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Stock Market Trend Prediction Using Deep Learning Approach

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Abstract
Since the dawn of financial market trading, traders have continually sought methods to enhance their predictive capabilities for future price movements. This pursuit is driven by the significant daily trading volumes observed in financial markets worldwide. While traditional econometric and statistical methods have historically dominated in forecasting the behaviors of stock exchanges such as the Pakistan Stock Exchange, there remains a relatively limited exploration into the realm of artificial intelligence (AI) and machine learning (ML) techniques for addressing the inherent unpredictability of these markets. This study aims to improve the accuracy of forecasting the closing index of the Pakistan Stock Exchange by leveraging AI-based models, particularly employing the Deep Learning (DL) Long Short-Term Memory (LSTM) recurrent neural network. These DL models are anticipated to outperform traditional time series methods in predicting market indices. The primary objective of this work is to empower short-term investors with more precise index forecasts, enabling them to make informed and strategic trading decisions through the application of AI-based models.

Keywords Artificial intelligence · Long-short term memory · Stock market · Forecasting problem

1 Introduction

Forecasting of unforeseen future has been studied and implemented for a significant time. However, with increasing use of intelligent and accurate resources numerous studies have been conducted to achieve accuracy in forecasting actual in contrast to predicted outcomes. On the other hand, financial decisions play a crucial role in economic wealth; therefore, forecasting financial and economic indicators is highly

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significant. The financial markets constitute a captivating platform characterized by complex dynamics in action, as described in Johnson and Jefferies (2003). Over the years, researchers have undertaken extensive investigations into the world of stock markets, which are notorious for their high levels of volatility. These inquiries have been driven by the desire to comprehend and decode the multifaceted facets of these markets, ranging from their inherent volatility to discernible trends and recurring patterns. Moreover, researchers have delved into the complexities of investor sentiments, economic propriety, and various financial factors that influence market behavior. Notably, fusion methodologies have emerged as indispensable tools in the stock of financial analysts and researchers, facilitating the extraction of essential insights and meaningful information from the vast sea of market data (Thakkar & Chaudhari, 2021a). Furthermore, it is worth noting that many individuals and organizations actively participate in these financial markets with a primary objective: to optimize their return on investment (Thakkar & Chaudhari, 2020). For them, the financial markets represent a strategic platform where they seek to navigate the complexities and capitalize on opportunities to enhance their investment portfolios.

Due to a multitude of impactful occurrences, it becomes crucial to examine the market. While thorough research and strategic trading can increase profits for traders, there is also a risk of losing valuable assets when venturing into the stock market (Thakkar & Chaudhari, 2020). Manual scrutiny can be challenging given the sheer volume of stock data that needs analysis. Consequently, diverse analytical tools and computational techniques have emerged, designed to extract valuable market insights and uncover potential hidden patterns. Nature-inspired algorithms have gained widespread acceptance across various applications, with these metaheuristic approaches also being integrated into different computational methods to enhance the predictive capabilities of financial markets (Thakkar & Chaudhari, 2021b).

Prediction of economic and financial time series data is a challenging task mainly due to the unprecedented changes in economic trends and conditions on one hand and incomplete information on the other. In addition, Market volatility in recent years has produced serious issues for economic and financial time series forecasting because of the pandemic situation over the globe. Therefore, assessing the accuracy of forecasts is necessary when employing various forms of forecasting methods, specifically forecasting using regression analysis, as they have many limitations in applications. Predicting stock market trends is a complex, real-world challenge. The accuracy of these predictions is greatly affected by several factors, including in-depth market analysis, comprehensive data collection and analysis, potential data integration, identifying relevant and informative variables, choosing an appropriate prediction model, and fine-tuning hyperparameters. Recent development in essential features of data science has transformed the course of commerce. By way of being an appealing invention, financial markets around the world have a significant impact on a nation's economy. Therefore, Stockholders pursue the tools and techniques to maximize the return while limiting the risk within the financial trades to identify the best possible mechanism to enable us to forecast the movements of the Stock market in Pakistan.

Pakistan Stock Exchange (PSX), previously regarded as the Karachi Stock Exchange, was combined with the Lahore Stock Exchange and Islamabad Stock

Exchange in Pakistan in January 2016. Currently, PSX is the only stock exchange in Pakistan. Historically, the Karachi Stock Exchange was initiated based on a stock index of fifty scrips. However, with time, the stock market growth required a more comprehensive representative index. On 1 November 1991, the KSE-100 index was introduced in the share market. The KSE-100 index is a capitalization-weighted index computed based on 100 companies that theoretically covers approximately 90% of Pakistan's stock market capitalization. PSX-100 index went through ups and downs based on volatility in the market due to external events. PSX began recovery from the adverse historical events and performed well against other emerging markets. Based on more than 40% return in 2012, PSX was the best-performing emerging Asian market. Following the growth with some adjustments in the market, the PSX-100 index reached 49,967, depicting an all-time high in the history of Pakistan in January 2017. However, in 2020, as soon as COVID hit the country's economy, the market dropped to 27,200 in March 2020.

This study will employ a novel approach involving a DL-based LSTM model. This LSTM model will offer advanced capabilities for analyzing and predicting Pakistan's financial markets. Additionally, to evaluate the effectiveness and accuracy of the LSTM model, we will conduct traditional time series analyses. These traditional methods will serve as benchmarks, allowing us to compare and contrast the LSTM model's forecasting performance against more conventional financial forecasting models. By combining the power of DL with established time series techniques, we aim to gain deeper insights into the dynamics of Pakistan's financial markets and improve the accuracy of our forecasts, which can have significant implications for financial decision-making and investment strategies.

Main contribution of this study is:

- This research endeavors to enhance the accuracy of predicting the Pakistan Stock Exchange closing index by employing AI-based models, specifically the Long-Short Term Memory recurrent neural network.
- Furthermore, it integrates DL techniques with traditional time series methods to create a hybrid approach, thereby providing deeper insights into Pakistan's financial market dynamics.
- The study aims to significantly improve index forecast accuracy, particularly benefiting short-term investors by empowering them to make more informed and strategic trading decisions.

The paper is structured as follows: Sect. 2 discusses Related Work, Sect. 3 presents the Proposed Methodology, Sect. 4 provides implementation and results details, Sect. 5 explores Future Directions, and Sect. 6 concludes the paper.

2 Related Work

In the financial markets, speculators and investors try to anticipate the behavior of asset prices. However, innumerable economic factors show that the market becomes a complex system whose evolution is conditioned by traders trying to profit from transactions. Faced with the complexity encountered in the financial markets, where the probability of winning or losing remains uncertain, it is evident that knowing the risk and the movement of assets makes it possible to obtain better performance. Thus, the forecast of financial series is a significant issue in the financial markets (Gupta, et al., 2007); indeed, a better anticipation of the evolution of asset prices can improve the profitability of investors. Nevertheless, this task remains difficult because financial assets are part of nonlinear, non-stationary, and chaotic processes. Forecasting Financial time series has always been a difficult job for researchers and actual traders in the market. Numerous studies support or reject the idea of making forecasts based on the Efficient Market Hypothesis (EMH) proposed (Fama, 1970). In the literature, EMH is linked to random walks, i.e., information constantly flows, and any new information immediately appears in stock price. Hence, future rates are unpredictable and random. According: "Financial market is said to be efficient if and only if all the information available concerning each financial asset quoted on this market is immediately integrated into the price of this asset." The formalization of this hypothesis (Fama, 1970) is based on the formation of asset prices.

The EMH excludes the possibility of beating the market and making exorbitant profits. When information is known and included in the prices, it becomes obsolete. It cannot be used to make substantial profits by buying an undervalued asset or selling an overvalued asset. The EMH has raised questions among financial theorists about "how prices instantly integrate information." While many authors (Fama, 1970; Gupta, et al., 2007; Thakkar & Chaudhari, 2021b) show the existence of information under reaction, other authors (Kudryavtsev, 2020) highlight an overreaction of prices to information. This initial overreaction is followed by a correction process reflecting the price adjustment to the action fundamental value. Historically, researchers have been dependent on traditional time series forecasting models. Studied (Bhowmik & Wang, 2019) time series models to forecast stock return volatility. They used the data from six Asian emerging markets collected data at various frequencies from 2007 to 2016. Forecasting techniques used by them involve ARMA and GARCH models. The results of the study depicted that forecasting short-term trading rules has better accuracy as compared to more extended forecasting models. Deployed (Naz et al., 2021) time series-based GARCH family models, including generalized autoregressive conditional heteroscedasticity (GARCH), asymmetric threshold GARCH (TGARCH), and exponential GARCH (EGARCH) on the Pakistan stock exchange in order to estimate volatility. The study results supported that time series models can enable investors to maximize returns by applying timing strategies.

Author (Srinivasan & Ibrahim, 2010) attempted to enhance the volatility forecasting models for the Indian Stock market. They used the daily index data of the Sensex and applied time series models mainly related to GARCH in order to estimate the conditional variance within the data. Results of the study after the application of a range of GARCH models from GARCH (1, 1) to complex TGARCH (1,1) and EGARCH (1,1) depict that asymmetric GARCH models outperform in estimating volatility of the stock market. Similarly (Kumar & Biswal, 2019), deployed GARCH family models to estimate the volatility of top emerging future stock markets that belonged to Pakistan, India, Brazil, and Indonesia.

They deployed the data from 2014 to 2018 and analyzed volatility using ARCH and GARCH time series models. The output of the study confirmed that time series ARCH/GARCH can predict stock market volatility.

Author (Chronopoulos et al., 2018) estimated the forecasted volatility using GARCH models. They used the data from 2004 to 2016 of the SP500 index. The study suggested that the introduction of a new variable that depicts the daily internet search volume index (SVI) can increase the forecasting ability of timer series-based GARCH models in a significant manner. All the discussed papers reveal that time-varying volatility in the stock market exists. Researchers have widely deployed and are still making efforts in time-series-based approaches to model this volatility.

The literature reveals a significant rise in AI and ML integration within financial markets. Key applications include algorithmic trading, risk management, fraud detection, credit scoring, and enhancing customer relations. These challenges encompass substantial implementation costs, deficiencies in data and infrastructure, privacy considerations, and the imperative to adhere to regulatory requirements. The qualitative investigation revealed the profound impact of AI and ML technologies on the financial workforce, highlighting concerns about potential job losses due to automation. However, it also underscored the potential for AI and ML to create new roles and career opportunities, provided that workers can adapt to this evolving landscape. Development in the field of artificial intelligence can play a vital role in increasing the accuracy of stock market-related forecasting. DL (Hiransha et al., 2018; Mukherjee et al., 2023; Torres et al., 2021) is a unique method of ML, similar to how the human brain works. It makes use of neural networks in order to analyze extensive data sets. Through DL, the system can absorb new content, link it to existing knowledge (Shen, 2019), and thus learn continuously. Because the system can check and question itself, it can learn without human intervention. Numerous studies tested the effectiveness of ML techniques in forecasting financial exchanges using AI.

Study suggested (Selmi et al., 2015) neural network training algorithms can support increasing the accuracy of forecasting time series. Similarly (Chronopoulos et al., 2018), expected that future work, such as the neural network ensemble forecasting paradigm, will incorporate the recently developed to enhance the model's explanatory power. In the presence of topical computations of time series forecasting of stock market volatility, it is evident that researchers have suggested the use of advanced AI-based models. In this research, ML-based algorithms combined with time series models to predict the volatility in the Pakistan Stock Exchange. Various authors previously discussed changes in time series models-based forecasting of Pakistan Stock Ex. The AI-based models can perform the same task by learning the logical pattern among time series of historical indexes. Suppose the accuracy is higher than the traditional time series models. In that case, an AI-based model can help us build a forecasting model that accurately predicts the closing index on day end. However, we are still determining whether advanced AI-based tools will be an effective solution for Pakistan stock market.

3 Methods & Materials

3.1 Dataset Details

To forecast the closing index of the Pakistan Stock Exchange, the dataset for this study will include daily historical closing indexes spanning over a decade, from January 1, 2009, to July 7, 2021.Therefore, the dataset handles around 2,980 data points in this study, tentatively covering about 12 years of trading days. Out of the total sample, the index's last 365 days' data will be used for evaluating the out-of-sample predicting ability of time series and DL models. Data for the study will be collected from Yahoo Finance API finance. Primarily, data of the closing index of PSX will be the variable of interest because the study will focus on designing a uni-variate model with an acceptable level of forecasting accuracy. If additional economic variables inclusion is deemed- necessary for designing an accurate forecasting model, the data of additional variables will be fetched from the Pakistan Statistical Bureau and State Bank of Pakistan website. During the data analysis of this study, the returns of the PSX-100 index are considered as log returns at time t. The returns were calculated using the following Eq. (1–3):

$$r_t = \log\left(\frac{p_t}{p_{t-1}}\right) \tag{1}$$

$$P_t = Closing\ PSX - \ 100\ Index\ at\ time\ t \tag{2}$$

$$P_{t-1} = \ Closing\ PSX\ -\ 100\ Index\ at\ time\ t\ -\ 1t \tag{3}$$

3.2 Dataset Preprocessing

Pre-processing of the data will be based on exploratory data analysis. Data will be arranged in chronological order as a time series. At first, we will visualize the data by plotting a graph of the closing index against the time. Visual representation of the data will help us identify the fact that there is some trend within the data. Theoretically, time series data is a combination of four trends: Secular Trend (T), Cyclical Trend (C), Seasonal Trend (S), and Irregular Trend (I). We will check such components within the time series data. At the same time, visual representation gives an idea of whether the time series is stationary. Mainly because in order to apply stationary time series models, data has to be stationary. Additionally, we will test the data for stationary using famous statistical tests such as the Augmented Dickey Fuller Test and KPSS test of testing stationary among the time series. We will convert the data into stationary time series if deemed necessary using a differencing technique.

3.3 Proposed Methodology

3.3.1 Traditional Time Series Models

Once the data is pre-processed, we will initiate fitting and testing the time series models. At first, we will partition the data into testing and training data sets. For this purpose, the data will be distributed in a 3:1 ratio, 75% of observations will be set aside for training the mode, whereas 25% will be used for testing the forecasting accuracy of the model. Further in the study, traditional time series models will be tested to forecast the market index in the following manner accurately.

(a) Auto Regressive Moving Average-*ARMA*.
The ARMA model combines AR(p) and MA(q) models. AR(p) part in the ARMA represents the stationary model that uses values from historical time and uses it as an input variable for the predictive regression equation. Similarly, MA(q) represents the model that uses historical error series and deploys that into a predictive regression equation of errors. AR and MA use correlation among past observations and errors to predict the time series accurately.
(b) Auto Regressive Integrated Moving Average-*ARIMA*.
The difference between ARIMA and ARMA is that an additional parameter d converts a non-stationary sequence into a stationary sequence, indicating that the order difference is converted into a stationary sequence. An ARIMA model is just an ARMA model on a different time series. The ARIMA model is symbolically represented by ARIMA (p, d, q). The autoregressive part of the p model incorporates the impact of past values into the model; that is, the historical value impacts the future. d is the integrated part of the model. The amount of difference required to make the time series stationary. The moving average part of the q model, where the model error can be a linear combination of error values observed at past time points.
(c) Seasonal Auto Regressive Integrated Moving Average-*SARIMA*.
The periodic time series can be used as an extension of ARIMA. Therefore, the periodicity needs to be removed first. SARIMA, a seasonal autoregressive moving average model with an exogenous regression model, abbreviated SARIMA. That is, based on ARIMA, a seasonal part is added. Sea- personality refers to repeating patterns in the data with a fixed frequency: patterns that repeat daily, every two weeks, every four months. The SARIMA model satisfies the multiplication principle; the first half represents the non-seasonal part, the latter represents the seasonal part, and s represents the seasonal frequency.
(d) ARCH/GARCH.
Previously deployed ARMA, ARIMA, and seasonal models generally assume that the variance of the interference term is constant. However, in many cases, the fluctuation of the time series variance is not constant. Therefore, it is essential to study how to characterize the variance. The ARCH and GARCH models are popularly used to describe conditional heteroskedasticity over time. In traditional econometric models, the variance of the disturbance term is assumed to be constant. However, many economic time series exhibit agglomerations of volatility,

in which case it is inappropriate to assume a constant variance. The ARCH model takes all the current available information as a condition and uses some autoregressive form to describe the variance variation. For a time-series, the available information at different times and the corresponding conditional variance are also different. The ARCH model can characterize the conditional variance that varies over time. Although the ARCH model is simple, many parameters are often required to describe the volatility process of returns fully.

In the realm of financial time series forecasting, selecting appropriate models like ARMA, ARIMA, SARIMA, and ARCH/GARCH depends on their ability to capture different aspects of data behavior crucial in financial markets. ARMA and ARIMA models (Selmi et al., 2015; Tahiri et al., 2021; Wu et al., 2020; Yu et al., 2020) are fundamental for modeling the autocorrelation and trend components, respectively, in financial data, which are often characterized by non-stationarity and temporal dependencies. SARIMA (Chronopoulos et al., 2018; Goodfellow et al., 2016; Kumar & Biswal, 2019; Xie & Metawa, 2021) extends ARIMA by incorporating seasonal components, essential for capturing periodic fluctuations common in economic indicators such as quarterly earnings or monthly sales. On the other hand, ARCH/GARCH models address volatility clustering and time-varying volatility often observed in financial returns, offering insights into risk management and portfolio optimization. Together, these models provide a comprehensive toolkit to handle the complexities inherent in financial time series, aiding in more accurate forecasts crucial for investment decisions and risk assessment in volatile market conditions. We will deploy both models in order to forecast the PSX-100 Index accurately.

3.3.2 AI-Based Time Series Models

Forecasting methods can be classified into quantitative or qualitative. Qualitative methods, such as the Delphi Method, involve the empirical knowledge and experience of experts and the opinion of consumers and are used when introducing new products to the market and in cases where no historical record of data or data is insufficient for mathematical modeling. On the other hand, in quantitative methods, it is assumed that the causes that characterized the historical series will continue in a future situation. These methods can be classified into causal or time series analysis. In causality analysis, historical data are used to analyze dependent and independent variables and seek to find causal relationships that influence the future scenario. In time series analysis, the data is organized in the form of time series so that we can recognize trends and seasonal patterns and analyze their behavior over time. This study's quantitative methodology aims to identify the most accurate model amongst the widely used time series and Artificial intelligence-based models in forecasting the PSX-100 Index. This study's methodology will include applying various statistical techniques such as Box-Whisker and Histogram plots for descriptive analysis of index volatility. Once data preprocessing is completed, we will analyze the predicting ability of time series and DL models and compare their predictive ability based on widely acceptable performance metrics. In order to test the capability of timer series models, this study will sequentially move from more straightforward modes to complex time series models while predicting variation in the PSX-100 Index. The choice of an appropriate forecasting method primarily depends on the pattern of available historical data and which technique best suits this pattern. From the data series, it is possible to extract information that allows the mathematical modeling of their behavior, assuming the historical behavior's continuity without the influence of external variables. The quality of forecasts resulting from these methods has proven superior to predictions based on managers' intuition. In addition, these models are updatable based on new data entry. Using a time series model for forecasting is a statistical technique known as extrapolation, in which a pattern is identified as existing over time, and it is assumed that future data will follow this pattern. Quantitative time series forecasting methods can be used if the following conditions are met: Historical information is available, Information can be quantified as numerical data, it is possible to assume that some aspects of the past will be repeated in the future. Previous Studies (Awad et al., 2023; Chandola et al., 2023; Nabipour et al., 2020) shows that Log returns are commonly used in financial analysis because they linearize the multiplicative process of asset price changes over time (PCOT), making it easier to interpret and model. By taking the DL method of the ratio of current and previous prices, log returns convert multiplicative changes into additive changes, which are easier to handle statistically. This transformation is particularly beneficial in predicting future price movements because it stabilizes the variance of the returns and simplifies the assumptions of many financial models. In DL applications, using log returns stabilize the training process by reducing the scale of input data, which can prevent issues such as vanishing or exploding gradients. Additionally, log returns often exhibit more Gaussian-like properties compared to raw price changes, which can improve the performance of neural networks that assume Gaussian distributions.

(a) Auto Regressive Models

Among a wide range of time series models, Autoregressive models assume that the means and variance of data should remain constant throughout the period. However, under practical time series data generated by the stock market, we can observe that the variance never remains constant due to the volatility of the closing index. Therefore, the core methodology of this research will aim toward applying Autoregressive Conditional Heteroskedasticity models. Specifically, we will focus on the various tuned versions of generalized ARCH models that were mainly introduced to consider the existence of heteroscedasticity within time series data. For a significant period, researchers and professionals remained inclined over time series-based GARCH models for predicting market volatility and minimizing the risk in their institutional investments. In the existing market dynamics and computing resources scenario, many researchers look towards artificial intelligence-based models. Neural networks introduced under the umbrella of DL algorithms proved to be more accurate than traditional time series models. Therefore, we will apply neural network-based algorithms

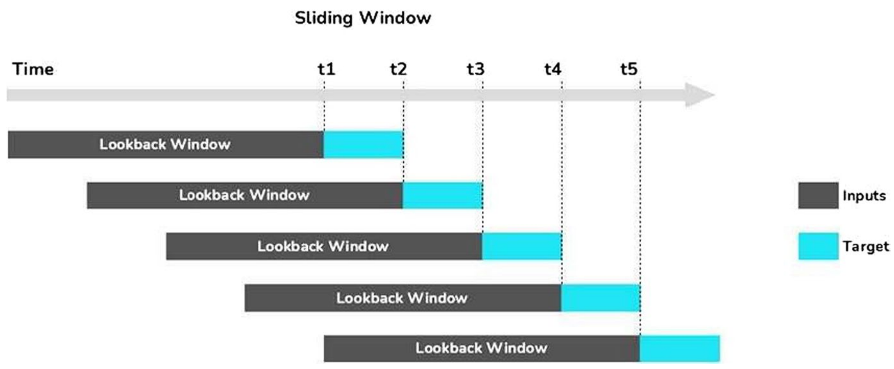

Fig. 1 Sliding Window

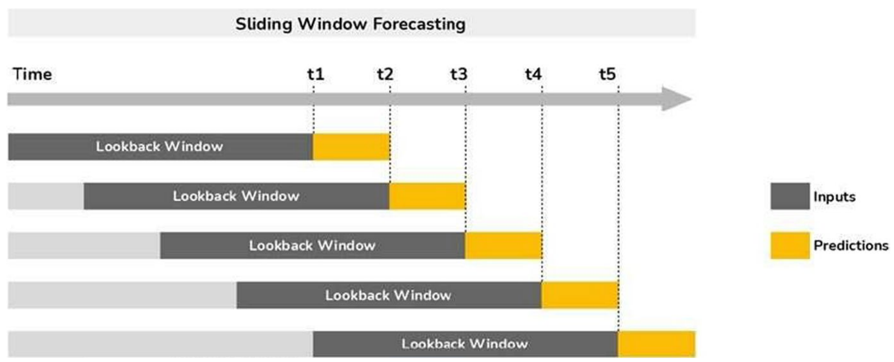

Fig. 2 Sliding Window Forecasting

to predict the PSX-100 index and test the accuracy against the best-fitted time series model. In order to forecast the PSX-100 index using the Neural Network-based algorithms, we will not initially input the whole data. Instead, we will be striding the data by one and ensuring to get all possible combinations of inputs and outputs. A pictorial demonstration of sliding windows can be observed in the following Fig. 1.

The same sliding concept will be deployed in order to generate predictions from the neural networks (Fig. 2).

For estimating the accuracy of DL models in predicting the PSX-100 Index, we will apply a fully connected neural network as a baseline model of DL and, later in the methodology, move towards tuned models of Neural Networks that are commonly described as Recurrent Neural Networks (RNN). RNN models in DL have proved to perform well in predicting time series data, especially for stock markets, and can process textual or multimedia-based data as inputs Fig. 3.

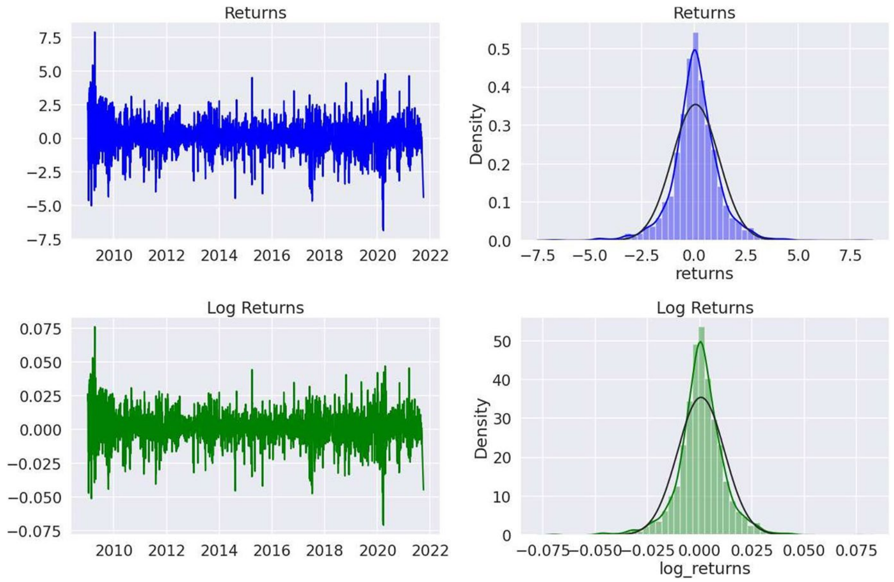

Fig. 3 Returns Volatility Distribution

4 Implementations & Results

4.1 PSX-100 Index Market Volatility Exploration

4.1.1 Returns Distribution

The distribution plots related to the PSX-100 Index returns log returns reveal that historical and implied volatility almost have zero skewness because the graph is symmetrical. This depicts that both the returns and the log return of the index follow a normal distribution. Additionally, it can be observed that the returns distributions are leptokurtic. In simple terms, they possess positive kurtosis because distribution peaks are higher than standard normal distribution. Figure 4 depicts the distribution of index returns and enables visual comparison with standard normal distribution:

The distributions of the returns are too noisy for shorter tenors and make it difficult to grasp any meaningful pattern. Therefore, by use of time intervals, we will classify the tenors and then visualize the historical volatility of the PSX- 100 index. It can be noticed in Fig. 5 that the volatility becomes mean-reverting and gets smoothed with longer tenors of time intervals.

4.1.2 Daily Volatility Exploration

In order to target a specific pattern of future volatility for prediction, we have plotted the future volatility based on changes in actual volatility in the market. The following graphs represent the current and future volatility for the whole data

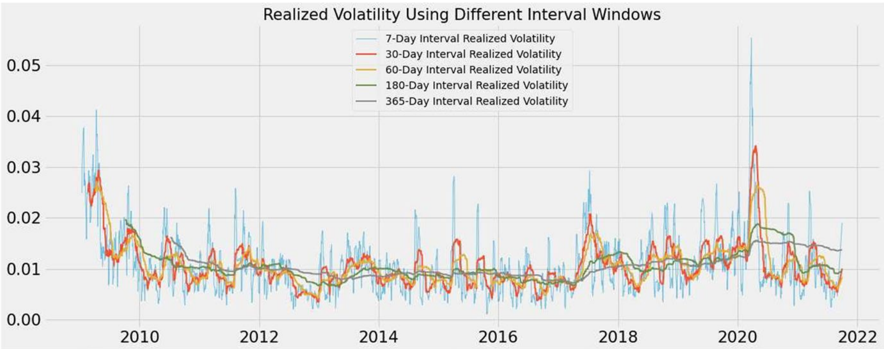

Fig. 4 Realized Volatility for diverse Intervals

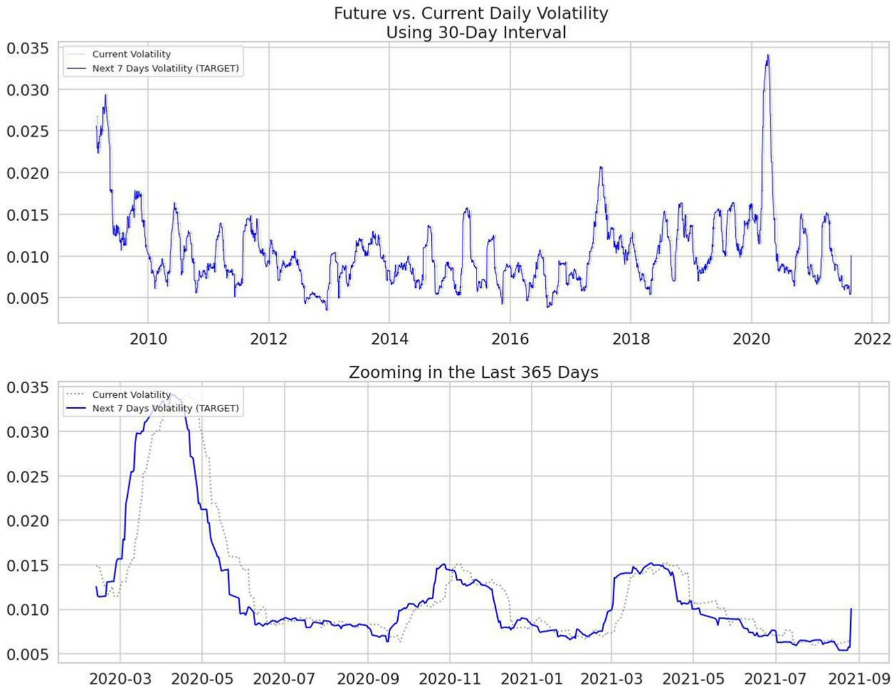

Fig. 5 Future vs. Current Daily Volatility

in the first plot and the recent year in the second plot in Fig. 6. As depicted in Fig. 6, the blue line indicates the target future value we will estimate using our time series and DL models. At the same time, the dotted gray line depicts the current realized volatility in the PSX-100 index. It shows that the current volatility is moved back to become a future index, which we will ultimately aim to predict in this study.

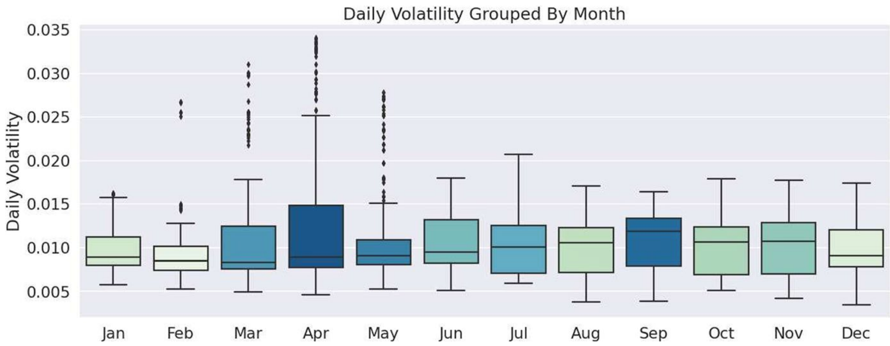

Fig. 6 Daily Volatility Grouped by Month

4.1.3 Daily Volatility Grouped by Month

The box plot of the grouped volatility every month reveals that most of the outliers in the data appeared during the first five months. The following plot depicts that volatility reaches its peak in March, April, and May. Whereas, from June onwards, there was no outlier on monthly levels, as shown in Fig. 7.

The outliers in March, April, and May likely occurred due to significant market events or economic factors affecting volatility during those months. Factors such as major geopolitical events (Election Held in Pakistan), economic data releases, or shifts in investor sentiment should have contributed to heightened volatility and the appearance of outliers in those specific months. As these months coincide with the peak period of volatility, it presents a period of heightened market uncertainty (PSX- 100 index) and fluctuation, influencing the presence of outliers in the data.

4.1.4 Daily Volatility Grouped by Year

Yearly grouped volatility in Fig. 8 depicts that the worst-case scenario of increased volatility was observed during 2020, mainly due to the country's economic turmoil

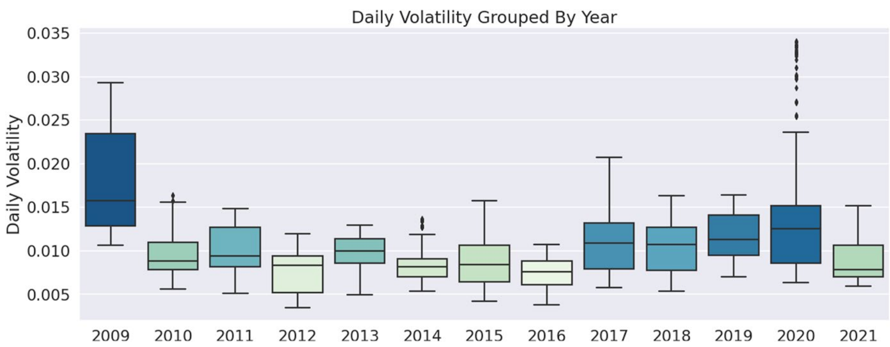

Fig. 7 Daily Volatility Grouped Annually

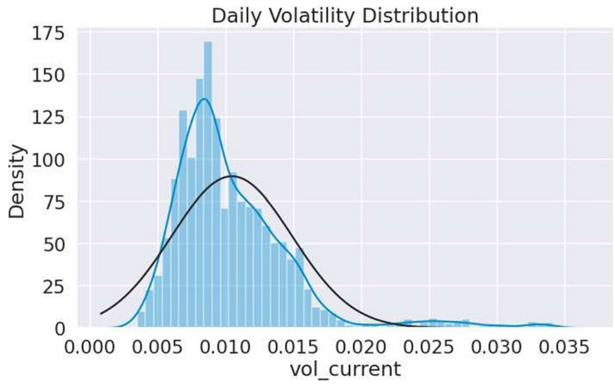

Fig. 8 Volatility Distribution

triggered by COVID-19. Whereas increased volatility after the election in 2013 can be observed in 2014. Other than that, there are no significant outliers in the volatility data points.

4.1.5 Daily Volatility Distribution

It can be observed in Fig. 9 that the distribution of daily realized volatility of the PSX- 100 Index closing appears to be skewed on the right side, along with some upper bound data spread thinly on the right. Statistically, a rightly skewed distribution will possess a lower median than the mean. At the same time, the mode of the values will be lower than the median (mode < median < mean).

4.1.6 Returns/Log Returns Stationary Checking

In order to apply time series models and understand the behavior of data concerning change in time, we tested the stationarity of PSX-100 Index returns and log returns based on the ADF KPSS test. The results of the statistical tests confirm that both

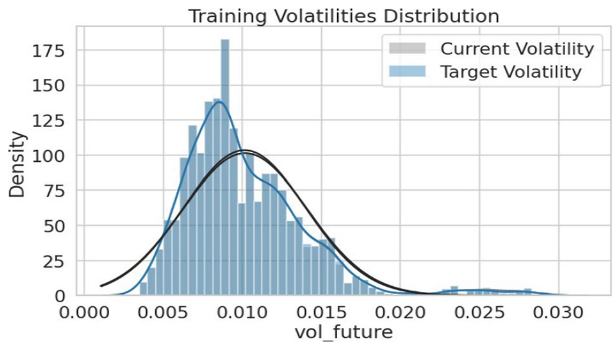

Fig. 9 After Scaling-Volatility Distribution

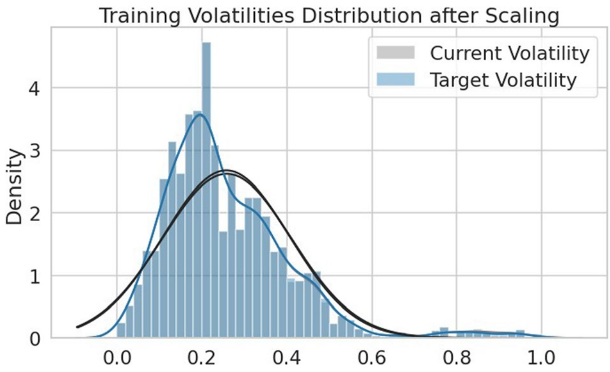

Fig. 10 Before Scaling-Volatility Distribution

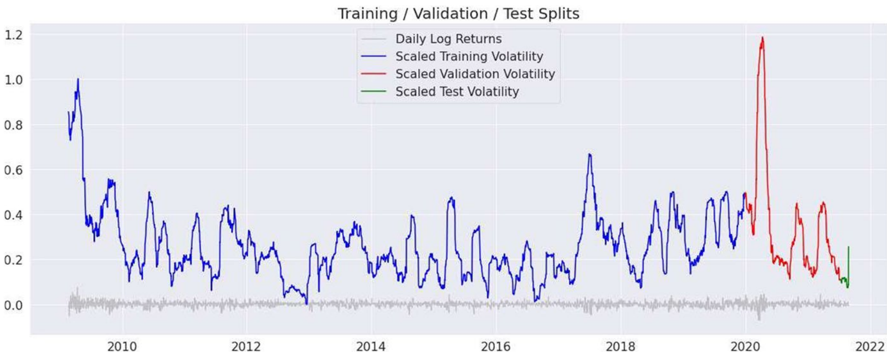

Fig. 11 Training/Validation Splits

return time series are stationary. At 95% confidence interval, the value of significance of all combinations of ADF and KPSS test on returns and log returns data were less than 0.05. Therefore, we can reject the null hypothesis and conclude that the time series is stationary. In order words, returns and log-returns of the PSX-100 index depend on time or some trend the market follows.

- Feature Normalization

During the analysis of this study, we have to build multiple models related to time series and DL-based algorithms. Therefore, we should normalize the PSX-100 index volatility and make generalizable forecasts by various models. On the analysis level, we tried various scalers and compared the results. After thorough practical attempts, we used MinMaxScaler to normalize the data. Figures 10 and 11 depicts the volatility distribution for the training data set before and after scaling the data. We will build various models based on different algorithms using different types of inputs. Normalizing the volatilities to standardize the predictions generated by different models would be better. After experimenting with different Scalers, we decided to use MinMaxScaler as it yielded the best results overall.

4.2 Dataset Division

In Fig. 12, it can be observed that the volatilities of the PSX-100 Index shifted in the range of (0, 1) compared to the original volatility that ranged from (0,0,035).

4.3 Model Evaluation Metrics

To evaluate the effectiveness of the proposed methodology, we have utilized the Root Mean Squared Error-RMSE, and Root Mean Squared Percentage Error-RMSPE. RMSE measures the average magnitude of the error in predictions compared to actual observed values. RMSPE is similar to RMSE but considers the relative percentage error rather than absolute error.

$$RMSE = \sqrt{\frac{\sum \left(s_a - \hat{s}_a\right)^2}{X - P}} \tag{4}$$

$$RMSPE = \sqrt{\frac{1}{x} \sum_{k=1}^{x} \left(\frac{s_a - \hat{s}_a}{s_a}\right)^2} \tag{5}$$

RMSE and RMSPE serve as key metrics in assessing how well a volatility forecasting model performs compared to actual data. Lower values of these metrics indicate more accurate predictions, which is crucial for making informed decisions in financial markets where volatility forecasting plays a significant role.

4.4 Baseline Models

In longer tenors, Volatility possesses an integral mean-reverting nature. Therefore, we will use this as the first baseline model since we have long-term time series data for forecasting the market index volatility. This model will forecast by showcasing the actual average of training data. The outcome of this mean-reverting model depicted an RMSE of 0.277 and an RMSPE of 0.512. Figure 12 reveals the model's volatility forecast, and a straight-line forecast can be observed, as stated above. Volatility has a well-known tendency to be autocorrelated and its clusters in the near term. A simple model that can forecast PSX-100 Index volatility by utilizing the daily Volatility at the most recent time step can be implemented using this characteristic. Therefore, at this analysis stage, we use the immediate interval's average daily volatility to make forecasts for the following seven days, simply using current and future volatility. Results of the model revealed an RMSE of 0.108 and an RMSPE of 0.273. Being a simpler model, the prediction improved significantly, as depicted in Fig. 13.

The GARCH model projection includes a predicted conditional volatility characteristic for the training section of the data set because it is fitted to training data. In order to compare it with volatility estimated in preceding models, the analysis fitted and scaled to the conditional volatility arrays in training data and plotted it in Fig. 14. Predicting the accuracy of analytical forecasting with GARCH depicted RMSE and RMSPE of 0.167 and 0.412, which stood lower than the baseline Random Walk Naive Model. The fundamental GARCH theory asserts that good and bad signals influence market volatility similarly. In truth, the effect is frequently asymmetric, with negative signals having a more significant influence on volatility than positive ones. Fig. 15 Glosten- Jagannathan-Runkle GARCH(GJR-GARCH) model of the GARCH family considers the asymmetry in shock responses. By altering the additional inputs, we have converted our model into GJR-GARCH. In this model, we have set $o=1$ in order to transform into GJR-GARCH with variance dynamics. This change asserts that the GARCH model will now hold one lag of an asymmetric shock. Model parameters depicted in Fig. 16 show that Log-likelihood increased compared to GARCH (1, 1). Compared with GARCH (1, 1), GJR-GARCH with Skewed Student's *T* depicted better prediction accuracy with RMSE of 0.159 and RMSPE of 0.408. As depicted in Fig. 17, the distance between the actual and predicted volatility of the PSX-100 Index decreased in this model, but it still lags behind the random walk naive model Fig. 18.

The Threshold Autoregressive Conditional Heteroskedasticity (TARCH) model in time series forecasting is used in this study for estimating volatility based on absolute data. It is specified by altering the default power of 2 into 1. This change in the model specification will specify that the variance shifts in squares. A dummy variable also includes asymmetric influence in the GARCH framework. The fitted TARCH model depicts in Fig. 19 similar results for Log-likelihood and AIC/BIC compared to the previously fitted GJR-GARCH model. Further, we have examined estimated conditional volatility compared with scaled current volatility. The predictive performance of the TARCH-based model depicted promising performance based on RMSE of 0.143 and RMSPE of 0.323, as depicted in This model has proved to be the best in the GARCH family for forecasting PSX-100 Index volatility. In addition to bootstrap-based forecasting of PSX-100 Index volatility, we tested the model performance based on simulation-based forecasting with the same settings as in A.9. Fig. 20. Both models depicted RMSPE of 0.323; hence, predicting accuracy is approximately equal. Among the time series models, TARCH, an asymmetric GARCH family model, best predicted the volatility in the PSX-100 Index. Therefore, we performed hyperparameter tuning for TARCH. This will help us identify the best possible values of p, q, and o for the TARCH model. Based on RMSPE, the best possible permutation of parameters was TARCH (2, 2, 0) based on RMSPE equal to 0.269, as depicted in Fig. 21.

4.5 Deep Learning Models

According to the efficient market hypothesis, highly efficient stock markets are unpredictable. Contrary to this, behavioral finance states otherwise. Traditional markets have been there since the oldest civilizations. Therefore, traders, being human beings, hold psychological tendencies that have developed based on historical evidence. In addition, there has been an event in which the participant's behavior drove the course of markets. Therefore, we cannot think that market movements are random and cannot be predicted. There must be some pattern if there is any involvement of market participant's behavior. DL models have proven their performance in artificial intelligence for mimicking the human brain. Therefore, to forecast the index movement of the PSX-100 index movement, we experimented with DL-based neural networks and came up with the best combination of model parameters. We modeled the index using a fully connected neural network as a baseline DL model. As depicted in Fig. 22 with an RMSPE of 0.258, a fully connected neural network with 100 training epochs performed well compared to the top-rated time series models. Theoretically, in DL, RNN are more precise in dealing with time series data than traditional connected neural networks. We have deployed LSTM in this study because it can hold significant information for long-term dependencies in time series data-related inputs. For fitting this model, we used a look-back window of 14 days. We tuned the model parameters based on model outcomes to increase prediction accuracy. LSTM network of one hidden layer and 20 units was initiated using Adam optimizer. As depicted in Fig. 23, the PSX-100 index forecast made by the LSTM model appeared to move closely like the actual current volatility. However, the results are different from the desired target for prediction accuracy.

Moving forward from simpler LSTM, we tried predicting the stock index using the Univariate Bidirectional LSTM model. The bi-directional LSTM model aims to offer added context to the neural network. It will train two LSTM models; the first will be based on original inputs, while the second will be trained on reversed copies of inputs. In addition, LSTM can learn long-term memories. Therefore, to test the predictive accuracy of the DL model in a competitive environment, we increased the past data to 1 month with an additional hidden layer to test the impact of long-term dependence memories of LSTM in predictive accuracy. It can be observed in Fig. 24 that Bidirectional LSTMs proved their superiority over the best time series models found earlier in this study. This Uni-variate Bidirectional LSTM model predicted the PSX-100 Index volatility with the lowest RMSPE of 0.220 and RMSE of 0.096.

Adding convolution layers in the bi-directional LSTM model was expected to help the model learn additional patterns in the time series with an increased look-back window. Generally, 1D convolution layers glide several kernels in a sequence. Therefore, we tested whether adding convolution layers can help increase the predicting accuracy of the DL models. Based on the RMSPE of 0.248 and RMSE of 0.101, we can conclude that adding a convolution layer did not help improve the model's performance, as depicted in Fig. 25 For testing the accuracy of DL-based models, till now, we have been using Adam optimizer. The model's performance based on some customized optimizer must also be examined.

Therefore, we deployed the Stochastic Gradient Descent (SGD). We tested the SGD optimizer with the best-performing model tested during the analysis, i.e., bi-directional LSTM. As depicted in the Fig. 26, the most significant learning rate was 6.9e-5. Therefore, we trained a model based on a tuned learning rate. Results of the model revealed that customized optimizer prioritized volatility's long-term tendency towards the average.

For this reason, it can be observed in Fig. 27 that the PSX-100 Index prediction drifts around the average. In addition, the RMSPE and RMSE of the model also declined to 0.525 and 0.314. Therefore, we used Adam optimizers to analyze the DL models further. In order to test the DL models up to this point, we used straightforward uni-dimensional inputs, which probably need to be improved in financial data analysis. This might be the cause for most models above apparent failure in generating better results that were superior to Naive Forecasting. The number of neurons, hidden layers, or the complexity of models does not matter; if we feed the inadequate data as inputs, then models are likely to yield subpar results. Therefore, we tried to build multivariate neural networks in further analysis to investigate if adding more features can boost performance in predicting the PSX-100 Index.

Further, in the data analysis of this study, we deployed feature engineering and derived two features that are significantly correlated with each other. The logarithmic difference between the maximum and minimum PSX-100 index on a trading day was a high-low spread and presented as a percentage of the closing PSX-100 index. The second feature was the spread of the opening and closing index of the PSX stock market. Activation functions used by the LSTM-based neural networks use Sigmoid and tanh as activation functions. Therefore, we normalized the data because of their sensitivity towards magnitude.

Based on multivariate LSTM models, we targeted forecasting weekly volatility of the PSX-100 Index based on three features derived using feature engineering. The features that will be used for our target forecasting are the high-low, open-close spread, and the current volatility of the market; in order to transform data as an input for multivariate LSTM, we reshape the data into the following form inputs: Size of the batch: Total number of observations in each batch. Past period: Depicts several past time steps that will be used as inputs for forecasting. Dimension of Inputs: Depicts the number of input features for the model. Moving forward, we deployed Multivariate 2-layered Bidirectional LSTM with Dropout. It was based on two bi-directional hidden layers LSTM model. The model under consideration had more chances of being overfit because of the increased features. Therefore, we will use Dropout layers in between to diminish the overfitting impact on the model outcomes. The results of the model were quite promising. As depicted in Fig. 28, the forecasted index volatility line shifted horizontally near the direction of target volatility and followed the line closely at various point internals with decreased noise. The RMSPE and RMSE of 0.176 and 0.08 proved the most accurate forecasts among the previously fitted time series and DL models.

In order to further test the capability of multivariate LSTM, we added more layers to the model and checked the change in forecasting accuracy. A

Multivariate three-layered bi-directional LSTM was opted for this purpose, as depicted in Fig. 29 The results of adding more layers depicted increased accuracy by increasing the RMSPE marginally from 0.176 to 0.171 and RMSE from 0.08 to 0.07. However, the four-layered model also depicted decreased performance, as depicted in Fig. 30. Moving towards the finalization of the most accurate models, we also made use of Talos for LSTM network tuning and fitted the model based on tuned parameters, as depicted in Fig. 31 Tuned LSTM model depicted RMSPE of 0.168 and 0.07, i.e., by far the best results we got from our forecasting models as depicted in the following Table 1.

5 Discussion

Table 1 providing insights into performance across different employed models with PSX-100 Index in this study. Traditional statistical models like GARCH (1, 1) and its variants show moderate performance, with RMSPE ranging from 0.269 to 0.412 and RMSE from 0.130 to 0.164. These models are valued for their simplicity and interpretability but may struggle with capturing complex nonlinear patterns in data, especially in highly volatile or skewed distributions. Moving to more advanced machine learning models, such as fully connected neural networks and LSTM-based architectures, significant improvements in forecasting accuracy are observed. The one-layered LSTM RNN exhibits an RMSPE of 0.247 and RMSE of 0.098, indicating better performance than most traditional models. The multilayered LSTM RNNs, particularly the two-layered bidirectional LSTM with or without convolutional layers, achieve even lower errors (RMSPE around 0.221 to 0.248 and RMSE around 0.096 to 0.101), showcasing their ability to capture temporal dependencies and nonlinear relationships effectively. However, the model's performance can vary based on hyperparameter tuning and architectural choices, as seen in the case of the two-layered bidirectional LSTM with SGD, which unexpectedly exhibits higher errors, highlighting sensitivity to optimization methods and learning rates. Overall, while traditional statistical models provide a baseline for comparison, machine learning techniques like LSTM RNNs offer substantial improvements in accuracy due to their ability to handle sequential data and learn complex patterns. However, these models require careful tuning and consideration of architectural choices to maximize their forecasting capabilities, underscoring the importance of empirical validation and optimization in model selection for time series forecasting tasks.

6 Future Direction

After the analysis carried out in the research document, the following recommendations are provided: Recommendations to future researchers and those interested in studying the volatility of the PSX-100 Index: We recommend that we consider the constantly evolving economic scenarios of the country because there are multiple factors other than the fundamental health of the market that can lead to an increase

Table 1 Summarized Performance Metric for Forecasting Models

Fitted models	RMSPE	RMSE	MSE
Mean Baseline	0.513	0.277	0.0767
Random Walk Naive Forecasting	0.273	0.108	0.0116
GARCH (1, 1) model with Normal Distribution/Const. Mean	0.412	0.164	0.0268
Analytical GJR-GARCH (1, 1, 1) with Skewed Distribution/Const Mean	0.408	0.160	0.0256
Bootstrap TARCH (1, 1) with Skewed Distribution/Const. Mean	0.323	0.143	0.0204
Simulation TARCH (1, 1) with Skewed Distribution/Const. Mean	0.324	0.143	0.0204
Bootstrap TARCH (2, 2, 0) with Skewed Distribution/Const. Mean	0.269	0.130	0.0169
Neural/Network Completely Connected NN	0.258	0.099	0.0098
One-layered LSTM RNN	0.247	0.098	0.0096
Two-layered Bidirected LSTM RNN	0.221	0.096	0.0092
Two-layered Bidirected LSTM RNN with Convolution Layer	0.248	0.101	0.0102
Two-layered Bidirected LSTM RNN with SGD and best learning rate	0.525	0.314	0.0985
Two-layered Multivariate Bidirected LSTM RNN	0.176	0.078	0.0060
Three-layered Multivariate Bidirected LSTM RNN	0.171	0.075	0.0056
Four-layered Multivariate Bidirected LSTM RNN	0.184	0.078	0.0060
Multivariate Two = layered Bidirected LSTM RNN (32/16 units), tanh	0.168	0.071	0.0050

in market volatility. A highly abundant US dollar in Pakistan is impacting the regular operations of many listed corporations, which will be reflected in stock price and eventually contribute towards shifting the market return. Therefore, it is recommended to do more research on significant events that can impact returns of the PSX-100 Index and include them in the multivariate LSTM RNN models to increase the predicting accuracy. The best model was able to touch the highest accuracy of 83%. Therefore, there must be some factors that can drive the accuracy above 90%. Likewise, experimenting based on higher frequencies data of the PSX-100 index, such as intra-day closing position at every 30 min, can provide a better basis for training forecasting models. In addition, NLP-based textual data can also be incorporated to test the impact of live news on the market returns of the PSX-100 index.

7 Conclusion

Comparative analysis of prediction analysis on the PSX- 100 Index validation dataset confirmed that DL models hold better accuracy in forecasting than traditional time series models. The LSTM model depicted an RMSPE of 0.168201, which is around 10.08% accurate compared to the top performing variant of GARCH models, such as TARCH (2, 2) holding RMSPE of 0.269004. Practically, dealers in the market do not have to get an exact estimate to have an optimistic assumption while partaking in stock market investments. The primary requirement of the market participants is to have a forecast that is beyond the consensus of the market and based on actual scientific phenomena. Traditionally, professionals in Pakistan prefer a simple forecasting model, and by far, GARCH can be termed the gold standard for forecasting related problems. However, the multivariate LSTM models can help market participants decide the parameters of their dealings based on better-forecasted figures. The added accuracy of LSTM models can provide an edge to the dealers in the market. The ultimate fitted LSTM model depicted an RMSPE of 0.168207 on a validation data set of the PSX-100 Index. Because RMSPE depicts the average magnitude of residuals. actual closing index, RMSPE of 0.16821 points towards performance accuracy around 83.17% on seven-day interval daily volatility forecasting during the study period. Due to the constant shift in the economic situation of Pakistan, the PSX-100 index depicts a time series of data that is regularly developing. Therefore, we cannot remain confident that a single forecasting model will be able to forecast the market volatility with high accuracy. Theoretically, the mean lifetime of any forecasting model lies within a six-month five-year interval mainly because of alpha decay, such as decreasing the accuracy of a model concerning time. Further, recent studies depicted that market returns decrease up to 58% mainly due to the periodical release of innovative edge techniques or market anomalies. In order to have a reliable forecast of the stock market, professionals need to constantly tune the forecasting modes with recent data and advanced techniques to remain up-to-date and advance over time.

8 Data Availability Statement

Dataset are available from the authors upon reasonable request and with permission of Author.

Appendix A

Forecasting Models

See Figs.12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31,

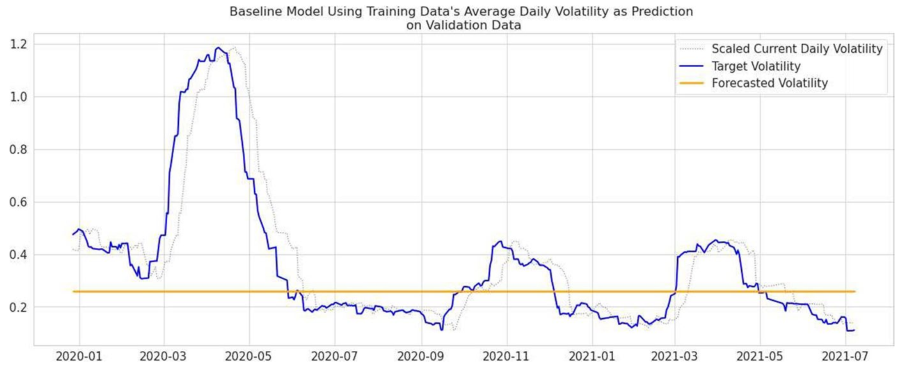

Fig. 12 PSX-100 Index Baseline Model Forecast

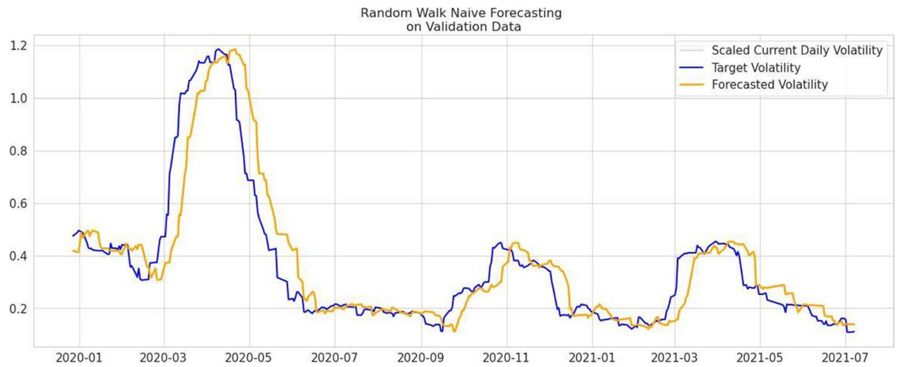

Fig. 13 PSX-100 Index Random Walk Naive Model Forecast

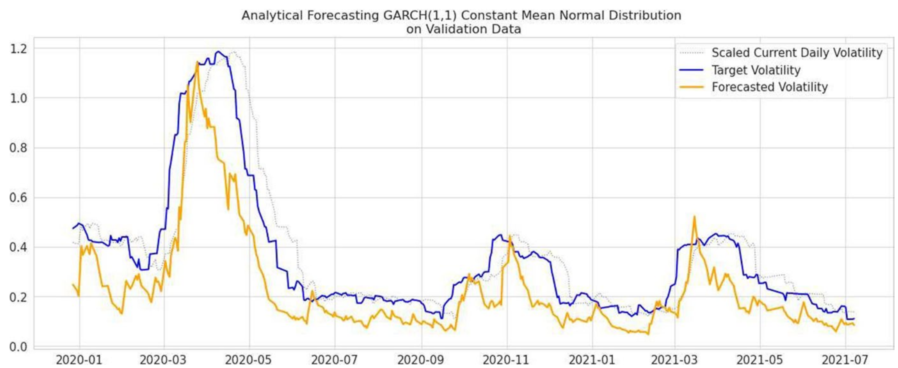

Fig. 14 PSX-100 Index Analytical Forecasting GARCH (1, 1) Constant Mean Normal Distribution

```
                     Constant Mean - GARCH Model Results
==============================================================================
Dep. Variable:                returns   R-squared:                       0.000
Mean Model:             Constant Mean   Adj. R-squared:                  0.000
Vol Model:                      GARCH   Log-Likelihood:               -3646.24
Distribution:                  Normal   AIC:                           7300.48
Method:            Maximum Likelihood   BIC:                           7323.95
                                        No. Observations:                 2615
Date:                Sat, Dec 10 2022   Df Residuals:                     2614
Time:                        19:51:49   Df Model:                            1
                                 Mean Model
============================================================================
                 coef    std err          t      P>|t|    95.0% Conf. Int.
----------------------------------------------------------------------------
mu             0.1105  1.889e-02      5.851  4.879e-09 [7.350e-02,  0.148]
                              Volatility Model
==============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
------------------------------------------------------------------------------
omega          0.0428  1.580e-02      2.706  6.805e-03 [1.179e-02,7.372e-02]
alpha[1]       0.1021  2.461e-02      4.149  3.344e-05   [5.387e-02,  0.150]
beta[1]        0.8594  3.422e-02     25.117 3.276e-139     [  0.792,  0.926]
==============================================================================

Covariance estimator: robust
```

Fig. 15 GARCH (1, 1) Model Summary

```
                      Constant Mean - GJR-GARCH Model Results
====================================================================================
Dep. Variable:                          returns   R-squared:                   0.000
Mean Model:                       Constant Mean   Adj. R-squared:              0.000
Vol Model:                            GJR-GARCH   Log-Likelihood:           -3552.63
Distribution:      Standardized Skew Student's t   AIC:                       7119.25
Method:                      Maximum Likelihood   BIC:                       7160.34
                                                  No. Observations:             2615
Date:                          Sat, Dec 10 2022   Df Residuals:                 2614
Time:                                  19:52:09   Df Model:                        1
                                 Mean Model
============================================================================
                 coef    std err          t      P>|t|    95.0% Conf. Int.
----------------------------------------------------------------------------
mu             0.0898  1.745e-02      5.150  2.609e-07 [5.565e-02,  0.124]
                              Volatility Model
==============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
------------------------------------------------------------------------------
omega          0.0442  1.221e-02      3.623  2.913e-04 [2.030e-02,6.815e-02]
alpha[1]       0.0484  1.226e-02      3.950  7.800e-05 [2.440e-02,7.244e-02]
gamma[1]       0.1589  3.800e-02      4.181  2.906e-05   [8.439e-02,  0.233]
beta[1]        0.8396  2.790e-02     30.092 6.220e-199     [  0.785,  0.894]
                                Distribution
==============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
------------------------------------------------------------------------------
```

Fig. 16 GJR-GARCH (1, 1, 1) Model Summary

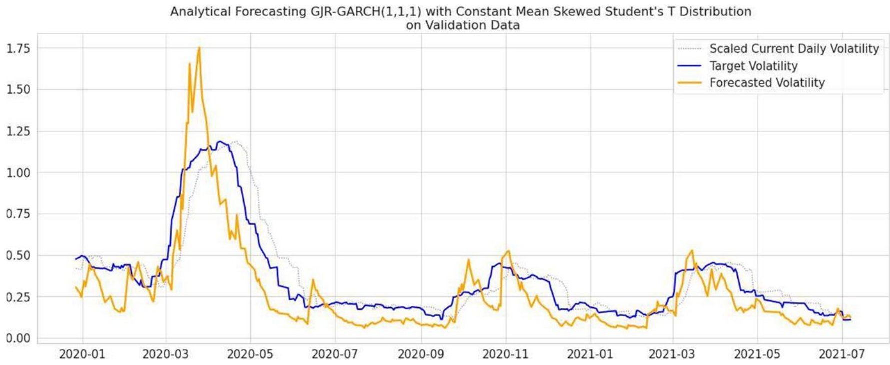

Fig. 17 PSX-100 Index Analytical Forecasting GJR-GARCH (1, 1, 1) with Constant Mean Skewed Student's T Distribution

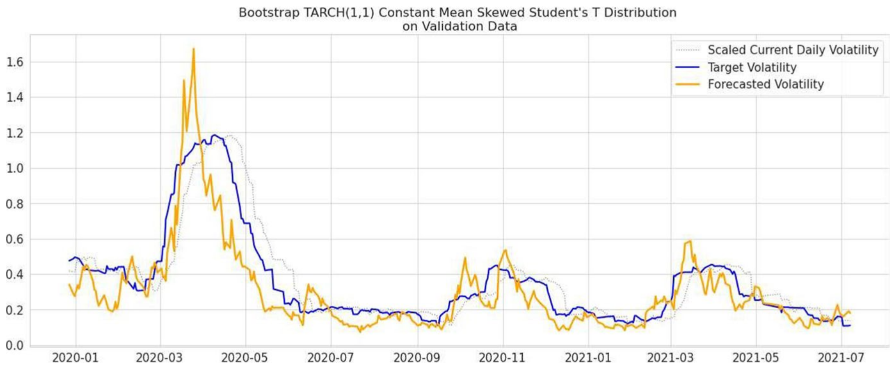

Fig. 18 PSX-100 Index Bootstrap TARCH (1, 1), Constant Mean, Skew Dist. Fore- casting

```
                      Constant Mean - TARCH/ZARCH Model Results
==========================================================================================
Dep. Variable:                              returns   R-squared:                       0.000
Mean Model:                           Constant Mean   Adj. R-squared:                  0.000
Vol Model:                              TARCH/ZARCH   Log-Likelihood:               -3543.06
Distribution:      Standardized Skew Student's t     AIC:                           7100.13
Method:                          Maximum Likelihood   BIC:                           7141.21
                                                      No. Observations:                2615
Date:                              Sat, Dec 10 2022   Df Residuals:                    2614
Time:                                      19:52:45   Df Model:                           1
                                Mean Model
===========================================================================
                 coef    std err          t      P>|t|     95.0% Conf. Int.
---------------------------------------------------------------------------
mu             0.0887  1.710e-02      5.189  2.120e-07 [5.522e-02,  0.122]
                             Volatility Model
=============================================================================
                 coef    std err          t      P>|t|       95.0% Conf. Int.
-----------------------------------------------------------------------------
omega          0.0446  1.156e-02      3.859  1.137e-04 [2.195e-02,6.725e-02]
alpha[1]       0.0658  1.256e-02      5.241  1.596e-07 [4.121e-02,9.045e-02]
gamma[1]       0.1249  2.247e-02      5.558  2.723e-08   [8.085e-02,  0.169]
beta[1]        0.8595  2.175e-02     39.523      0.000     [  0.817,  0.902]
                              Distribution
==============================================================================
                 coef    std err          t      P>|t|        95.0% Conf. Int.
------------------------------------------------------------------------------
eta            6.3859      0.748      8.542  1.323e-17      [  4.921,  7.851]
lambda         0.0143  2.426e-02      0.591      0.555 [-3.321e-02,6.187e-02]
==============================================================================
```

Fig. 19 TARCH (1, 1) Model Summary

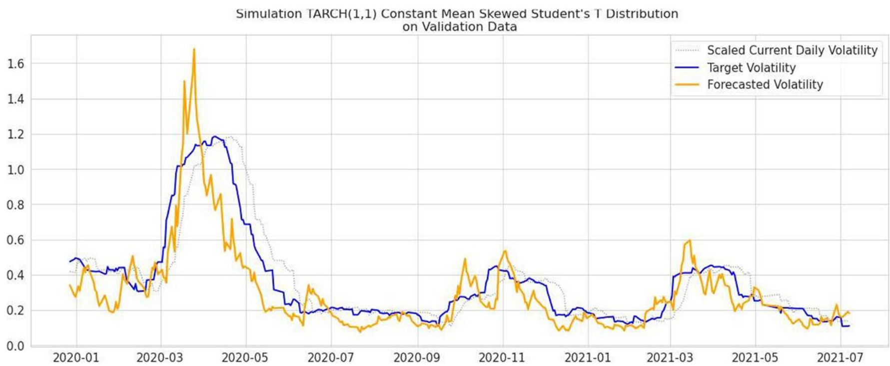

Fig. 20 PSX-100 Index Simulation TARCH (1, 1), Constant Mean, Skew Dist. Forecasting

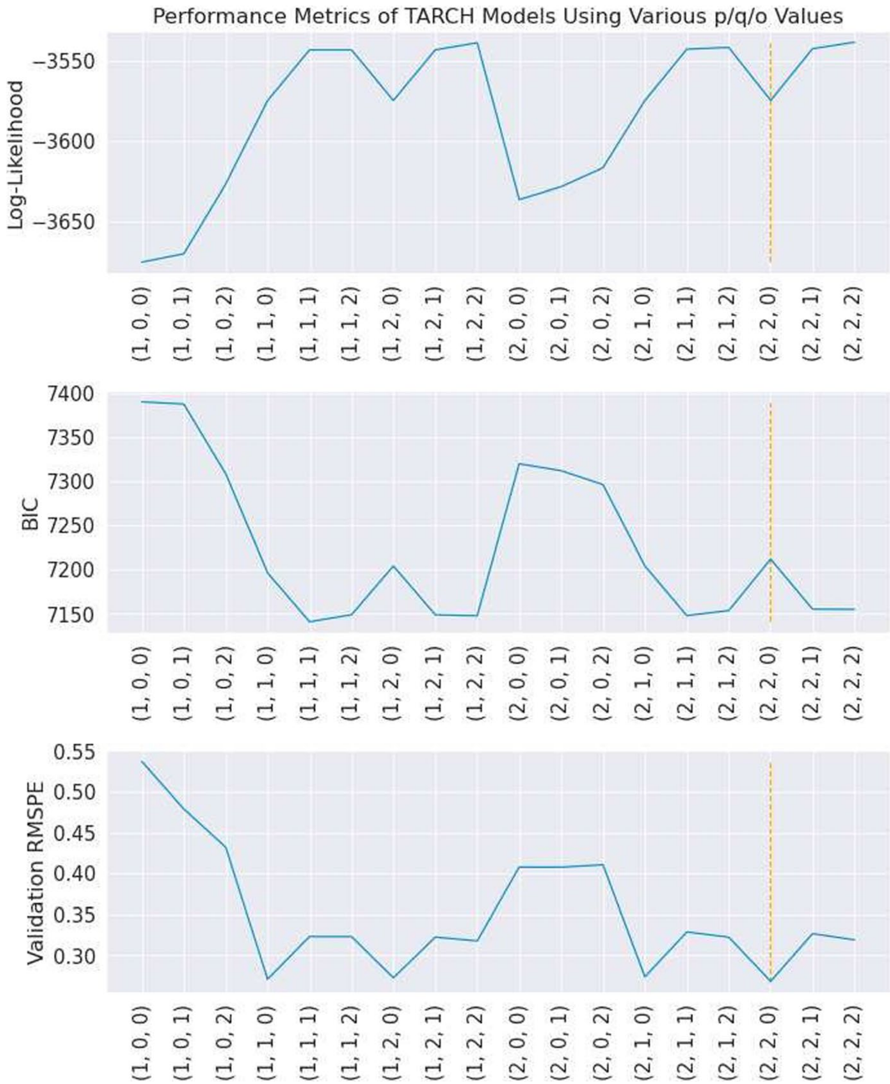

Fig. 21 Performance Metrics of TARCH for different p/q/o

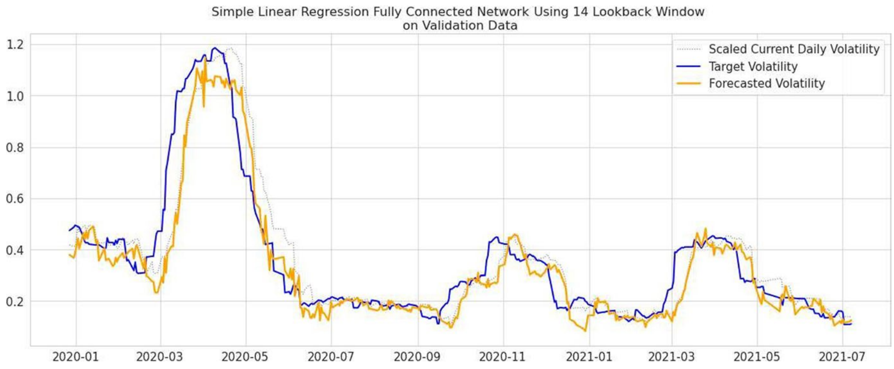

Fig. 22 Fully Connected Neural Network

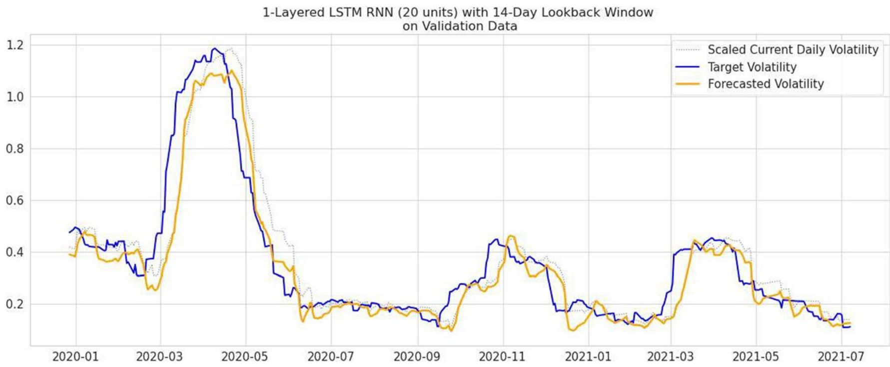

Fig. 23 One-layered LSTM RNN

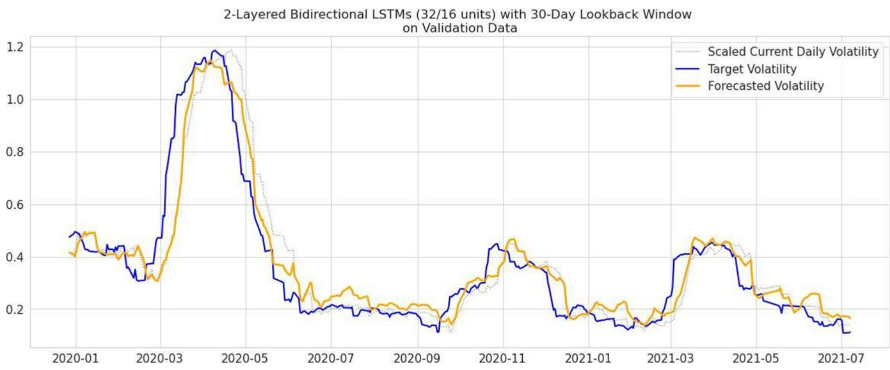

Fig. 24 Two-layered Bidirectional LSTM RNN

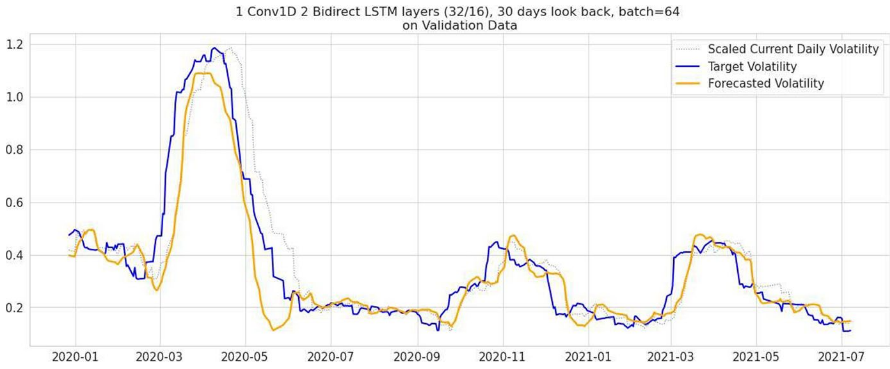

Fig. 25 Two-layered Bidirectional LSTM RNN with Convolutional Layer

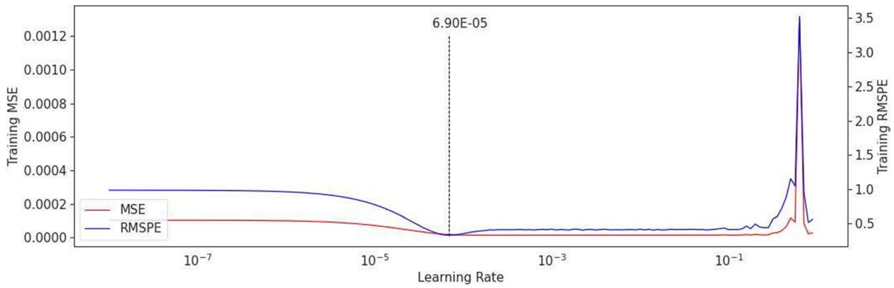

Fig. 26 Learning Rate

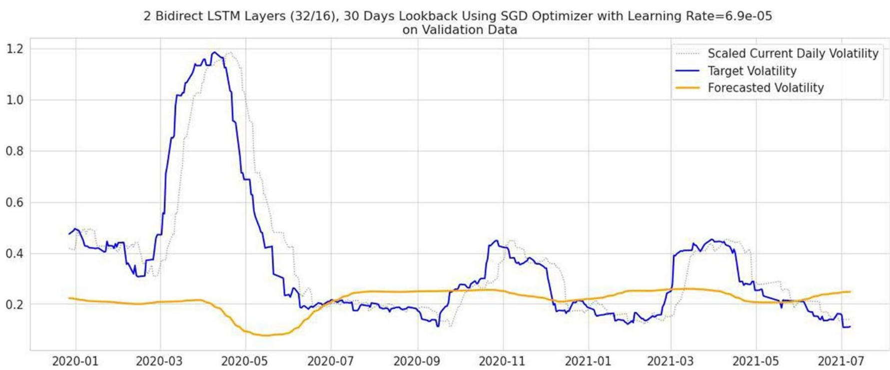

Fig. 27 Two-layered Bidirectional LSTM RNN using SGD Optimizer with best Learning Rate

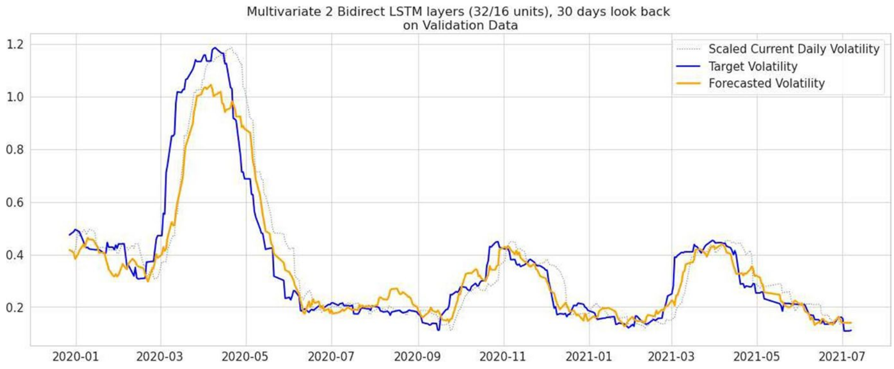

Fig. 28 Multivariate Two-layered Bidirectional LSTM RNN

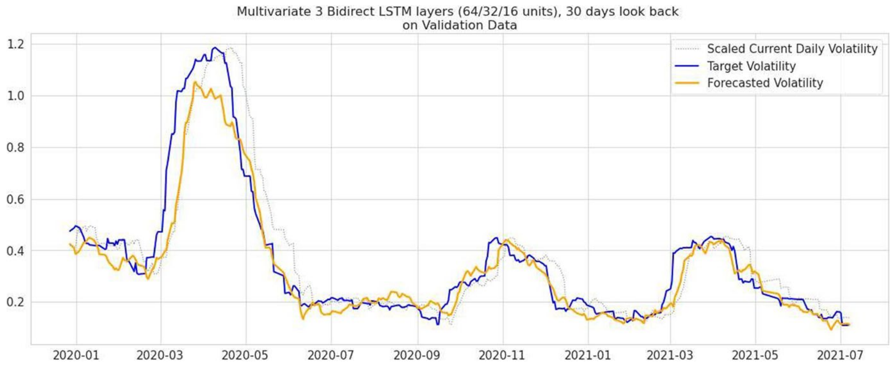

Fig. 29 Multivariate Three-layered Bidirectional LSTM RNN

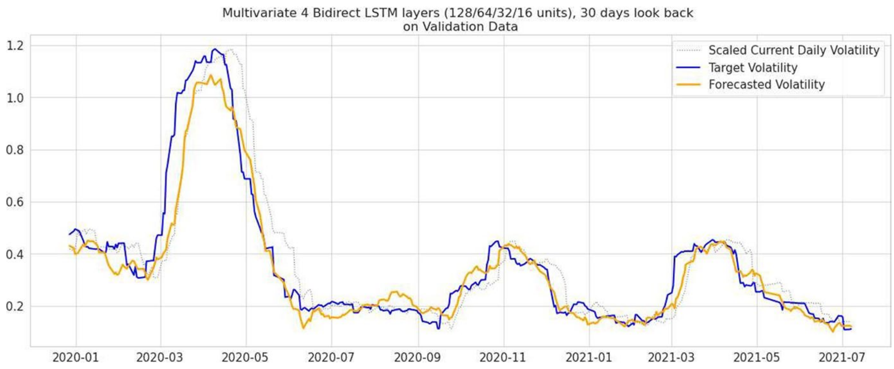

Fig. 30 Multivariate Four-layered Bidirectional LSTM RNN

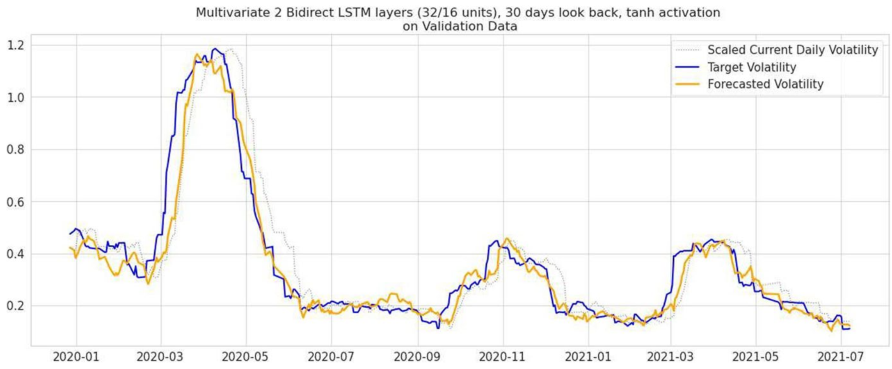

Fig. 31 Multivariate Two-layered Bidirectional LSTM RNN with tanh activation

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Declarations

Conflict of interest There is no conflict of interest.

Ethics Approval Approved.

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