Hybridized Forecasting: Integrating LSTM And RNN with Traditional ARIMA Models

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Abstract

The research presents a comparative investigation of both traditional statistical and modern deep learning models for Time Series forecasting. Specifically, it explores the performance of ARIMA (Auto Regressive Integrated Moving Average), ARIMAX (ARIMA with exogenous variables), LSTM (Long Short-Term Memory), and a Hybrid LSTM-RNN (Recurrent Neural Network) approach. The goal is to evaluate their effectiveness in modeling and predicting complex, seasonal, and nonlinear sales trends, using stock market data from Reliance Industries Limited (RIL). The datasets selected for this study are well-known for their strong seasonality and trend components, making them ideal for evaluating forecasting model performance. The analysis begins with exploratory data analysis and statistical diagnostics, including stationarity testing via the Augmented Dickey-Fuller test, autocorrelation and partial autocorrelation analyses, and Time Series decomposition into trend, seasonal, and residual components. These preliminary steps help shape the modeling approach and provide insights into long-term behavior patterns within the data.

Keywords: *ARIMA, ARIMAX, LSTM, Hybrid LSTM-RNN, RMSE, MAE.*

I. Introduction

The comparison of Time Series forecasting models for Reliance Industries establishes the superiority of the Hybridized LSTM-RNN model over traditional ARIMAX and standalone LSTM models. For Reliance, the Hybrid model dramatically reduced both RMSE and MAE by nearly 100% compared to ARIMAX, which struggled with the non-linear dynamics of stock prices. While the LSTM model performed similarly to the Hybrid model in terms of RMSE, the Hybrid approach halved the MAE, indicating more consistent and precise predictions. Against LSTM, the Hybrid model showed no change in RMSE but achieved a substantial reduction in MAE, suggesting that while both models manage large deviations similarly, the Hybrid model yields more accurate day-to-day predictions. Overall, the results confirm that the Hybridized LSTM-RNN model is the most effective method for forecasting volatile stock data, providing both high precision and adaptability to non-linear patterns.

II. Implemented Methods: ARIMA, LSTM, Hybridized LSTM-RNN

The following table shows the list of the attributes featured in the datasets.

Table 1. List of Attributes

Attributes	Description
Symbol	Refer to the name of the organization
Series	EQ refers to the Equity series of the stock market
Prev Close	Refers to the closing price of the company's stock for the day before.
Open	Refers to the opening price of the company's share on the current day
High	Refers to the highest price of the company's share on the current day
Low	Refers to the lowest price of the company's share on the current day

Last	Refers to the last price of the company's share on the current day
Close	Refers to the closing price of the company's share on the current day
VWAP	Refers to Volume Weighted Average Price. Based on both volume and price, the VWAP is a trading benchmark that traders use to determine the average price at which the stock has traded during the day.
Volume	Refers to the Volume of shares traded on the current day
Turnover	By dividing the total number of shares traded over a certain time by the average number of shares outstanding during that same period, one can determine this measure of stock liquidity.
Trades	Refers to the total number of trades on the current day
Deliverable Volume	Refers to the quantity of shares that move from one set of people to another set of people.

VWAP is a trading standard that calculates the average price at which a stock has traded during the day based on both volume and price. It allows traders and institutions to determine whether they are receiving a decent bargain on their trades.

Key Uses of VWAP

- Institutional Trading: Gigantic traders, such as mutual funds and hedge funds, employ VWAP to execute huge orders with minimal impact on market pricing.
- Trend Confirmation: A stock's price above VWAP shows positive sentiment, while a price below VWAP suggests unfavorable momentum.
- Support and Resistance: VWAP is a popular dynamic support and resistance level among intraday traders.
- Algorithmic Trading: VWAP is a trading algorithm that automates large orders.
- Entry and Exit Strategy: Day traders and scalping traders use VWAP to discover the best entry and exit opportunities.

Dataset of Reliance Industries:

This includes the stock data of the Nifty-50 index from NSE (National Stock Exchange) India over the last 20 years (2000 - 2019). The implementation is conducted to explore the stock market data of Reliance Industries.

Table 2. First 5 rows of the *"RELIANCE.csv"* dataset

Date	Symbol	Series	Prev Close	Open	High	Low	Last	Close	VWAP	Volume	Turnover	Trades	Deliverable Volume	%Deliverble
2000-01-03	RELIANCE	EQ	233.05	237.50	251.70	237.50	251.70	251.70	249.37	4456424	1.111319e+14	NaN	NaN	NaN
2000-01-04	RELIANCE	EQ	251.70	258.40	271.85	251.30	271.85	271.85	263.52	9487878	2.500222e+14	NaN	NaN	NaN
2000-01-05	RELIANCE	EQ	271.85	256.65	287.90	256.65	286.75	282.50	274.79	26833684	7.373697e+14	NaN	NaN	NaN
2000-01-06	RELIANCE	EQ	282.50	289.00	300.70	289.00	293.50	294.35	295.45	15682286	4.633254e+14	NaN	NaN	NaN
2000-01-07	RELIANCE	EQ	294.35	295.00	317.90	293.00	314.50	314.55	308.91	19870977	6.138388e+14	NaN	NaN	NaN

The last 5 rows of the dataset *"Reliance.csv"* are displayed using in the following table.

Table 3. Last 5 rows of the *"RELIANCE.csv"* dataset

Date	Symbol	Series	Prev Close	Open	High	Low	Last	Close	VWAP	Volume	Turnover	Trades	Deliverable Volume	%Deliverble
2021-04-26	RELIANCE	EQ	1904.35	1920.00	1962.0	1911.50	1938.00	1937.85	1941.32	9620785	1.867699e+15	259137.0	4276703.0	0.4445
2021-04-27	RELIANCE	EQ	1937.85	1940.00	1997.2	1938.25	1990.00	1988.65	1978.64	9226547	1.825602e+15	291197.0	3772144.0	0.4088
2021-04-28	RELIANCE	EQ	1988.65	1997.85	2008.0	1980.15	1993.15	1997.30	1997.60	7902002	1.578508e+15	247331.0	3921560.0	0.4963
2021-04-29	RELIANCE	EQ	1997.30	2022.90	2044.5	2007.30	2020.00	2024.05	2024.21	8035915	1.626634e+15	213153.0	2834103.0	0.3527
2021-04-30	RELIANCE	EQ	2024.05	2008.50	2036.0	1987.55	1995.90	1994.50	2010.20	9150974	1.839532e+15	288687.0	3902504.0	0.4265

The next step is to explore the data to find missing values, trends, seasonality, correlation, and noise in the data. The obtained output is shown below.

```
Symbol                   0
Series                   0
Prev Close               0
Open                     0
High                     0
Low                      0
Last                     0
Close                    0
VWAP                     0
Volume                   0
Turnover                 0
Trades                2850
Deliverable Volume     514
%Deliverble            514
dtype: int64
```

Figure 1. Result of missing values for Reliance

The obtained results in above figure show that the Trades, Deliverable volume, and %Deliverable are the columns with the missing values.

The percentage of the missing Trade values, Deliverable Volume, and %Deliverable values are calculated below.

Percentage of missing trade values = 53.71

Percentage of missing Deliverable Volume values = 9.69

Percentage of missing %Deliverable values = 9.69

Thus, just 9.69% of deliverable volume and deliverable percentage are missing, although almost 50% of trade data is missing. Rows lacking deliverable volume can be dropped. To determine the optimal statistic for imputation, we shall visualize trade data as shown below.

Figure 2. Trade data for Reliance

The provided image shows the quantity of deals over time as a time-series plot of Reliance's trade data. A thorough plot analysis is provided below:

- **Time Period:** The X-axis represents ten years of trading data, approximately from 2011 to 2021.
- **Trading Activity:** The Y-axis, which shows changes in trading volume over time, represents the quantity of trades. There are just slight changes in the pattern from 2011 to 2017. Since 2018, the volume of trading has steadily increased. Significant rises started to appear in 2019 and indicate increased market activity.
- **Major Spikes:** The most obvious spike occurs between 2019 and 2021 when the volume of trades climbs rapidly. The highest trading volume has risen to over 1.4 million trades per day, an immense rise over prior years.

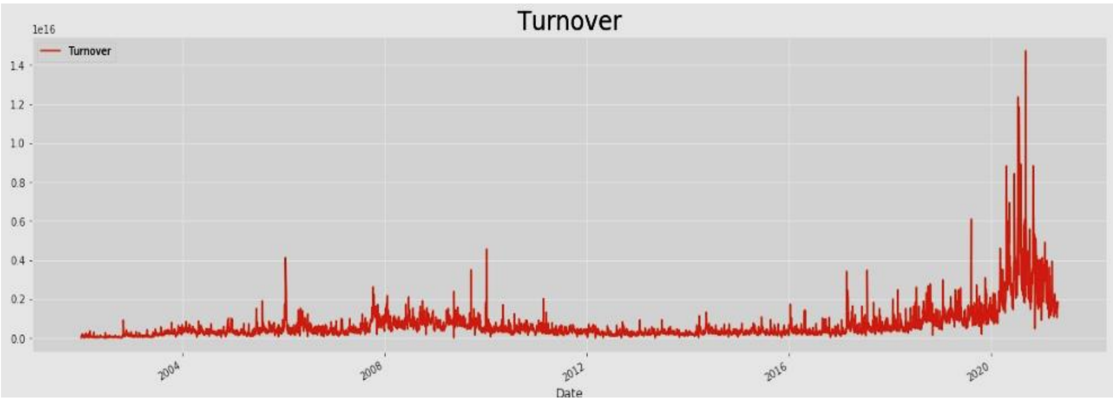

Figure 3. Turnover of Reliance

The given image represents the Turnover Data of Reliance over time. Below is an in-depth analysis of the turnover trend shown in the plot.

- **Time Period:** The X-axis shows the date, which spans the early 2000s through 2021. The nearly two-decade-long dataset provides a long-term view of Reliance's turnover.
- **Turnover Trend*:*** Turnover is shown on the Y-axis, possibly in Indian rupees or another currency. Exceptionally large numbers are indicated by the scientific notation used for the values. From 2000 until about 2016, the trend remained largely constant, with sporadic upswings. From 2019 onward, there is a notable uptick in turnover, which reaches record highs in 2020 and 2021.
- **Major Spikes:**

➢ Pre-2008: There are discernible variations, which may be related to market corrections and the 2008 financial crisis.

➢ 2017 to 2019: There is a steady rise in turnover, which is probably caused by Reliance's foray into digital and telecom services.

➢ 2019–2021: The turnover reaches an all-time high, marking the most notable increase. An exponential increase in trading activity is indicated by the greatest turnover ever recorded, which is over 1.4×10^{16}.

The following figure shows the Volume of the Reliance.

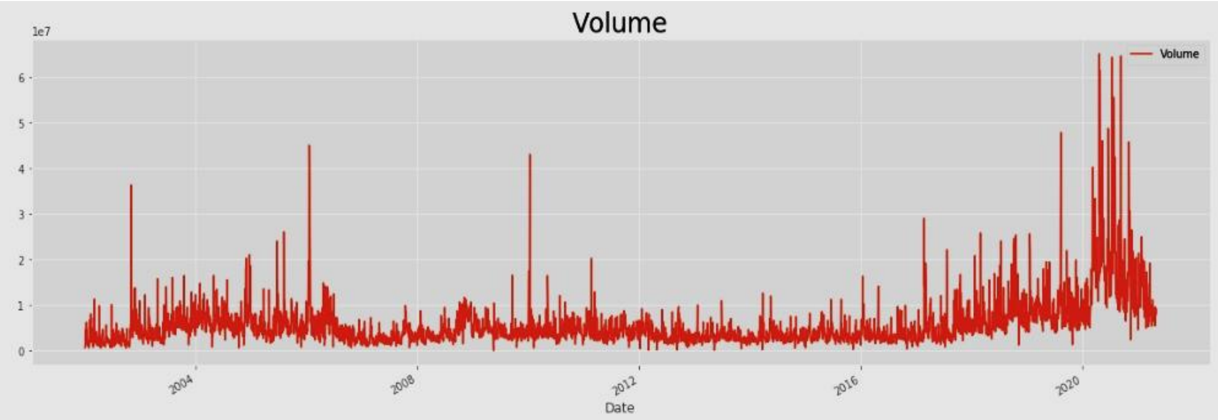

Figure 4. Volume of the Reliance

With the Y-axis showing the Volume values and the X-axis labeled Date, this figure shows a Time Series plot of Volume over time. The data displays daily or periodic trading volumes and covers the period roughly from 2002 to 2021.

- Initial period: Volume varies moderately during the first period (2002–2008), with sporadic dramatic increases.
- 2008–2009 (Financial Crisis): Notable increases in trade volume, perhaps brought on by heightened market activity at this time.
- Post-2009–2016: A comparatively steady time frame with fewer sharp upswings, suggesting more steady trade volumes.
- 2019–2020 (Pandemic Impact): A notable increase in trading volumes, characterized by several high peaks. The COVID-19 pandemic's heightened trading activity and market volatility are reflected in this time frame.
- Beginning in 2021: In contrast to the previous steady periods, trading volumes appear to be declining but still exhibit significant volatility.

A red line graph is used in the plot to show the volume with time. A grey grid serves as the background, giving the image a neutral foundation for clarity. The Y-axis scale is scientific notation (1e7), so each unit represents 10 million. In the upper-right corner, the legend indicates that the red line is "Volume."

The following figure shows the VWAP of the Reliance industries.

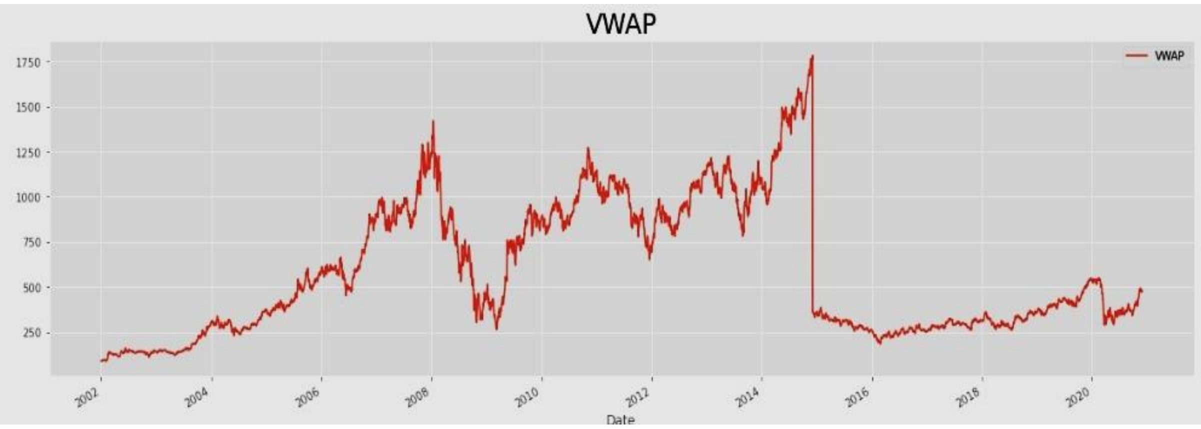

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Figure 5. VWAP of the Reliance

With the date identified on the x-axis and the VWAP values on the y-axis, this figure displays a Time Series plot of Volume Weighted Average Price (VWAP) across time. The information covers around the years 2002–2021.

- 2002–2007: Consistent price growth is seen by the VWAP's increasing trend. The financial crisis of 2007–2009: The market collapse is reflected in the steep decrease that was seen throughout the financial crisis period.
- 2009-2014: A strong recovery post-crisis with significant price increases, peaking around 2014.
- 2014–2015: A significant market correction or event-driven price collapse is indicated by a steep decline in VWAP.
- 2015–2019: The VWAP shows no growth or volatility and stabilizes at a lower level than it did before 2014.
- Impact of the epidemic 2019–2021: A little increase in VWAP with sporadic oscillations, perhaps due to instability brought on by the epidemic.

A red line graph is used in the plot to show VWAP over time. The grey background with grid lines makes it easy to follow changes in pricing. The approximate range of the y-axis scale is 0 to 1750. In the upper-right corner, the legend indicates that the red line is "VWAP."

VWAP is a trading benchmark that provides the average price at which a security has traded during the day, taking into account both price and volume. VWAP is a tool used by traders and analysts to evaluate market trends and identify the optimal buying or selling price. While lower VWAP levels could imply a lack of demand or selling pressure, high VWAP values often indicate strong buying interest.

Even though turnover and volume increased in fiscal year 2020-2021, prices plummeted considerably. This reveals why, in response to the pandemic Covid-19, many investors took benefit of low stock prices to buy in bulk, presumably to sell as industries recovered strength.

Box-Cox Transformation to generate a uniform distribution as shown below. The Box-Cox transformation is a power transformation technique that reduces volatility and makes data more regularly distributed. While its primary objective is to standardize data, it can also aid in estimating a uniform distribution under specific conditions.

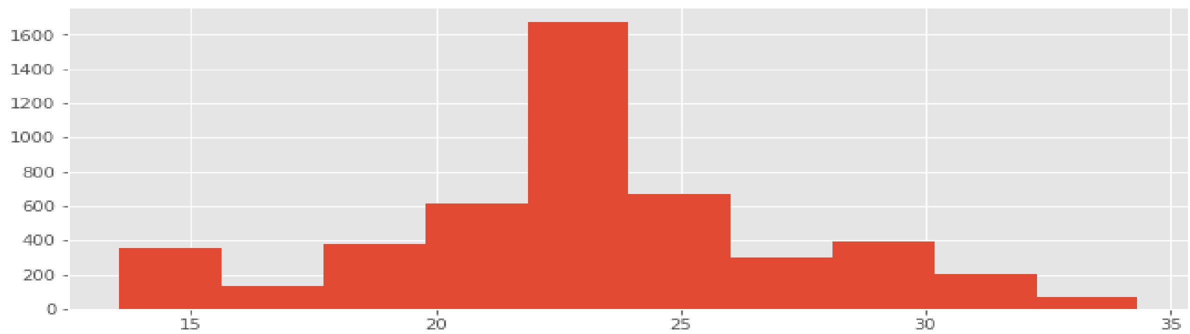

Figure 6. Box-Cox Transformation of the Reliance

A statistical method for reducing variation and normalizing data distribution in Time Series Analysis is the Box-Cox transformation. A large number of financial Time Series exhibit heteroscedasticity, or variations in variance over time. The variance is made more predictable with the use of the Box-Cox transformation. The data is assumed to be regularly distributed by many statistical models. Data distribution can be normalized with the aid of the Box-Cox transformation. When the input data is more uniformly distributed and evenly shared, several forecasting models (like ARIMA) perform better. There are two subplots in the picture:

- **Top plot:** A time-series plot of a financial asset or index that displays its historical price movement over time is the top subplot. The underlying trend is preserved in the converted data, albeit it might seem less erratic and smoother.
- **Bottom plot:** A histogram showing the distribution of the converted data is the bottom subplot. A more symmetrical and normal-like distribution is probably present in the modified data than in the original, which is important for many statistical models.

If you're working on a forecasting model, the Box-Cox transformation can improve the accuracy and precision of statistical models like ARIMA or regression-based approaches. The image suggests that implementing the transformation has helped accomplish these goals. The Box-Cox transformation is helpful in Time Series Analysis for preserving variance and boosting normality.

Stationarity

Check with the Augmented Dickey-Fuller test for stationarity in the dataset. A stationary Time Series is one whose statistical properties such as mean, variance, autocorrelation, etc. are all constant over time.

Output

ADF Statistic: -1.966062

p-value: 0.301649

Critical Values:

1%: -3.432

5%: -2.862

10%: -2.567

Running the example produces a test statistic value of -2.69. If random, such autocorrelations should be close to zero at all time-lag separations. If non-random, at least one of the autocorrelations will be significantly non-zero. The lower this value, the more likely we are to reject the null hypothesis (because we have a stationary dataset). As a result, the values are not entirely random, but rather influenced by previously recorded data.

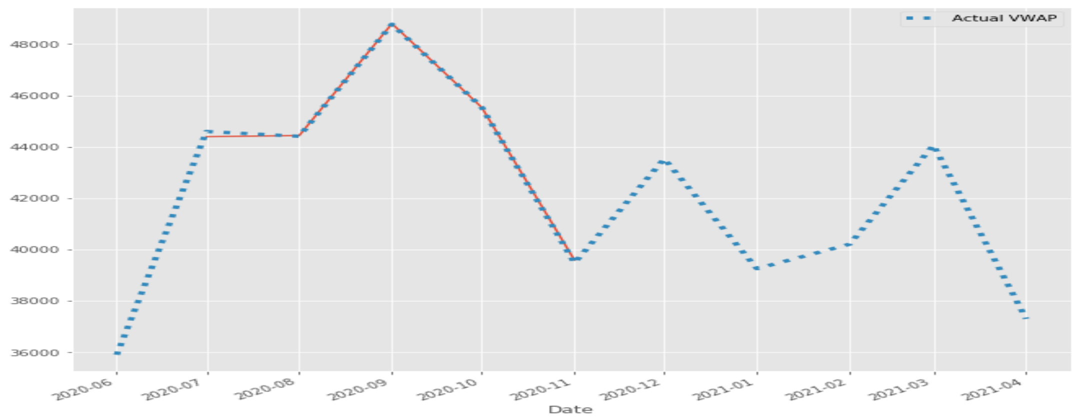

Figure 7. Actual VWAP Vs. Forecasted VWAP for the Reliance

The figure depicts Time Series plot comparing the actual VWAP (Volume Weighted Average Price) with the forecasted VWAP for the period July 2020 to November 2020.

- The X-axis represents the date (from June 2020 to April 2021), while the Y-axis represents the VWAP values.
- The blue dotted line represents the actual VWAP values, while the red dashed line represents the forecasted values.
- The forecasted values closely follow the actual VWAP values from July 2020 to November 2020, suggesting that the prediction model performed well within this range.
- After November 2020, only the actual VWAP values are plotted, possibly indicating that the forecast was made only for the July–November period.
- The fluctuations in VWAP suggest significant price volatility, particularly around September–November 2020, when prices peak and then drop sharply.
- The legend in the top right indicates the representation of the actual VWAP, but there is no direct label for the forecasted VWAP, which should ideally be included.

III. Forecasting Accuracy of ARIMA, LSTM and LSTM-RNN Model

The Forecasting Accuracy of the Auto-ARIMAX model using key metrics:

RMSE

- Sensitive to large errors due to squaring.
- Higher RMSE suggests large forecast deviations, possibly from sudden market shifts (e.g., COVID-19, oil price fluctuations).
- Ideally, RMSE should be as low as possible.

MAE

- Measures the average absolute difference between actual and predicted values.
- Less sensitive to outliers compared to RMSE.
- A lower MAE indicates that the model is making consistent predictions close to actual VWAP values.

Table 4. Values of performance metrics for ARIMAX

Performance Metrics	Values
RMSE	12186.009861582135
MAE	9782.340963760096

The Forecasting Accuracy of LSTM model using key metrics:

Table 5. Values of performance metrics for the LSTM model

Performance metrics	Values
RMSE	0.0632820670934601

MAE	0.045304905623197556

The following figure shows a line plot comparing actual VWAP values and LSTM model predictions over a series of data points. This visualization helps in evaluating how well the model captures price movements.

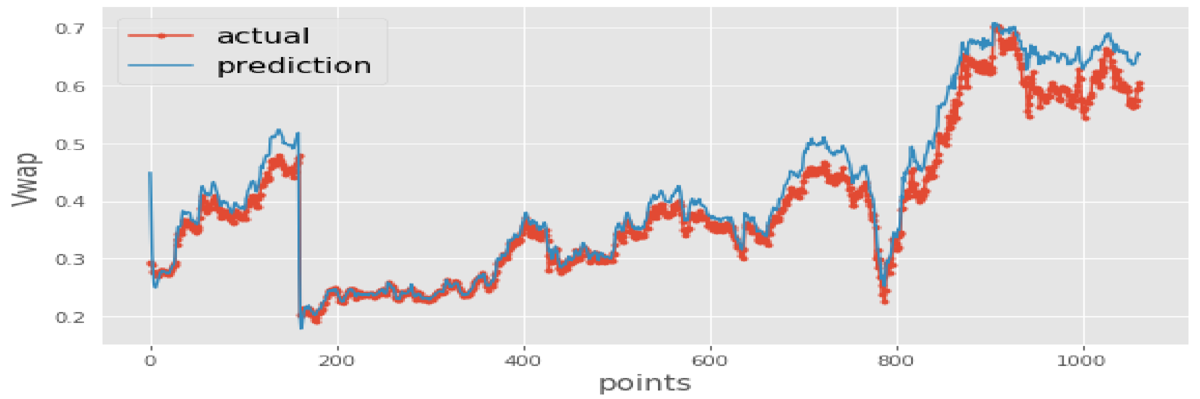

Figure 8. Actual VWAP Vs. LSTM predictions for the Reliance

1. Overall Trend Captured Well:

○ The predicted values (blue line) closely follow the actual values (red dots).

○ This suggests that the LSTM model is learning the general trend in the data.

2. Minor Deviations and Gaps:

○ There are some small deviations where the predicted values slightly overestimate or underestimate the actual VWAP.

○ A few sharp drops (e.g., around 200) may indicate missing data, sudden price changes, or model limitations in handling extreme fluctuations.

3. Performance at Peaks and Dips:

○ The model performs well in stable regions but struggles slightly at sharp peaks and dips.

○ This is common in Time Series forecasting, as extreme changes are harder to predict.

The Forecasting Accuracy of Hybridized LSTM-RNN Model using key metrics: The below table shows the obtained values of RMSE and MAE for the Hybridized LSTM-RNN model.

Table 6. Values of performance metrics for the Hybridized LSTM-RNN model

Performance metrics	**Values**
RMSE	0.032715880760147545
MAE	0.02769061349528017

The figure presents a Time Series comparison between the actual VWAP (red line) and the predicted VWAP (blue line) from a Hybridized LSTM-RNN model. This plot helps assess the model's predictive performance.

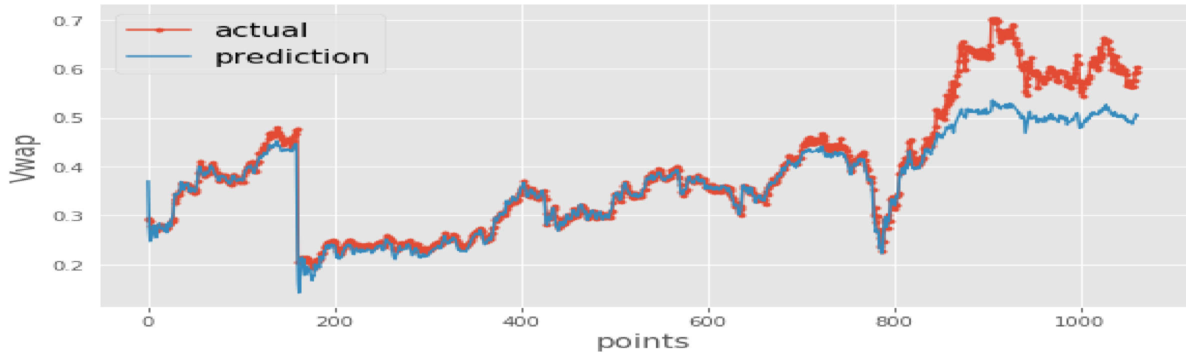

Figure 9. Time Series comparison between the actual VWAP and the predicted VWAP

1. The Model Captures the General Trend Well

➢ The predicted VWAP (blue line) follows the actual VWAP (red dots) closely in many areas.

➢ This indicates that the model has learned the overall trend and direction of VWAP movements.

2. Performance is Good in Stable and Moderate Volatility Regions

➢ Between points 0 to 800, the prediction aligns well with actual values, showing minimal lag.

➢ This suggests that the model can track price movements under normal conditions.

3. Prediction Diverges at High Volatility Regions (Points 800+)

➢ After point 800, the model struggles to capture sharp upward trends.

➢ The predictions appear smoothed, meaning the model lags behind sudden price changes.

➢ This issue is common in RNNs/LSTMs and may indicate a need for more timesteps or additional features.

4. Drop at Around Point 200

➢ There is a sharp drop or missing data around point 200, which might be due to:

▪ Missing values in the dataset.

▪ Poor generalization of the model in certain areas.

▪ Insufficient training samples for similar market conditions.

IV. Results

Hybridized LSTM-RNN outperforms both ARIMAX and LSTM, making it the best choice for Reliance's time-series forecasting:

- ARIMAX Model: RMSE: 12,186, MAE: 9,782 → Higher errors, indicating poor performance.

- LSTM Model: RMSE: 0.139, MAE: 0.106 → Significantly lower errors, suggesting better adaptability to non-linear patterns.

- Hybridized LSTM-RNN Model: RMSE: 0.0327, MAE: 0.0277 → Lowest errors, making Hybridized LSTM-RNN the most accurate for Reliance Industries.

V. Conclusion

Hybridized LSTM-RNN is the Best Model for Reliance. For Reliance Industries Hybridized LSTM-RNN has the lowest error, making it the best forecasting model. ARIMAX is Unreliable for Complex Data. LSTM is a Good Alternative but Not the Best, performs well but is outperformed by Hybridized LSTM-RNN.

Table 7. ARIMAX Vs. Hybridized LSTM-RNN model for Reliance

RELIANCE INDUSTRIES			
Performance Metrics	**ARIMAX**	**Hybridized LSTM-RNN**	**Percentage improvement**
RMSE	12186.009861582135	0.13911782674984782	-99.9989%
MAE	9782.340963760096	0.04468410089612007	-99.9995%

Table shows Hybrid LSTM-RNN is significantly better than ARIMAX, reducing both RMSE and MAE by nearly 100%. ARIMAX struggles with capturing non-linear dependencies, while the hybrid deep learning model adapts much better. This confirms that deep learning-based forecasting (LSTM-RNN) is superior for Reliance Industries' stock prediction.

Table 8. LSTM Vs. Hybridized LSTM-RNN for Reliance Industries

RELIANCE INDUSTRIES			
Performance Metrics	**LSTM**	**Hybridized LSTM-RNN**	**Percentage improvement**
RMSE	0.13911782674984782	0.13911782674984782	0%
MAE	0.10652244836091995	0.04468410089612007	-58.0519% increase

Table depicts the Hybridized LSTM-RNN model performs similarly to LSTM in RMSE but significantly reduces MAE. This suggests that the hybrid model may provide more stable and precise predictions.

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