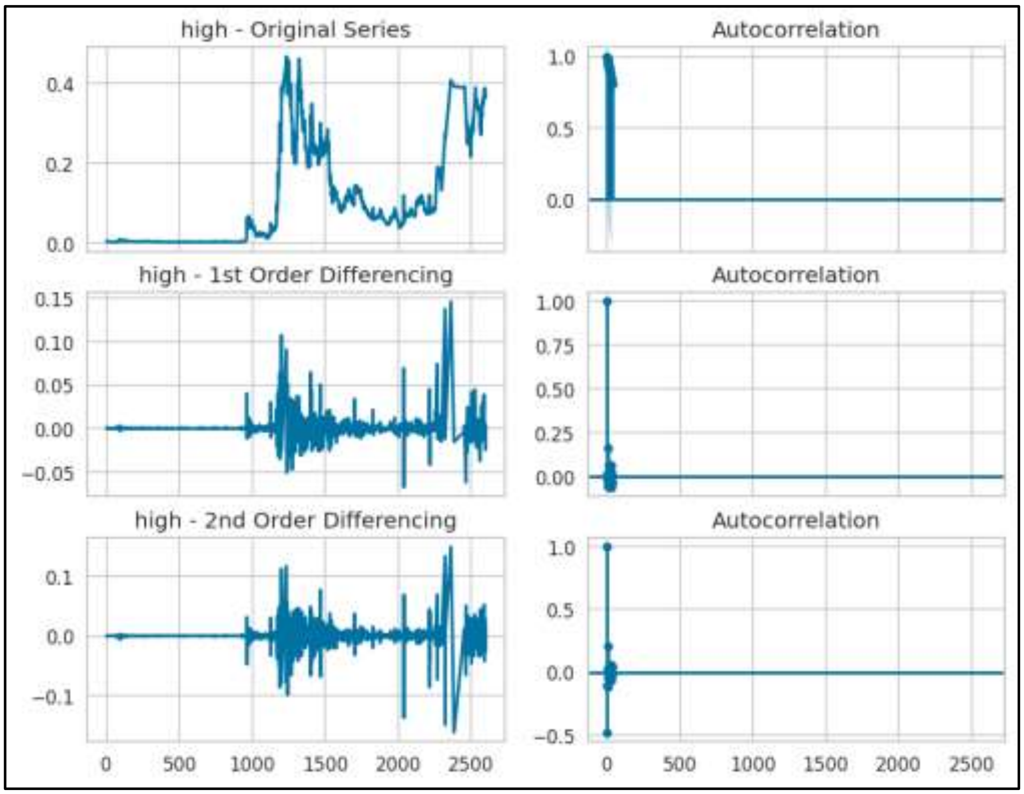
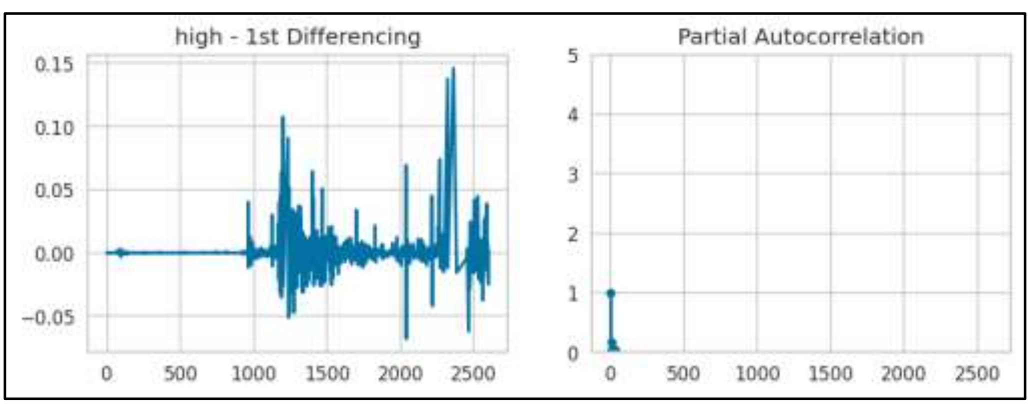


Figure 11 : High - Original series high, 1st, 2nd and 3rd Order Differencing - Autocorrelation Function (ACF)



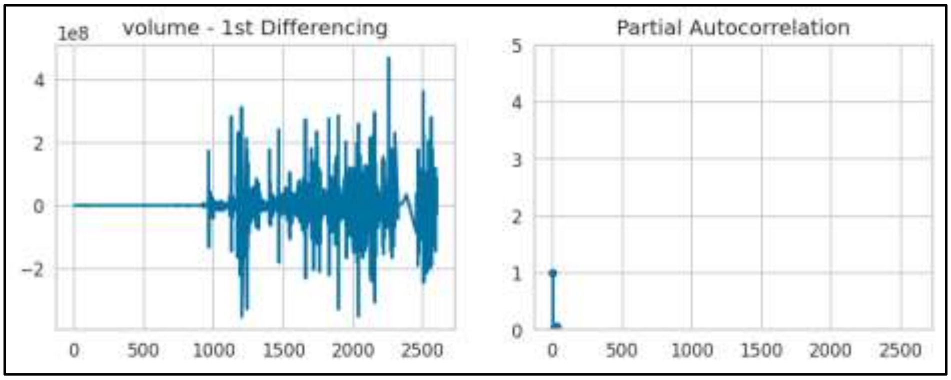
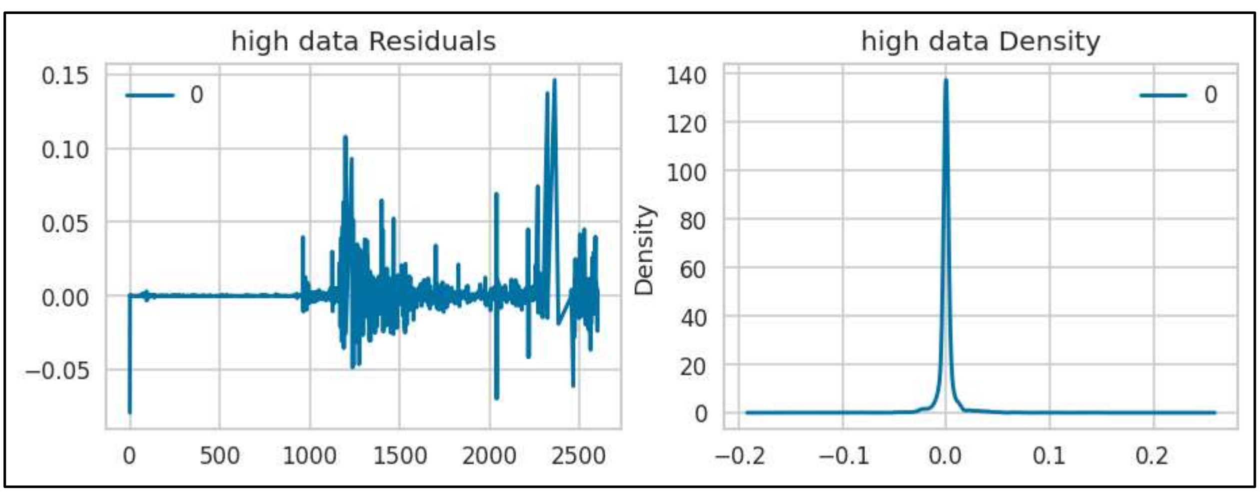


Figure 12: High - Original series high, 1st, 2nd and 3rd Order Differencing - Partial Autocorrelation Function (PACF)

Splitting its time series data into modelable ARIMA requires the differencing level adjustability to achieve stationarity. As the initial correlation ADF (ADF) proves that the given variables are non-stationary (in this case-'high' and 'volume'), difference is brought to induce the stationarity. Charts 11 and 12 show series-type, first-order difference, and second-order difference for 'high' and 'volume' variables respectively. The LHS column is the trend-free time series data with the first-order difference, whereas the RHS bars are the corresponding autocorrelation function plots. The ACF plot analysis observes the lagged number of terms exhibiting significance in autocorrelation. Since there is quite rapid decay of ACF plots on the third and further lags for both "high" and "volume" variables, MA terms of exactly one or two may be sufficient enough to eliminate any leftover autocorrelation in the stationary series after we make it stationary. By running the diagnostics plots, it is possible to extract useful information concerning the stationarity and autocorrelation structure of the considered series data into the ARIMA model, ensuring an appropriate choice of model parameters.

Evaluation of Forecast Accuracy

The evaluation of forecast accuracy includes examining the predictive ability of the Stellar XLM cryptocurrency forecasting model. Different metrics were used for this purpose such as mean absolute percentage error (MAPE), mean error (ME), mean absolute error (MAE), and root mean squared error (RMSE). Such indicators give a detailed view of the stability and efficiency of the forecasting model. The robustness of the model depends on the residuals analysis which is the difference between the observed and predicted values as depicted in Figure 13.



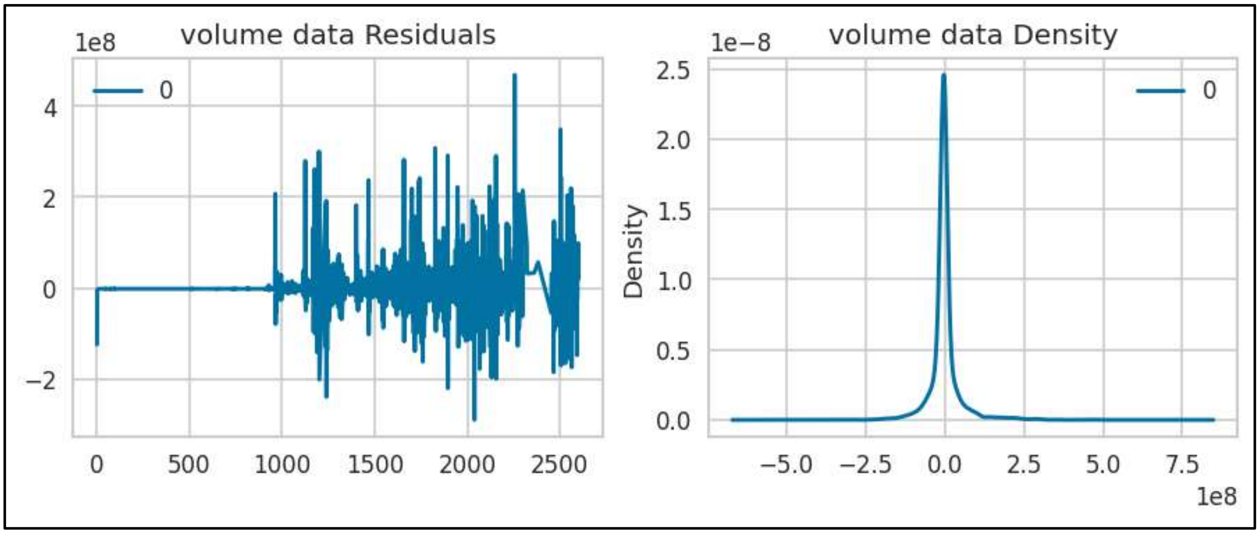


Figure 13: Residual Analysis for High and Volume Data

Plots of residuals help to highlight any patterns and systematic errors in the model. The residual means and variances are quite constant, which implies that the model is correctly describing the underlying patterns in the data. The fitted lines in both the 'high' and 'volume' data are as shown below: Here, on the left is given a time series plot of residuals, and on the right is a density plot. Such residuals are monitored by visually checking for any systemic trending or deviation from randomness. The outcome of the regression would be residuals that are randomly distributed around an average of zero, implying a good fit of the model that reflects the variation in the data points.

Predict The Result Of Actuals Against The Fitted Values From High Data: Figure 14 illustrates the predicted high prices of Stellar XLM cryptocurrency in daily exchange compared to the observed high prices.

Figure 14: Predicted vs. Observed High Prices of Stellar XLM Cryptocurrency

The demonstration of high prices along with green dashed lines are constructed as actual lines that came from the real data. The red dashed lines are the one-step-ahead forecasts of the model generated by the ARIMA model. This value is anticipated according to the model's forecasts for prices over the coming months. Also, the shaded portion surrounding the forecasted prices of the maximum prices is the confidence interval with which the actual true high prices will fall within a given confidence degree. Visualization of the model makes it possible to have a distinct comparison between it and the actual values that have been observed, hence unravelling the sentiment of the model's accuracy and proficiency in this area of stellar XLM cryptocurrency forecasting.

Forecast Model Performance: The result of model performance evaluation table 2 is a succinct comparison of model accuracy in predicting the Stellar XLM cryptocurrency prices. MAPE = 0.0426 indicating the average percentage difference of 4.26% between actual prices and the modeled ones. The low Mean Squared Error (MSE) value of 0.000248 implies that the predicted prices are basically by the real values. The Mean Absolute Error (MAE) equals 0.00652 means that there is an average deviation of about 0.00652 between the predicted prices and the actual ones. The model has a negative MPE of about -0.00143 which is a little more than the actual prices on average. The RMSE of 0.01576 means that the model is on average wrong with the predicted prices by the magnitude of the error. The high correlation coefficient of 0.9888 shows that there is a strong positive linear relationship between the prices that are predicted and the actual ones. The model shows high precision with an Accuracy of 0.9574 metric which is a good indicator of its ability to predict prices. On the other hand, the R-squared value of 0.9775 indicates that the model accounts for 97.75% of the variation in Stellar XLM price movements.

Table 2: Forecast model performance evaluation

Metric	Value
MAPE (Mean Absolute Percentage Error)	0.0426
MSE (Mean Squared Error)	0.000248
MAE (Mean Absolute Error)	0.00652
MPE (Mean Percentage Error)	-0.00143
RMSE (Root Mean Squared Error)	0.01576
Correlation	0.9888
Min-Max Error	0.0386
Accuracy	**0.9574**
R-squared	**0.9775**

DISCUSSION

The findings suggest that the model has a good forecasting capability on Stellar XLM crypto-asset prices. The model which can forecast forthcoming price movements facilitates the understanding of the financial industry market participants. Nevertheless, additional efforts at optimization and adjustment may be necessary to enhance the model as well as to deal with the drawbacks that might show up during the evaluation stage. All in all, the results and discussion section of this model will give you a detailed representation of the findings, emphasizing on the strengths, weaknesses and implications of forecasting Stellar XLM cryptocurrency prices.

CONCLUSION

In conclusion, through ARIMA the output is shown as highly accurate and reliable with a probability of about and correct. A high-performing version of the model achieved a MAPE of 0.0426 and MSE of 0.000248 while measuring a highly consistent forecast with a low error. Besides, the correlation coefficient with a value equaling 0.9888 (98.88%) and the Accuracy score at 0.9574 (95.74%) prove the high performance of this model, because it is quite accurate when determining the tendency of price changes. Forecasting, the question of which directions to follow is imperative. The model prognostication could be additionally improved by such methods as the incorporation of advanced machine learning algorithms or adding more information sources into the model that would improve predictability. The discovery of benefits that other factors like market sentiment, regulatory changes, and the technological development of cryptocurrencies may bring into the model is helpful for long-term forecasting. Finally, the developed model is undoubtedly the most robust instrument for viewers and analysts who may want accurate predictions in the ever-changing cryptocurrency market circumstances.

REFERENCES

Minjeong Kim, Yujin Kwon, Yongdae Kim. (2019). Is Stellar As Secure As You Think. arXiv: Distributed, Parallel, and Cluster Computing.

Nida Khan, Tabrez Ahmad, Radu State. (2019). Feasibility of Stellar as a Blockchain-Based Micropayment System. doi: 10.1007/978-3-030-34083-4_6.

Stephen Boyer, Oliver Dain, Robert K. Cunningham. (2005). Stellar: A Fusion System for Scenario Construction and Security Risk Assessment. doi: 10.1109/IWIA.2005.16.

Ashraf, S., Ali, S. Z., Khan, T. I., Azam, K., & Afridi, S. A. (2024). Fostering sustainable tourism in Pakistan: Exploring the influence of environmental leadership on employees' green behavior. Business Strategy & Development, 7(1), e328.

Zewen Chi, Shaohan Huang, Li Dong, Shuming Ma, Saksham Singhal, Payal Bajaj, Xia Song, Furu Wei. (2021). XLM-E: Cross-Lingual Language Model Pre-training via ELECTRA. arXiv: Computation and Language.

Yingjia Zhao, Xin Tao. (2021). ZYJ@LT-EDI-EACL2021: XLM-RoBERTa-Based Model with Attention for Hope Speech Detection.

Khan, N., Ahmad, T., & State, R. (2019, October). Feasibility of stellar as a blockchain-based micropayment system. In International Conference on Smart Blockchain (pp. 53-65). Cham: Springer International Publishing.

Lokhava, M., Losa, G., Mazières, D., Hoare, G., Barry, N., Gafni, E., ... & McCaleb, J. (2019, October). Fast and secure global payments with stellar. In Proceedings of the 27th ACM Symposium on Operating Systems Principles (pp. 80-96).

Barański, S., Szymański, J., Sobecki, A., Gil, D., & Mora, H. (2020). Practical I-voting on stellar blockchain. Applied Sciences, 10(21), 7606.

Cagli, E. C. (2019). Explosive behavior in the prices of Bitcoin and altcoins. Finance Research Letters, 29, 398-403.

Canh, N. P., Wongchoti, U., Thanh, S. D., & Thong, N. T. (2019). Systematic risk in cryptocurrency market: Evidence from DCC-MGARCH model. Finance Research Letters, 29, 90-100.

Farooq, A. J., Akhtar, S., Hijazi, S. T., & Khan, M. B. (2010). Impact of advertisement on children behavior: Evidence from pakistan. European Journal of Social Sciences, 12(4), 663-670.

Assaf, A., Mokni, K., Yousaf, I., & Bhandari, A. (2023). Long memory in the high frequency cryptocurrency markets using fractal connectivity analysis: The impact of COVID-19. Research in International Business and Finance, 64, 101821.

Chowdhury, M. S. R., Damianov, D. S., & Elsayed, A. H. (2022). Bubbles and crashes in cryptocurrencies: Interdependence, contagion, or asset rotation?. Finance Research Letters, 46, 102494.

Kim, M., Kwon, Y., & Kim, Y. (2019, June). Is stellar as secure as you think?. In 2019 IEEE European Symposium on Security and Privacy Workshops (EuroS&PW) (pp. 377-385). IEEE.

Mokdad, I., & Hewahi, N. M. (2022). Empirical Evaluation of Blockchain Smart Contracts: Ethereum, EOSIO, and Stellar as Examples. Journal of Blockchain Research.

Jam, F.A., Khan, T.I., Zaidi, B., & Muzaffar, S.M. (2011). Political Skills Moderates the Relationship between Perception of Organizational Politics and Job Outcomes.

Afandi, E. P. N. (2019). A Comparative Analysis of Cryptocurrency on Investment Portfolio Performance (Study on ETFs, Stocks, and Commodities Portfolio during The Periods of 2015-2018) (Doctoral dissertation, Universitas Brawijaya).

Shamsi, K., Shayegan, M. J., Uddin, M., & Chen, C. L. (2022). A Fair Method for Distributing Collective Assets in the Stellar Blockchain Financial Network. Sustainability, 14(9), 5311.

Shayegan, M. J., & Shamsi, K. (2021). A Fair Method for Distributing Collective Assets in the Stellar Blockchain Financial Network. arXiv preprint arXiv:2107.00059.

Bracciali, A., Grossi, D., & de Haan, R. (2021, February). Decentralization in open quorum systems: Limitative results for Ripple and Stellar. In 2nd International Conference on Blockchain Economics, Security and Protocols, Tokenomics 2020 (p. 5). Schloss Dagstuhl-Leibniz-Zentrum fur Informatik GmbH, Dagstuhl Publishing.

Barański, S., Szymański, J., Sobecki, A., Gil, D., & Mora, H. (2020). Practical I-voting on stellar blockchain. Applied Sciences, 10(21), 7606.

Zhuo, X., Irresberger, F., & Bostandzic, D. (2023). Blockchain for Cross-border Payments and Financial Inclusion: The Case of Stellar Network.

Roy, I. (2020). Blockchain development for finance projects: building next-generation financial applications using Ethereum, Hyperledger Fabric, and Stellar. Packt Publishing Ltd.