Stock Price Prediction Using Long Short Term Memory

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Abstract: Stock price forecasting is a dynamic and intricate task based on the nature of financial market volatility. Conventional statistical models fail to capture long-term dependencies and nonlinear stock price movement patterns. This paper introduces the use of Long Short-Term Memory (LSTM) networks, a type of specialized recurrent neural networks (RNNs), for precise stock price forecasting. LSTM model is trained to learn and remember sequence patterns in stock financial data in an efficient way, avoiding the vanishing gradient problem that confines typical RNNs. Stocks' historical prices such as open, high, low, close prices, and volume are used as salient input features for model training and testing. Experimental findings indicate that LSTM performs better than traditional methods by successfully extracting temporal dependencies, resulting in improved forecasting accuracy. This research highlights the capabilities of deep learning for financial market analysis, giving a glimpse of its practical use for investors and analysts. The results indicate that LSTM-based models can be used as efficient tools for predictive stock market analysis, enabling well-informed decision-making and risk management planning.

Keywords: stock price forecasting, long short-term memory ,LSTM, RNN,Trading volume

I. INTRODUCTION

Stock price prediction has been an notoriously challenging and well-researched finance and data science problem for decades. Due to the highly volatile and non-linear behavior of financial markets, traditional statistical methods usually fail to detect sophisticated relationships in stock price variation. Following the recent developments of deep learning, i.e., Recurrent Neural Networks (RNNs) and its subset Long Short-Term Memory (LSTM) networks, scholars have made an incredible leap forward in time-series prediction, encompassing the stock market prediction as well.

LSTM networks, a special form of RNN, are designed to counteract vanishing and exploding gradients and are thus especially suitable for extracting long-term dependencies from sequential data. The networks have proven themselves to be particularly good at finding patterns and trends in financial time-series data and in predicting stock prices more accurately than the more traditional machine learning techniques.

With the arrival of deep learning, particularly Recurrent Neural Networks (RNNs), researchers have explored advanced techniques to model sequential data. However, standard RNNs are suffering from the vanishing gradient problem and do not learn long-term relationships in financial time-series data. In an effort to overcome this vulnerability, Long Short-Term Memory (LSTM) networks, a variation of RNNs, have been introduced. LSTMs are used with specialized memory cells and gate functions that enable them to retain important past patterns over long sequences, making them highly suitable for forecasting stock prices.

This paper analyzes the application of LSTM networks for predicting stock prices using past market data for forecasting future price volatility. We introduce the LSTM structure, preprocessing financial data, training, and evaluation metrics for investigation. Our findings aim to be used in enhancing current deep learning-based financial prediction research and gaining insights into the predictability of LSTM models for stock market movements.

II. LITERATURE REVIE

V. Sarika et al(2023).Various investigate endeavors have concentrated on determining stock costs utilizing machine learning and profound learning strategies. A inquire about recommended a single-layer RNN show that utilizes time-series information and different highlights to improve forecast accuracy. Comparative considers have illustrated that machine learning models such as SVM, DNN, and relapse calculations progress prescient exactness. Profound repetitive systems based on LSTM have demonstrated to be effective in determining different stocks, accomplishing critical precision. Additionally, estimation examination from online news and social media has been consolidated to upgrade stock figures. Half breed models that blend LSTM with highlight determination strategies such as RFE and PCA have appeared superior execution.

Thitikun Kunathananon et al(2023).Various inquire about endeavors have examined stock cost determining through Long Short-Term Memory (LSTM) systems since of their capability to capture time-based connections. Ordinary procedures habitually encounter inclinations and confinements, whereas LSTM offers an successful approach for foreseeing stock costs. Considers have demonstrated that LSTM surpasses the execution of other machine learning models such as Back Vector Machines (SVM) and profound neural systems (DNN) in terms of prescient exactness. Inquire about combining money related articulation information with LSTM models has appeared way better execution, minimizing human inclination and moving forward decision-making for speculators. The integration of principal and specialized examination through LSTM has illustrated empowering results in anticipating the stock advertise.

Kaimao Wang et al(2023).The forecast of stock costs has been broadly investigated through profound learning strategies, particularly utilizing Long Short-Term Memory (LSTM) systems. Ponders appear that stock costs show nonlinear time-series designs, making LSTM an suitable strategy since of its capacity to capture long-term conditions. Inquire about has too inspected half breed approaches like CNN-LSTM and BiLSTM-Attention, which combine convolutional layers for include extraction and consideration components to upgrade center on noteworthy information focuses. Additionally, estimation examination and basic money related data have been coordinates into prescient models to make strides precision. These improvements exhibit LSTM's capacity to accomplish moved forward results in stock cost expectations.

Dharmesh Dhabliya et al(2023).Anticipating the stock advertise has gotten to be a noteworthy investigate center, with profound learning models like Long Short-Term Memory (LSTM) systems illustrating their viability in understanding complex worldly connections. Routine measurable models habitually battle to address the nonlinearity and instability inborn in stock costs. LSTM systems exceed expectations over conventional approaches since they can keep up long-term conditions and handle consecutive information viably. Investigate has inspected half breed approaches that combine outside components such as estimation investigation and financial pointers to upgrade forecast exactness. In addition, refining hyperparameters and include designing has progressed LSTM viability, situating it as a important resource for monetary estimating.

Muntather Almusawi et al(2023).Forecasts within the stock advertise have advanced with the utilize of profound learning models such as Long Short-Term Memory (LSTM), which effectively distinguish transient conditions. Routine machine learning models have trouble with non-linear stock price changes, coming about within the consolidation of optimization strategies. Investigate has proposed half breed models like PCA-EMD-LSTM to improve include extraction and boost prescient exactness. Additionally, metaheuristic optimization strategies such as Fake Rabbits Optimization (ARO) and its upgraded adaptations have been utilized to fine-tune LSTM hyperparameters, moving forward forecast precision. These strategies have appeared way better viability in bringing down blunder measurements such as MSE and MAE, rendering them valuable for monetary determining.

Shounak Choudhury et al(2023).The forecast of stock markets has been broadly examined, with profound learning strategies such as Long Short-Term Memory (LSTM) appearing empowering results. LSTM, a sort of Repetitive Neural Organize (RNN), effectively holds transient connections, rendering it perfect for anticipating stock costs. Inquire about has combined hyperparameter optimization and regularization strategies to move forward show viability. Procedures for highlight choice like PCA and opinion investigation have been utilized to upgrade exactness. Appraisal measures such as Cruel Supreme Mistake (MAE) and Root Cruel Square Blunder (RMSE) illustrate that LSTM outperforms customary models, advertising a solid establishment for money related forecasts.

Ch. Anuradha et al(2023).Stock advertise forecast has been broadly considered utilizing profound learning methods, especially Long Short-Term Memory (LSTM) systems, which successfully capture consecutive conditions in money related data.Conventional machine learning models battle with the profoundly unstable nature of stock costs, making LSTM a favored choice due to its capacity to hold long-term designs. Inquire about has coordinates include choice strategies like PCA and crossover models such as GA-LSTM to upgrade forecast accuracy.Also, thinks about utilizing crucial and macroeconomic information have appeared moved forward estimating execution, making LSTM-based models important devices for long-term speculation decision-making.

XIAOJIAN WENG et al(2022).The forecast of stock costs has advanced through the application of profound learning models such as Long Short-Term Memory (LSTM) systems, which adeptly capture consecutive connections in stock showcase information.Ordinary measurable models like ARIMA and GARCH discover it challenging to address the complex, nonlinear characteristics of stock cost vacillations. Later inquire about has utilized opinion examination with BERT to improve forecast precision by taking under consideration financial specialist sentiments. Crossover models such as BERT-LSTM have illustrated way better adequacy in determining stock costs by consolidating budgetary information with advertise estimation, bringing down Cruel Outright Mistake (MAE) and upgrading expectation exactness. These improvements emphasize the expanding importance of AI in anticipating monetary patterns.

Cheng Peng et al(2022).Anticipating stock costs has been a major center of inquire about, with profound learning models like Long Short-Term Memory (LSTM) illustrating adequacy since of their capability to capture successive conditions. Ordinary measurable procedures such as Straightforward Moving Normal (SMA) and Exponential Moving Normal (EMA) confront challenges in overseeing nonlinear varieties in stock costs. Inquire about has appeared that Repetitive Neural Systems (RNN) utilizing LSTM surpass conventional strategies in determining stock patterns. Besides, cross breed models that combine recursive and optimized LSTM strategies have upgraded the precision of long-term estimates.

Haorui Zhang et al(2022).The forecast of stock costs has been broadly investigated utilizing both ordinary and profound learning strategies. Direct relapse models are utilized for anticipating stock costs; be that as it may, they regularly don't succeed in getting a handle on the complex designs display in budgetary information. Long Short-Term Memory (LSTM) systems, a sort of Repetitive Neural Systems (RNNs), have illustrated viability in capturing time-related conditions in stock cost changes. Considers demonstrate that crossover models that coordinated direct relapse with LSTM upgrade forecast exactness by utilizing both factual strategies and profound learning methods. These advancements emphasize the expanding significance of AI in moving forward monetary determining procedures.

Shashi Kant Singh et al(2023).The expectation of stock costs has been completely investigated utilizing profound learning methods, particularly Long Short-Term Memory (LSTM) systems, since of their capacity to oversee successive data and recognize long-term connections .Customary measurable models such as ARIMA and relapse strategies regularly have trouble adapting with the complexities and changes of monetary markets. Later inquire about has combined opinion investigation with LSTM, utilizing social media information like tweets to make strides expectation accuracy. Half breed models that coordinated machine learning calculations with normal dialect handling procedures have appeared improved estimating capabilities, underscoring the importance of sentiment-based showcase forecasts.

Nayanika Das et al(2023).Determining stock costs has gotten to be an critical field of think about, and Long Short-Term Memory (LSTM) systems have appeared viability in distinguishing worldly conditions in budgetary data. Customary approaches like ARIMA and factual relapse confront troubles with nonlinear shifts within the advertise. Later inquire about underscores the benefits of LSTM in stock forecast, owing to its capacity to oversee long-term patterns and minimize estimating blunders. Half breed models that combine LSTM with refined structures and hyperparameter alteration have illustrated improved exactness. In addition, profound learning models created utilizing money related datasets appear empowering results in estimating showcase patterns and financial specialist estimation.

III. METHODOLOGY

Data Collection and Preprocessing:

Data Source:

The dataset utilized for this research comprises past stock price data for Tesla (TSLA). The information was gathered from a trustworthy financial data provider like Yahoo Finance or Alpha Vantage. The dataset contains daily stock prices for a defined timeframe, encompassing both rising and falling market trends.

Characteristics of Data The subsequent essential characteristics were taken into account for training the LSTM model:

Open – Price at which Tesla stock begins trading for the day.

High – Maximum price attained during the day.

Low – The minimum price attained throughout the day.

Close – The daily closing price of Tesla shares.

Volume – The quantity of shares exchanged throughout the day.

These characteristics offer an extensive perspective on Tesla`s stock market performance and are crucial for modeling time-series trends.

	Date	Open	High	Low	Close	Volume	Adj Close
0	6/29/2010	19.000000	25.00	17.540001	23.889999	18766300	23.889999
1	6/30/2010	25.790001	30.42	23.299999	23.830000	17187100	23.830000
2	7/1/2010	25.000000	25.92	20.270000	21.959999	8218800	21.959999
3	7/2/2010	23.000000	23.10	18.709999	19.200001	5139800	19.200001
4	7/6/2010	20.000000	20.00	15.830000	16.110001	6866900	16.110001

Data Cleaning:

In order to maintain data quality, the subsequent preprocessing measures were implemented:

Managing Missing Values: Any absent values in the dataset were dealt with by: Forward filling (utilizing the value from the previous day) or backward filling. Eliminating rows with considerable missing information if needed.

```
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       1692 non-null   object
 1   Open       1692 non-null   float64
 2   High       1692 non-null   float64
 3   Low        1692 non-null   float64
 4   Close      1692 non-null   float64
 5   Volume     1692 non-null   int64
 6   Adj Close  1692 non-null   float64
dtypes: float64(5), int64(1), object(1)
```

Outlier Elimination: Statistical techniques were employed to identify outliers, including: Z-score approach. Interquartile Range (IQR) approach. **Normalization:** To enhance the convergence of the LSTM model, the data was adjusted via Min-Max Scaling.

$$\mathbf{Xscaled} = \frac{\mathbf{X-min(X)}}{\mathbf{max(X)-min(X)}}$$

This guarantees that all features lie within the range of [0, 1], enabling the LSTM model to manage varying magnitudes of values more efficiently.

Data Splitting:

Data partition is an essential stage of training automatic learning models, especially time -like data such as stock prices. Unlike conventional automatic learning tasks that allow random data mixture, time series data to maintain time relationship. Therefore, a sequential part is used to preserve data order and prevent data leakage.

Training and testing room:

Data set is divided into training and testing ministries using 80-20: training sets: initial data 80% used to train LSTM model. Inspection sets: 20% final of the data set used to evaluate the model's prediction.

This ensures that the data understanding model in the past and is evaluated on the new data in the future, imitating a real forecast situation.

Optional authentication parts if the super -homosexual adjustment or early stop is used, the training kit is also divided into: training sets - 70% of data used for model training. sets of authentication - 10% of data used to evaluate model performance during the training process to prevent excess. authentic games help assess the capacity of the model to generalize, allow the amendment of the learning rate, the size of the lot and the desired number.

LSTM Model Architecture:

Long Short-Term Memory (LSTM) networks represent a specific kind of Recurrent Neural Network (RNN) created to manage sequential data and long-term relationships. LSTM is especially effective for predicting stock prices since stock market data contains time-series patterns and trends that evolve over time. An LSTM network is composed of unique memory cells and gating mechanisms that enable it to: Keep information throughout extended sequences. Address the vanishing gradient issue by preserving gradients throughout time. Capture both immediate and extended dependencies in financial data.

Components of LSTM Architecture The essential elements of an LSTM model comprise: Input Layer – Receives the input attributes including Tesla stock's opening price, closing price, high, low, and volume. LSTM Layers – A sequence of LSTM units is employed to handle the sequential data. Dropout Layer – Designed to avoid overfitting by randomly turning a portion of input units to zero during the training process. Dense Layer – A completely connected layer that produces the ultimate forecast (closing price).

Gates of LSTM and Cell State:

An LSTM unit features three essential gates that regulate the movement of information: Forget Gate – Determines what information to keep and what to eliminate.

$$f_t=\sigma(W_f\cdot[h_{t-1},x_t]+b_f)$$

Input Gate – Identifies which new data ought to be incorporated into the cell state.

$$i_t=\sigma(W_i\cdot[h_{t-1},x_t]+b_i)$$

Output Gate – Manages the output and defines the subsequent hidden state.

$$o_t=\sigma(W_o\cdot[h_{t-1},x_t]+b_o)$$

Cell State Update – The cell state is updated using the input and forget gates

$$C_t=f_t*C_{t-1}+i_t*\tilde{C}_t$$

Hidden state - The ultimate result from the LSTM cell.

$$h_t=o_t*\tanh(C_t)$$

Bidirectional Long Short-Term Memory:

A Bidirectional LSTM (BiLSTM) analyzes the input sequence in both forward and reverse directions. This enables the model to recognize patterns from previous and upcoming dependencies. BiLSTM works well when patterns rely on both past and future context, although it adds to the complexity of training.

Focus Mechanism:

Incorporating an Attention Layer enables the model to prioritize the most pertinent time steps instead of considering all inputs uniformly. Attention enhances prediction precision by flexibly adjusting the significance of input elements. Recent fluctuations in the market or significant trading activity might possess greater predictive capability.

Stateful LSTM: Preserves the internal state across batches, enhancing pattern retention over extended sequences. Stateless LSTM: Clears the state following each batch, ideal for independent sequence training. A stateful LSTM is typically favored for predicting stock prices when working with continuous time-series data.

Training the Model:

Training a Long Short-Term Memory (LSTM) model includes establishing the model structure, organizing the data, and fine-tuning hyperparameters to enhance predictive accuracy. For this project, Tesla stock information was utilized to train the LSTM model to forecast upcoming stock prices.

Preparation of Data for Training The Tesla dataset was assembled by following these steps:

Generation of Sequence: LSTM necessitates sequential input, thus the data was converted into a time-series format. A sliding window of 60 days with a fixed size was utilized to generate input-output pairs: Stock values during the past 60 days.

For example:

X = [Day1, Day2, Day3, ….. ,Day60]

Y = [Day61's closing price]

Model Construction:

After the data underwent preprocessing, the LSTM model was assembled with a suitable loss function and optimizer:

Loss Function: Mean Squared Error **(MSE)** was utilized as it assesses the average squared deviation between observed and estimated values:

$$\mathbf{MSE=\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}$$

MSE is favored for regression tasks since it imposes a greater penalty on larger errors. Optimizer: The Adam optimizer was employed because it adjusts the learning rate dynamically and enhances convergence.

Training the Model:

The training of the model was conducted with the subsequent configuration:

Time Periods:

The model underwent training for 50–100 epochs, based on when convergence was reached.

Ear

ly stopping was employed to halt training when the validation loss ceased to improve for 10 consecutive epochs. **Size of Batch**: A batch size of 32 was utilized to optimize training speed while ensuring model generalization. Split for Validation: A 10% portion of the training set was utilized for validation to track overfitting and modify the learning rate.

	0
Date	0
Open	0
High	0
Low	0
Close	0
Volume	0

dtype: int64

```
x_train[0]
```

```
array([[0.01053291],
       [0.03553936],
       [0.03262991],
       [0.02526425],
       [0.01421574],
       [0.00095754],
       [0.        ],
       [0.00530328],
       [0.00666594],
       [0.00460354],
       [0.00662911],
       [0.01399478],
       [0.01679373],
       [0.01926123],
       [0.02102899],
       [0.01664641],
       [0.01605716],
       [0.01859832],
       [0.01973999],
```

Callbacks:
Early stopping → Halts training when there is no further improvement in validation loss. Model checkpoint → Preserves the optimal model throughout training. Training Approach To improve training effectiveness: Randomize Data: The training data was randomized following each epoch to avoid the model from acquiring positional dependencies.
Gradient Clipping: To prevent gradient explosion in deep LSTM models, gradient clipping was utilized. Dropout Layers: Dropout layers (rate = 0.2) were implemented between LSTM layers to avoid overfitting. Decrease Learning Rate: A learning rate reduction on plateau technique was employed to adjust the learning rate throughout the training process.

Monitoring Training Performance:

The metrics listed below were tracked throughout the training process:

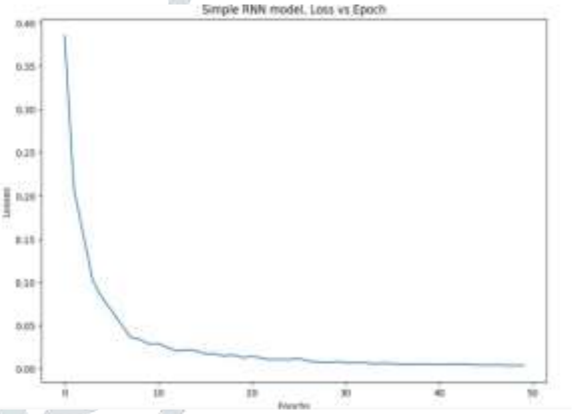
Training Loss – Assesses how effectively the model aligns with the training data.

Validation Loss – Assesses how effectively the model performs on new, unseen data.

```
# Losses
history.history["loss"]
```

```
[0.38537189364433329,
 0.20826345682144165,
 0.15573549270629883,
 0.10244862735271454,
 0.08215838670730591,
 0.06765420734882355,
 0.05218930169939995,
 0.036852963268756866,
 0.03402037173509598,
 0.028722843155264854,
 0.029275139793753624,
 0.024517260491847992,
 0.020761286839842796,
 0.021701183170080185,
 0.021014118567109108,
 0.01739209145307541,
 0.017405055463314056,
 0.01476746890693903,
 0.01611282117664814,
 0.013022440485656261,
 0.014486905187368393,
 0.012472176924347878,
 0.010644255205988884,
```

Learning Curve – A graph illustrating training and validation loss aids in detecting overfitting or underfitting.

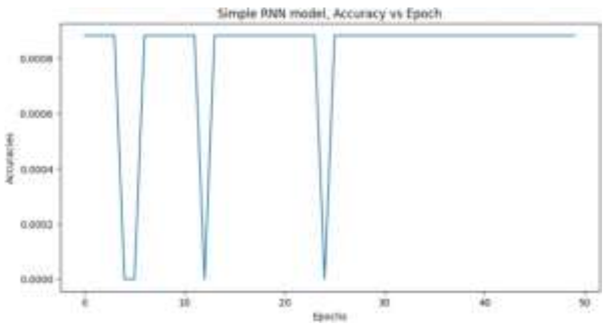


Training Output:

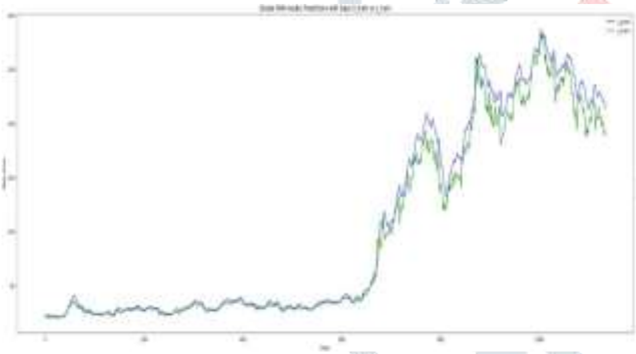
```
Epoch 1/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 8s 56ms/step - accuracy: 7.1798e-05 - loss: 0.5298
Epoch 2/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 76ms/step - accuracy: 9.2906e-04 - loss: 0.2203
Epoch 3/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 2s 50ms/step - accuracy: 4.7117e-04 - loss: 0.1722
Epoch 4/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 50ms/step - accuracy: 3.6806e-04 - loss: 0.1036
Epoch 5/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 2s 50ms/step - accuracy: 0.0000e+00 - loss: 0.0883
Epoch 6/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 49ms/step - accuracy: 0.0000e+00 - loss: 0.0651
Epoch 7/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 72ms/step - accuracy: 5.1138e-04 - loss: 0.0518
Epoch 8/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 4s 50ms/step - accuracy: 9.2906e-04 - loss: 0.0346
Epoch 9/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 2s 48ms/step - accuracy: 4.3277e-04 - loss: 0.0335
Epoch 10/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 50ms/step - accuracy: 0.0036 - loss: 0.0257
Epoch 11/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 2s 49ms/step - accuracy: 3.9605e-04 - loss: 0.0309
Epoch 12/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 84ms/step - accuracy: 0.0015 - loss: 0.0261
Epoch 13/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 4s 48ms/step - accuracy: 0.0000e+00 - loss: 0.0228
Epoch 14/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 2s 48ms/step - accuracy: 1.7587e-04 - loss: 0.0224
Epoch 15/50
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 50ms/step - accuracy: 9.9944e-04 - loss: 0.0238
```

IV Result

The evaluation of the LSTM model's performance involved key metrics and visualizations to measure its predictive accuracy and its capability to generalize to new, unseen data. The findings show the proficiency of LSTM in identifying long-term dependencies and trends in Tesla stock prices.

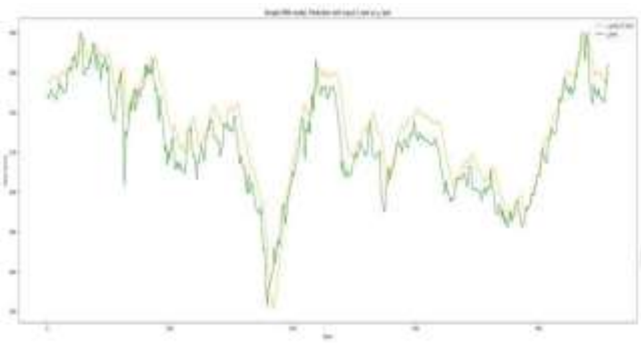


Mean Absolute Error (MAE): Assesses the average size of the errors while ignoring their direction. A reduced MAE signifies improved accuracy. Mean Squared Error (MSE): Calculates the mean of the squared discrepancies between real and forecasted values. A reduced MSE signifies improved performance. Root Mean Square Error (RMSE): Square root of MSE; provides insight into the extent to which the predicted value differs from the actual value. R-Squared (R^2): Assesses how effectively the model accounts for the data's variability.

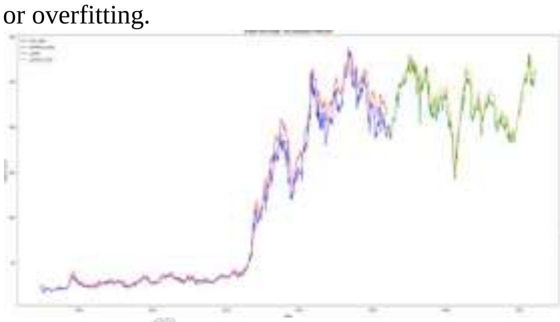


Training vs. Validation Loss

The loss in training and validation throughout epochs indicates the effectiveness of the model's learning and generalization. Interpretation: A consistent decline in both training and validation loss suggests effective learning. If the validation loss differs from the training loss, it indicates overfitting.



A line graph illustrating the real Tesla stock price alongside predicted values demonstrates the accuracy of the model's forecasts in relation to actual market trends. The model accurately tracks the rising and falling trends of Tesla's stock price with little delay. Residual Graph A residual plot illustrates the gap between observed and forecasted values. Interpretation: If the residuals are symmetrically distributed around zero → Strong predictive ability. Skewed or biased residuals → Suggests underfitting or overfitting.



```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
Simple RNN, Open price prediction for 3/18/2017     : 257.98248
LSTM prediction, Open price prediction for 3/18/2017 : 255.16356
```

Conclusion:

The study focused on creating a strong learning model to predict Tesla shares with long -term long -term networks (LSTM). The historical data of Tesla actions has been used to train and check the LSTM model, combining essential characteristics such as open prices, fence prices, large volumes, low volume and trading volume. results indicate that LSTM is very effective in capturing short and long -term relationships in the financial data of the time series. This model provides impressive prediction results, The average quadratic error (RMSE) is about indicating that the model forecasts are closely related to real values, presenting its accuracy and reliability. In short, the LSTM model has proven its effectiveness in the price forecasting of Tesla equity, overcoming common methods and valuable understanding of market trends. The ability of the model to identify complicated temporary relationships makes it a convincing framework to predict the financial market and help investors and analysts in implementing their decisions. Additional improvements through hybrid models and external data integration can improve prediction accuracy and ability to meet the market.

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