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(RESEARCH ARTICLE)

Forecasting stock index closing points using ARIMA-GARCH with a rolling data window

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Abstract

This research develops and examines the efficacy of a hybrid ARIMA-GARCH model, augmented by a rolling data window approach, to enhance the accuracy of stock index prediction, specifically focusing on the NEPSE index. Accurate predictions of stock indices are of paramount importance to investors, analysts and policy makers to navigate and circumvent the market uncertainties. The AutoRegressive Integrated Moving Average (ARIMA) model captures linear trends and temporal dependencies in time series data, while the General AutoRegressive Conditional Heteroskedasticity (GARCH) model addresses volatility clustering—ubiquitous character of financial time series—thereby providing a comprehensive framework for prediction. Utilizing a dataset comprised of daily closing points of NEPSE index approximately three years and nine months, the study identifies the ARIMA (5,1,0)-GARCH (1,1) model as optimal fit, upon integrating 180-day rolling data window. This model achieved a Mean Percentage Error of -0.0058% and a correlation of 0.995, which is indicative of superior fit to the underlying time series data. These findings underscore the hybrid model's capacity to adaptively respond to dynamic market conditions and acclimatize prediction parallel to most recent market trends and volatility. This research is useful for optimizing investment strategies for those invested in Nepalese stocks. Also, this research lays a foundational framework for future investigations into application of this advanced forecasting method in other emerging markets, financial instruments and indices.

Keywords: ARIMA-GARCH Model; Rolling Data Window; Volatility Clustering; Forecast Accuracy; NEPSE index

1. Introduction

Stock market forecasting plays a crucial role in financial decision-making, setting strategies for trading or investing, and even policy making. Accurate predictions of indices allow market participants assess the future vicissitudes of the market such that participants get the privilege to make informed decision. Forecast models are useful in simulating scenarios, stress testing and many more. With the evolving factors influencing market, a robust model is always desired to reduce the uncertainty of market movements. Forecast models has utility for investors to optimize investment portfolios, for financial analysts to develop strategic insights and to time market entry and exit points, for policy makers to anticipate market volatility on broader economic variables such as inflation, employment and economic growth, contributing to their effort to ensure market stability. Forecasting stock prices present several intrinsic challenges, primarily posed by volatility, market fluctuations and exogenous factors. Notably, NEPSE (Nepal Stock Exchange)—major focus of this research—went through exogenous shocks such as Gorkha Earthquake, 2016 and covid-19 pandemic, 2020. But Karki D. suggests that Nepalese market is semi-strongly inefficient on premise that these factors didn't impact didn't impact the returns of the market. Further making this research more awaited. [1] Unpredictability of variables, coupled with frequent periods of high and low volatility, complicates the task of making accurate price forecasts. In context of Nepal, NEPSE index is indicative of multiple broader economic variables due to its significant correlation with monetary variable. [2] NEPSE has been serving as barometer of nation's financial health since January

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13, 1994, tracking people's confidence in some of nation's great corporations.[3] NEPSE commenced with base value of 100 from the very date and has since been calculated with the following formula: [3]

$$NEPSE\ Index = \frac{\sum(Current\ Market\ Capitalizations)}{\sum(Base\ Market\ Capitalizations)} \times 100$$

Where,
Current Market Capitalization = Price of the stock × Number of shares outstanding (for each company).
Base Market Capitalization is the market capitalization at the base period (when the index was started).
Base Index Value is typically set at 100 when the index is first established.

1.1. Time Series Models for Stock Price Forecasting

One of the hottest areas of research right now is time series data forecasting techniques. Time series data are being produced in an increasing number of fields. It encourages the advancement of time series research and supplies data for the study of the time series analysis method. The creation of large-scale, intricate time series data makes it more difficult to create forecasting models for time series data. High time series data complexity, weak prediction model generalization capabilities, and low accuracy are the primary obstacles to time series modeling. One of the hottest areas of research right now is time series data forecasting techniques. Time series data are being produced in a growing number of disciplines. [4] They capture patterns and trends using historical data. By modeling temporal dependencies and recurring behavior in data, time series techniques offer structured approach for forecasting dynamic environments. For accurate stock price forecasts, traditional econometric models have been set aside in favor of the ARCH model proposed by Engle in 1982. [5]

1.1.1. ARIMA Model for Linear Patterns

Among these models, the ARIMA (AutoRegressive Integrated Moving Average) model is widely used for handling linear trends in time series. ARIMA identifies and models the autocorrelations within the data, making it suitable for datasets where past price movements can inform future predictions. It stabilizes non-stationary data through differencing, enhancing its applicability in financial time series. [6]

$$\emptyset_p(L)(1-L)^d y_t = \theta_q(L)\epsilon_t$$

Where:
$\emptyset_p(L)$ represents the autoregressive (AR) part with p lags.
$\theta_q(L)$ represents the moving average (MA) part with q lags.
L is the lag operator: $L^k y_t = y_{t-k}$.
D is the order of differencing to make the time series stationary.
y_t is the time series at time t.
$\in_t$ is white noise (error term)

1.1.2. GARH Model for Volatility Clustering

However, stock prices also exhibit volatility clustering, where periods of high volatility are followed by high volatility and low volatility follows low. This behavior is captured by the GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) model, which extends the ARIMA model by modeling the variance of the errors. [7]

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

Where:
σ_t^2 is the conditional variance (volatility) at time t.
α_0 is a constant term.
$\alpha_i \epsilon_{t-i}^2$ captures the ARCH terms (impact of past squared residuals)
$\beta_j \sigma_{t-j}^2$ captures the GARCH terms (impact of past variances)
P is the number of lagged variances (GARCH terms)
Q is the number of lagged squared residuals (ARCH terms)

1.1.3. ARIMA-GARCH Hybrid Model

ARIMA-GARCH is a combination which combined linear time series ARIMA with GARCH conditional variance. We call this the conditional mean and conditional variance model. To suggest a hybrid ARIMA-GARCH model, two steps need to be taken. The non-linear portion of the data is contained in the residuals of the linear model, which is initially fitted using the best ARIMA model on stationary and linear time series data. We employ the GARCH model in the second stage to capture patterns of non-linear residuals. This hybrid model is used to forecast and analyze oil price returns, stock prices, forex rates and many more. It incorporates the nonlinear residuals patterns of the GARCH and ARIMA models. To suggest a hybrid ARIMA-GARCH model, two steps need to be taken. The residuals of the linear model, which is first fitted using the best ARIMA model on stationary and linear time series data, contain the non-linear fraction of the data. In the second stage, we use the GARCH model to capture non-linear residual patterns. The financial time series future data points are forecasted and analyzed using this hybrid model. It integrates the GARCH and ARIMA models' nonlinear residuals patterns. [8]

1.2. Rolling Data Window for Model Optimization

A rolling data window is a technique in time series forecasting where a fixed-sized subset of historical data is used for model training, and this subset is continually updated as new data points become available. Unlike static dataset, rolling window uses data by shifting forward with each iteration. This allows the model to adapt to changing market conditions. Zivot et al. suggest that the economic environment often changes considerably, and it may not be reasonable to assume that a model's parameters are constant and a common technique to assess the constancy of a model's parameters is to compute parameter estimates over a rolling window of a fixed size through the sample. [9] They express that if the parameters are truly constant over the entire sample, then the estimates over the rolling windows should not be too different. Also, successes of use of rolling data window in diverse time series prompts this paper to use rolling data window. [9]

1.3. Overview of Preceding Studies and Research Gaps

There is a substantial body of research exploring stock price prediction realm, providing impeccable edifice for theoretical foundation and empirical evidence. Li documented a complete stepwise analysis process of financial time series using stock prices of Jinnan Hi-Tech Development. [7] YANG et al. worked on ARCH model and fitted the intraday high-frequency trading data of China National Trade stocks; they discovered higher accuracy of confidence intervals compared to traditional econometric model. ARCH has multiple extended models including GARCH, EGARCH, FIGARCH and many more. YANG et al. suggested that utilizing one of these would improve accuracy of the results. [5] Pahlavani et al. compared the forecasting performance of the ARIMA model and ARIMA-GARCH models by using daily data of the Iran's exchange rate against the U.S. Dollar (IRR/USD) for over a year; they found ARIMA- ((7,11,12),(4)-GARCH (2,0) to be the best fit model, using AIC and BIC. [10] Dritsaki used ARIMA-GARCH model in Forecasting Oil Prices and tested its performance. [8]

The major research gap is the use of rolling data window. So, this paper focuses on identifying, implementing and testing efficacy of AIRMA-GARCH model, using a rolling window of 180-days data points, on a stock index of an emerging market economy.

1.4. Rationale and Objective of the Study

The rationale for combining ARIMA and GARCH models lies in the need to capture both the linear patterns and volatility dynamics intrinsic to stock market data. In hybrid model, one like ARIMA-GARCH, the ARIMA is effective with linear structure of time series, capturing trends and seasonality, while the GARCH model is well-suited for addressing volatility clustering. [10] Given that the NEPSE index exhibits such characteristics, a hybrid ARIMA-GARCH model offers a more comprehensive framework for forecasting closing prices, accounting for both price movement trends and volatility spikes. And rolling data window makes the analysis efficient as it adapts continuously with the most recent data. [9] This dynamic approach helps model remain relevant and responsive over time. The paper's methodology could be highly relevant to underdeveloped and emerging stock markets (one like NEPSE) that experience high volatility and market inefficiencies, as this hybrid model is robust to capture non-stationary data and volatility dynamics of the market. [1]

The primary objective of this research is to evaluate the efficacy of the ARIMA-GARCH hybrid model in predicting NEPSE index closing prices using a rolling data window approach. The study aims to assess the accuracy of the forecasts and demonstrate how this method improves prediction performance compared to static models. This research also aims to lay groundwork for future investigations of similar emerging market indices using this hybrid modeling technique. So, this research is hoped to enhance portfolio optimization and informed decision making for investors in real time.

1.5. Structure of the Paper

This paper is organized as follows: **The Materials and Methods** section outlines the dataset, data pre-processing, and the ARIMA-GARCH model used for forecasting. The **Results and Discussion** section presents the model fitting results and forecasted data, along with an analysis of accuracy and discussion on each results. Finally, the **Conclusion** summarizes the key insights and offers recommendations for future research and applications in stock market forecasting.

2. Materials and Methods

2.1. Data collection

The primary dataset used in this study consists of daily closing prices of the NEPSE index. Data is sourced from publicly available records of the Nepal Stock Exchange (NEPSE) and covers a time period of about 3 years and 9 months beginning from January 1, 2020 to September 29, 2024.

2.2. Data Pre-processing

Prior to modeling, the data was subjected to several preprocessing steps. Firstly, the data set was examined for missing entries. Then, z-score analysis was done with rolling data window of 180 data points. Finally, the Augmented Dickey-Fuller (ADF) test was conducted to assess the stationarity of the time series. The non-stationary series was transformed using first-order differencing to achieve stationarity, as indicated by the ADF test results.

2.3. Model Specification

Stepwise Akaike Information Criterion(AIC) minimization procedure was endured to estimate the best fit model for forecasting. Data is subjected to split into training and test samples; then, the order of ARIMA model is determined. ARIMA residuals are tested for ARCH effect using Lagrange Multiplier Test (LM Test). Upon finding ARCH effects in ARIMA residuals, parameters of the GARCH model is determined.

2.4. Rolling Window Approach

A rolling window technique was implemented to enhance the model's adaptability to evolving market conditions. A 180 data points window was utilized, wherein the model is trained on the most recent 180 data points to forecast the next closing price. Iterative forecasting acclimatizes to shifting market conditions, updating the data points with each new data point to ensure forecasts incorporate the latest market trends.

2.5. Model Evaluation

The model's performance was assessed through residual analysis: post modeling, residuals are analyzed to detect any remaining autocorrelation or patterns, using tools like the Ljung-Box test, QQ plots, ACF and PCF, etc. Finally, the accuracy of the model is assessed using statistical measures including Mean Percentage Error, Root Mean Squared Error, correlation, etc.

By using these materials and these methodologies, the study aims to estimate a reliable model for forecasting NEPSE index's closing points.

3. Results and Discussion

Following the methodologies as aforementioned, this paper endures the following steps in order to perform data analysis and visualization.

3.1. Data Pre-Processing

Data pre-processing is an important step in the data mining process, which refers to the cleaning, transforming and integrating of data in order to make it ready for analysis. Firstly, this paper has assured that no data point is missing, there are no significant outliers, and duplicates. Since, data was taken from single source, there is no requirement for integrating data. As we are dealing with time series data, for further analysis, we need to assure that data is stationary or stabilize. This paper does stationarity tests and differencing to stabilized the data.

3.1.1. Stationarity Test on Original Series

Stationarity is a fundamental concept in time series data analysis that refers to the consistency of statistical properties of time series data over time. Particularly, a time series data is said to be stationary if its key characteristics—mean, variance, and auto-covariance—do not change with time. [7]

To test the stationarity, the ADF (Augmented Dickey-Fuller) test is conducted on the time series data. After analysis the results depicted in Figure 1 is obtained.

```
ADF Test on Closing Prices (Before Differencing):
ADF Statistic: -2.229767513673927
p-value: 0.19561946838091493
Critical Values:
   1%: -3.436540010983293
   5%: -2.8642730819775406
   10%: -2.5682251959417948
```

Figure 1 ADF Test on Closing Points of NEPSE Index on Original Time Series Data

Since p-value > 0.05, the alternative hypothesis of the stationarity of data cannot be proven; time-series is not stationary. [7]

3.1.2. First Order Differencing Followed by Stationarity

To achieve stationarity, a differencing method must be used to eliminate unit roots. Thus, this paper performs first-order differencing on the original series, and is subjected to the same ADF test. The result is showcased in Figure 2. [7]

```
ADF Test on Closing Prices (After First Order Differencing):
ADF Statistic: -8.46891900013519
p-value: 1.496022915431599e-13
Critical Values:
   1%: -3.436540010983293
   5%: -2.8642730819775406
   10%: -2.5682251959417948
```

Figure 2 ADF Test on closing prices after first order differencing

Since p-value < 0.05, the alternative hypothesis of stationarity of series is proven.

3.2. Time Series Modeling

3.2.1. Model Parameter Identification and Order Determination

The Akaike Information Criterion (AIC) is a widely used measure for model selection in statistical modeling, especially in time series analysis and regression. A stepwise search to minimize AIC is conducted as ARIMA model with minimum AIC is considered the best model. [11]

The AIC is defined as:

$$AIC = 2k - 2\ln(L)$$

Where,

k is number of parameters in the model. L is the likelihood of the model given the data.

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=inf, Time=1.10 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=8993.691, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=8842.007, Time=0.05 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=inf, Time=0.17 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=8991.691, Time=0.02 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=8665.056, Time=0.03 sec
 ARIMA(3,1,0)(0,0,0)[0] intercept   : AIC=8633.431, Time=0.17 sec
 ARIMA(4,1,0)(0,0,0)[0] intercept   : AIC=8599.799, Time=0.22 sec
 ARIMA(5,1,0)(0,0,0)[0] intercept   : AIC=8564.925, Time=0.28 sec
 ARIMA(5,1,1)(0,0,0)[0] intercept   : AIC=inf, Time=0.45 sec
 ARIMA(4,1,1)(0,0,0)[0] intercept   : AIC=inf, Time=0.46 sec
 ARIMA(5,1,0)(0,0,0)[0]             : AIC=8562.926, Time=0.13 sec
 ARIMA(4,1,0)(0,0,0)[0]             : AIC=8597.800, Time=0.14 sec
 ARIMA(5,1,1)(0,0,0)[0]             : AIC=inf, Time=0.58 sec
 ARIMA(4,1,1)(0,0,0)[0]             : AIC=inf, Time=0.56 sec

Best model:  ARIMA(5,1,0)(0,0,0)[0]
Total fit time: 4.454 seconds
Best ARIMA order: (5, 1, 0)
Best ARIMA order (p, d, q): (5, 1, 0)
```

Figure 3 Performing stepwise search to minimize AIC

The best model established as per the AIC minimization is ARIMA (5,1,0) model. ARIMA(5,1,0) is a model that uses 5 lagged values of the time series to predict its current value, applies first order differencing to stabilize the mean of the series, and does not include any lagged forecast error terms.

3.2.2. Testing for ARCH Effects

ARCH effect is tested using Lagrange Multiplier Test

```
Lagrange Multiplier (LM) Test for ARCH Effects:
LM Statistic: 18.62690858309945
P-value: 0.04526553886209871
```

Figure 4 Testing for ARCH effects using Lagrange Multiplier Test

From the Figure, P-value = 0.0453: Since this p-value is below 0.05, we can reject the null hypothesis of no ARCH effects at the 5% significance level. GARCH(1,2) has the smallest AIC values but the difference compared to GARCH(1,1) is insignificant. Moreover, having a higher number or parameters in GARCH model results in instability in the model. This article proceeds with GARCH(1,1). [7]

Most financial time-series use GARCH(1,1), which has one lag each in both ARCH and GARCH terms. It models volatility clustering, where large changes in asset prices are followed by large changes (high volatility), and small changes are followed by small changes (low volatility). Notably, this model strikes a balance between model complexity and fit; more complex GARCH models (with higher lags) may overfit the data, while GARCH(1,1) is usually sufficient for many applications.

3.2.3. Model Fitting Results

This paper fitted the ARIMA(5,1,0)-GARCH(1,1) model and the following parameters is estimated as shown in Figure. For all the coefficients, the P-value is less than 0.001. (NaN implies substantially small value).

```
ARIMA Model Summary:
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0860      0.025      3.416      0.001       0.037       0.135
ar.L2         -0.0686      0.025     -2.714      0.007      -0.118      -0.019
ar.L3          0.1349      0.025      5.314      0.000       0.085       0.185
ar.L4         -0.0171      0.024     -0.702      0.482      -0.065       0.031
ar.L5          0.0319      0.025      1.288      0.198      -0.017       0.081
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):                24.56
Prob(Q):                              0.94   Prob(JB):                         0.12
Heteroskedasticity (H):               1.21   Skew:                            -0.27
Prob(H) (two-sided):                  0.07   Kurtosis:                         3.29
===================================================================================

GARCH Model Summary:
                               Mean Model
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
mu            -2.3780      0.956     -2.487  1.288e-02 [ -4.252, -0.504]
                             Volatility Model
==========================================================================
                 coef    std err          t      P>|t|    95.0% Conf. Int.
--------------------------------------------------------------------------
omega         89.0972     28.821      3.091  1.992e-03 [ 32.609,1.456e+02]
alpha[1]       0.1810  3.438e-02      5.266  1.393e-07   [  0.114,  0.248]
beta[1]        0.7430  3.862e-02     19.238  1.764e-82   [  0.667,  0.819]
==========================================================================
```

Figure 5 ARIMA and GARCH Model Summary

The ARIMA(5, 1, 0) model exhibits statistically significant autoregressive terms and shows promising results. Specifically, the first three autoregressive lags (ar.L1, ar.L2, and ar.L3) are statistically significant at the 0.05 level, indicating that past values have a notable impact on future prices. Notably, ar.L1 has a positive coefficient; this implies past price increments influence future prince increments. Conversely, arL2 has negative coefficient of -0.068, depicting market characteristics of correcting after an upward movement. The positive coefficient for ar.L3 (0.1349) suggests significance of momentum in price movement. Lack of significance of ar.L4 and ar.L5 raises question about inclusion of these terms in our model. While model selection is based on the edifice of AIC and BIC, there is always weighed trade-off between model complexity and interpretability during model selection.

The diagnostic tests conducted on the residuals present mixed picture. The Ljung-Box test indicates that model has no significant autocorrelation in residuals (p-value= 0.00), suggesting that the ARIMA model has captured the autocorrelation structure of the data. For normality test, the Jarque-Bera test (p-value=0.12), which indicates that the residuals are normally distributed. Both autocorrelation and normally tests are further explored in section 3.2.4 with visualizations. The Heteroskedasticity (p-value = 0.07), which is very close to conventional significance level of 0.05, indicates model may have slightly been unable to accommodate heteroscedasticity, but following ARIMA model, we have implemented General AutoRegressive Conditional Heteroskedasticity (GARCH) model in combination, which accommodates heteroscedasticity. Skewness value is not of significant concern as skewness is relatively small. However, it does indicate that the residuals deviate slightly from normality. If skewness is pronounced, it could suggest that the model might benefit from transformations (e.g., log or square root) to normalize the residuals. Since, it is at satisfactory level, we do not consider performing further transformations. Kurtosis of 3.29 suggests slight leptokurtic characteristics, suggesting a distribution that has somewhat heavier tails and sharper peak than a normal distribution. This value is satisfactory, as it does not signal extreme deviations from normality. Overall, further transformations are not necessary; most of the parameters are at satisfactory levels.

Following the ARIMA analysis, a GARCH model was applied to address the volatility clustering observed in the closing prices. The results indicate that the mean model's constant term (mu = -2.3780) is significant, suggesting a stable mean return. The GARCH model results reveal that the parameters omega (89.0972), alpha[1] (0.1810), and beta[1] (0.7430) are all statistically significant, with their values indicating a strong relationship between past volatility and future price behavior.

The parameter omega reflects the baseline level of volatility, while alpha[1] captures the effect of past shocks on current volatility. The significant positive coefficient for alpha[1] suggests that positive price shocks tend to increase future volatility, which is consistent with the phenomenon of volatility clustering seen in financial markets. The parameter beta[1] indicates that the impact of past volatility decays over time; however, since alpha[1] + beta[1] = 0.924, the sum being less than one suggests that the GARCH process is stationary. This is an important finding, as it implies that shocks to volatility will eventually dissipate.

3.2.4. Visualizing Residual Autocorrelation and Normality Test

The ARIMA-GARCH model upon being subjected to tests for residual auto-correlation and impedance.

Performing Ljung-Box Tet to check if there exist auto-correlation in residuals. The results in figure depicts p-value whereby we cannot reject the null hypothesis. Hence, there is no auto-correlation among the residuals.

```
Ljung-Box (L1) (Q):        0.01
Prob(Q):                   0.94
```

Figure 6 Results of Ljung-Box Test

Again, the autocorrelations can be tested by Auto Correlation Function (ACF) and Partial Auto Correlation function (PACF). Both of them satisfy the autocorrelation tests too. [7][8]

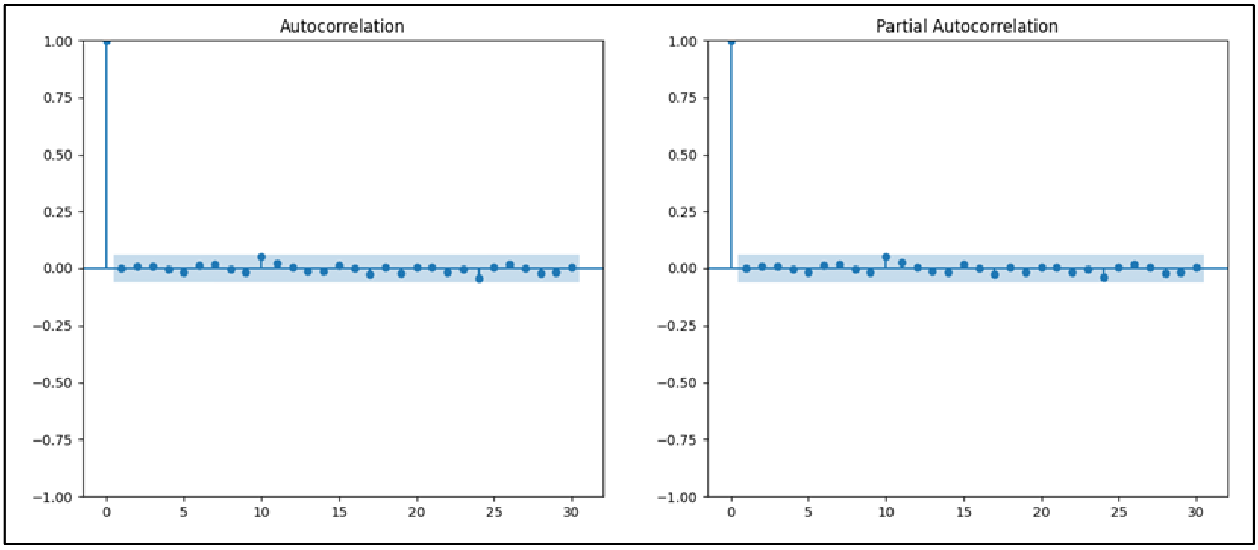

Figure 7 Visualization of ACF and PACF

Further, the model residuals data is subjected to QQ plot for Normality test. The residuals satisfy for normality test. [7][8]

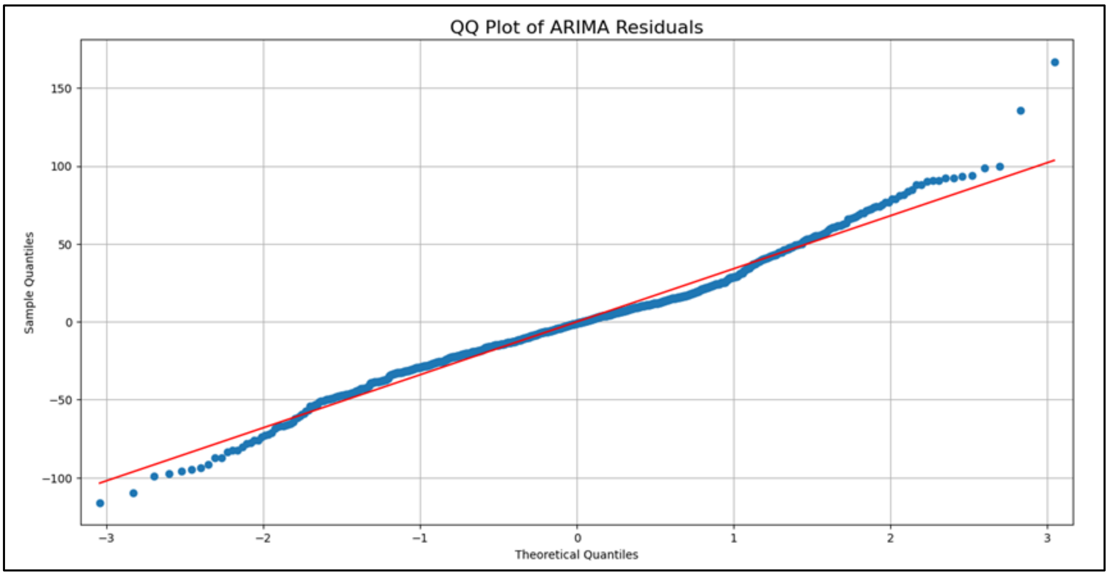

Figure 8 QQ plot of model's residuals

3.3. Forecasting and Accuracy Analysis

The data model is now subjected to forecasting. Now the process is iteratively implemented to 180 points data window. The iterative forecasting approach adopted in this study, utilizing 180-day rolling data-window, offers advantages in enhancing the model's performance. Unlike static models that rely on a fixed dataset, this model is adaptive to evolving dataset with newer trends and shift in volatility. [9] Also ARIMA model is a linear model, its performance is at its peak if the data progresses linearly, which is seen in small data-window.

3.3.1. Forecasted Data Visualization

The training data, actual data and forecasted data are juxtaposed in the Figure 9. The forecasting is done iteratively using most recent 180-days data window.

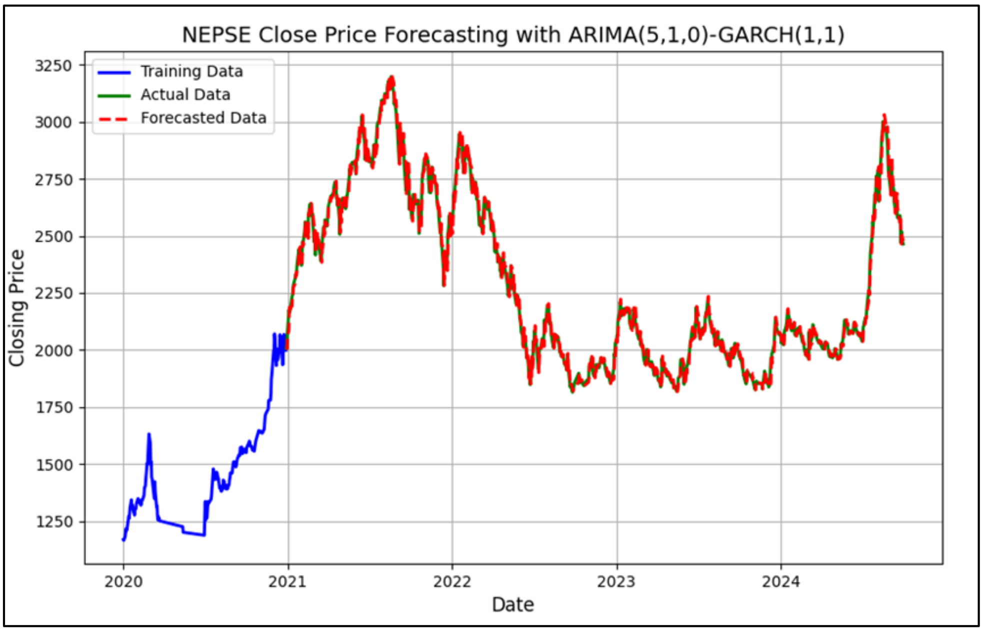

Figure 9 Visualization of training data, actual data and forecasted data

The forecasted values (dashed red line) closely follow the actual closing prices (green line) post 2021, indicating that the ARIMA-GARCH model effectively captures the underlying data patterns. The erratic movements post-2021 highlight periods of high volatility, which the model appears to account for. The minimal divergence from actual data depicts the reliability of the model in forecasting future prices.

3.3.2. Accuracy Evaluation

Accuracy assessment illustrated in Figure 10 depicts that the model's forecasted values exhibit -0.0058% Mean Percentage Error and correlation of 0.995, which depicts that the model fits the time series. Mean Error(ME) of -0.31 indicates a slight negative bias in the forecasts, meaning that on average, the model slightly underpredicts the actual values. Root Mean Squared Error (RMSE) of 35.44 and Mean Absolute Error (MAE) suggests quite accurate prediction considering that average index value is 2160 (approx.) Inferences from the tests imply that the trained ARIMA-GARCH model is capable of forecasting the closing-points of the NEPSE index with fairly high degree of accuracy.

```
Mean Error (ME): -0.30694381176903374
Root Mean Squared Error (RMSE): 35.44476599837749
Mean Absolute Error (MAE): 26.022868283176045
Mean Percentage Error (MPE): -0.0057568542340243915%
Correlation between actual data and forecasted data: 0.9953671508241151
```

Figure 10 Results of accuracy testing using different statistical measures

3.4. Limitations and Future Directions

Despite the informative results, several limitations warrant consideration. The slight departure (though, from QQ plots, normality of data is satisfactory) from normality in the residuals of the ARIMA model suggests that there is slight possibility of additional factors influencing price movements that are not captured by the current model specifications. Future research could explore alternative specifications, such as the incorporation of exogenous variables (ARIMAX) or seasonal effects (SARIMA), to enhance model robustness.

Moreover, despite the fact that the GARCH model addresses volatility clustering, it assumes that the conditional variance follows a specific functional form. Future studies can investigate the efficacy of different volatility models, like EGARCH or GJR-GARCH, which has possibility to better capture asymmetries in a volatile series.

4. Conclusion

The implemented ARIMA-GARCH model fits the time series data of the closing points of NEPSE index, and it forecasts the next closing prices with fairly high accuracy, as depicted by the error analysis in Figure. ARIMA-GARCH model has high accuracy for linearly progressing data and it is highly precise for short-term forecasting. A rolling data window in forecasting can continuously acclimatize to the evolving vicissitudes of the market. Also, it is crucial to weigh the trade-off between model complexity and interpretability. That said, there could be some stark incident of some parameters departing from expectations even when the model fits the most. It should always be considered, though, that there should be no autocorrelation in the residuals for model to capture most of the characteristics of a time series data. Similar approach can be endured in order to implement forecast model in other stock indices or stock prices. Specifically, this methodology is useful in forecasting stock prices in other emerging markets that experience similar economic environment alike to NEPSE.

Compliance with ethical standards

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