

# STOCK MARKET FORECASTING USING TIME SERIES ANALYSIS

UNDER THE SUPERVISION OF SRI. PHULEN MAHATO

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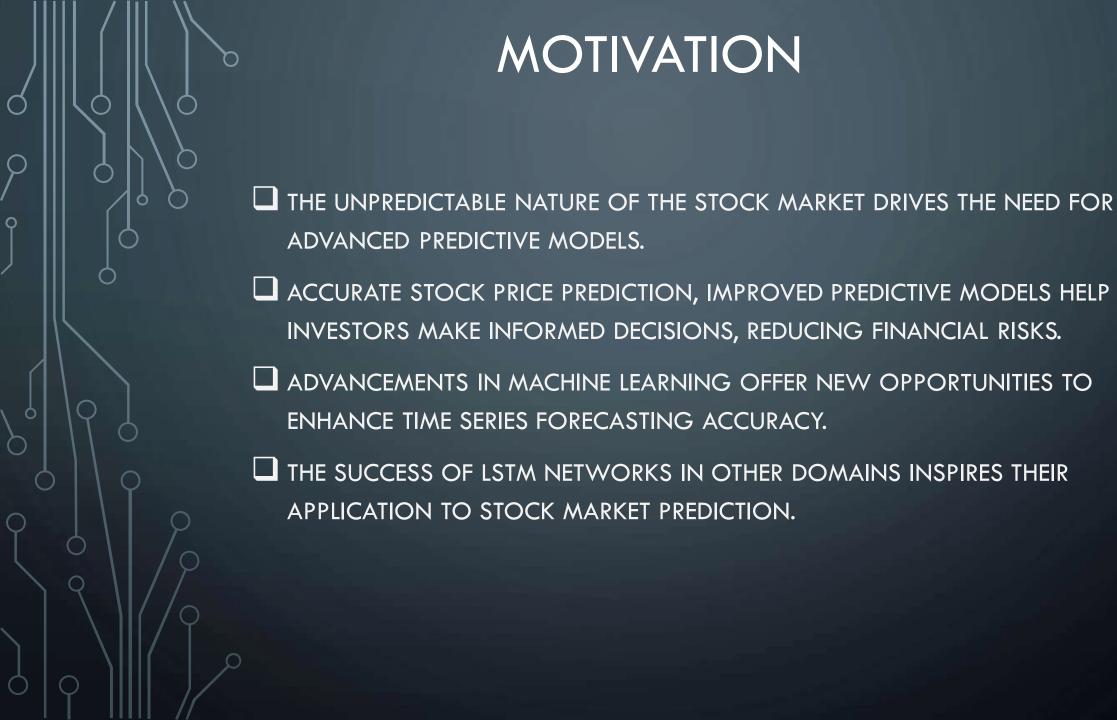
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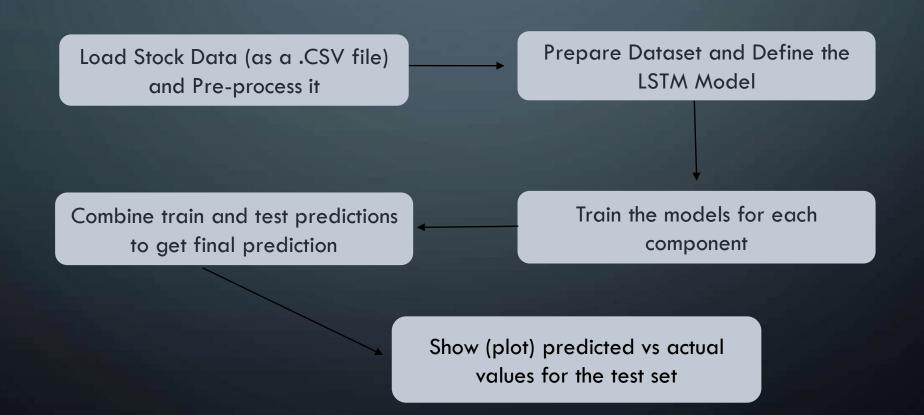
# INTRODUCTION

- THE STOCK MARKET IS A PLACE WHERE STOCKS REPRESENTING COMPANY OWNERSHIP ARE BOUGHT AND SOLD.
- IMPLEMENTING THE CONCEPT OF ALGORITHMIC TRADING WHICH USES AUTOMATED, PRE-PROGRAMMED TRADING STRATEGIES TO PREDICT STOCK PRICES.
- TIME SERIES FORECASTING (PREDICTING FUTURE VALUES BASED ON HISTORICAL VALUES) APPLIES WELL TO STOCK FORECASTING.
- MACHINE LEARNING MODELS LIKE SVR, ANN, AND RNN HAVE IMPROVED TIME SERIES FORECASTING.
- LSTM NETWORKS EXCEL IN STOCK PREDICTION BY STORING AND UTILIZING PAST INFORMATION EFFECTIVELY.



# **OBJECTIVE**

The main objective of our model is to predict the close price of a stock by analyzing complex historical data of the same, using Long Short-Term Memory (LSTM) networks by executing the following taks.



# TECHNOLOGY USED



Python Language
Python is a rich
language for Data
Science and Al



Libraries Used pandas, sklearn, numpy, tensorflow, etc.

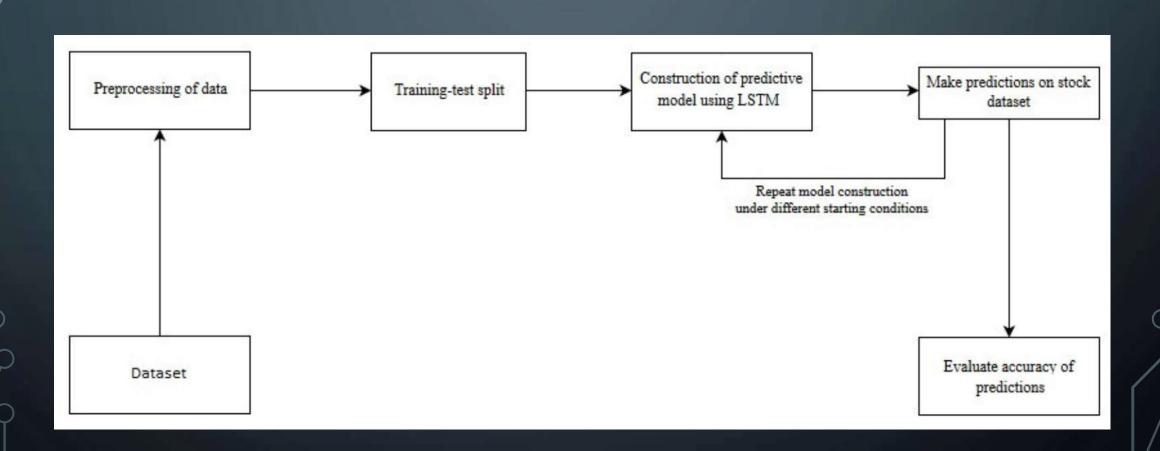


Algorithm
Long Short Term Memory
(LSTM)



Environment
Google Colab is a cloudbased platform to execute
Python codes.

# GENERIC MODEL FOR STOCK MARKET FORECASTING



## DATASET

The dataset used in this project is <u>TSLA</u> (Tesla) from June 29, 2010 to December 31, 2020. This is a series of data points indexed in time order or time series. Our goal was to predict the closing price for any given date after training.

| Date       | Open  | High  | Low   | Close | Adj Close | Volume   |
|------------|-------|-------|-------|-------|-----------|----------|
| 29-06-2010 | 3.8   | 5     | 3.508 | 4.778 | 4.778     | 93831500 |
| 30-06-2010 | 5.158 | 6.084 | 4.66  | 4.766 | 4.766     | 85935500 |
| 01-07-2010 | 5     | 5.184 | 4.054 | 4.392 | 4.392     | 41094000 |
| 02-07-2010 | 4.6   | 4.62  | 3.742 | 3.84  | 3.84      | 25699000 |
| 06-07-2010 | 4     | 4     | 3.166 | 3.222 | 3.222     | 34334500 |
| 07-07-2010 | 3.28  | 3.326 | 2.996 | 3.16  | 3.16      | 34608500 |
| 08-07-2010 | 3.228 | 3.504 | 3.114 | 3.492 | 3.492     | 38557000 |
| 09-07-2010 | 3.516 | 3.58  | 3.31  | 3.48  | 3.48      | 20253000 |
| 12-07-2010 | 3.59  | 3.614 | 3.4   | 3.41  | 3.41      | 11012500 |

Table 1: TESLA Stock Data

#### DATA PREPROCESSING

The Steps of Preprocessing of Data is shown below:

Load Stock Data (as a .CSV file)

Filter Data

Resample Data

Seasonal Decomposition and drop NaN values

Read the CSV file.

Convert the 'Date' column to datetime.

Set 'Date' as the index.

Exclude data after 2020-12-31 due to too much noise (COVID-19 effect).

Resample to weekly frequency using the mean of daily adjusted close prices.

Perform seasonal decomposition with a multiplicative model and a period of 52 weeks.
Extract trend, seasonal, and residual components.
Drop Not a Number values.

## DATA PREPROCESSING

Scale Data

Normalize the 'trend', 'seasonal', and 'residual' components to a range of 0 to 1, ensuring all values fall within this interval. Fit and transform each component to achieve uniform scaling, improving model training and performance.

Split Data

Split the data into training and testing sets (last 24 months for testing).

Prepare Dataset

Define the number of previous weeks (n\_input) to use for prediction.

Set the number of weeks to predict (n\_output).

# STOCK PRICE PREDICTOR MODEL

As the name suggests, the Stock Price Predictor Model is designed to forecast the close price of a stock by analyzing complex historical data. It is built using Long Short-Term Memory (LSTM) networks. Using LSTM networks for stock price prediction ensures the model can effectively capture long-term dependencies and patterns in financial time series data, thereby improving accuracy and reliability in forecasting future stock prices.

**How it Works? (LSTM)** 

- ☐ The key to LSTM is the **Memory Cell state** which stores the information. It runs straight down the entire chain.
- LSTM has the ability to **remove or add information** to these cell state, regarded by structures called **gates**.
- Gates are composed of sigmoid neural net layer and a multiplication operation.
- ☐ Sigmoid layer outputs are zero or one.
- ☐ It consists of 3 gates: Input Gate, Forget Gate, Output Gate.

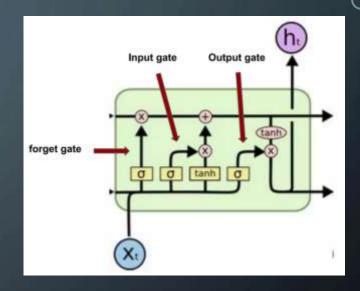


Fig 1: LSTM Architecture

#### First,

- Forget gate looks at  $h_{t-1}$  and  $x_t$  and outputs a number between 0 and 1.
- 1' represents **keep the information**'0' represents **remove the information**.

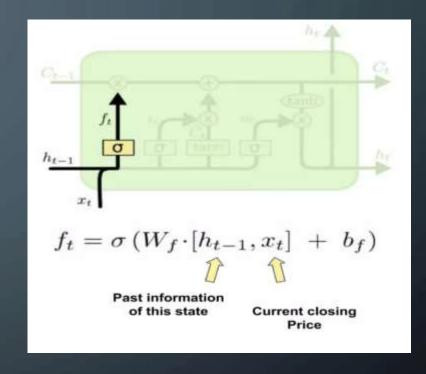


Fig 2: Working of Forget Gate

#### First,

- Forget gate looks at  $h_{t-1}$  and  $x_t$  and outputs a number between 0 and 1.
- '1' represents keep the information'0' represents remove the information.

#### Second,

- Input gate decides which values will be updated, in order to do that a tanh layer creates a vector of  $C_t$  (bar).
- Combining these two, create an update to the state.

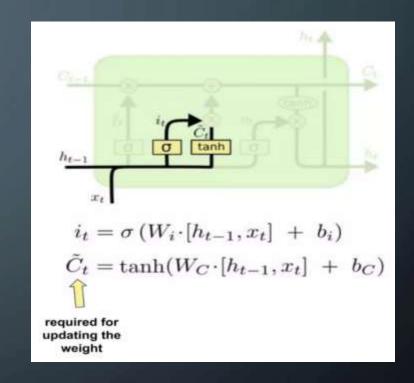


Fig 3: Working of Input Gate

#### First,

- Forget gate looks at  $h_{t-1}$  and  $x_t$  and outputs a number between 0 and 1.
- '1' represents keep the information'0' represents remove the information.

#### Second,

- Input gate decides which values will be updated, in order to do that a tanh layer creates a vector of  $C_t$  (bar).
- Combining these two, create an update to the state.

#### Third,

 $\Box$  It's time to update the old cell  $c_{t-1}$  to c  $c_t$ 

#### Fourth,

- Output will be based on our **cell state**.
- A sigmoid layer will decide what parts of the cell state we are going to output.

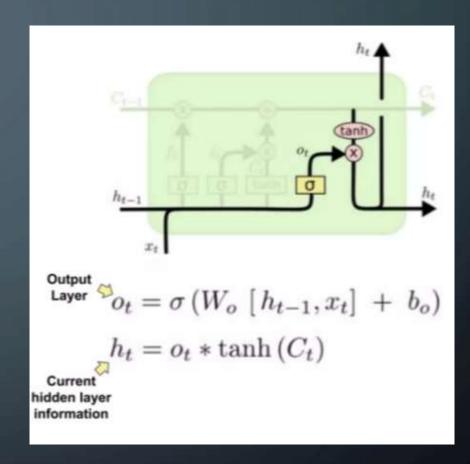
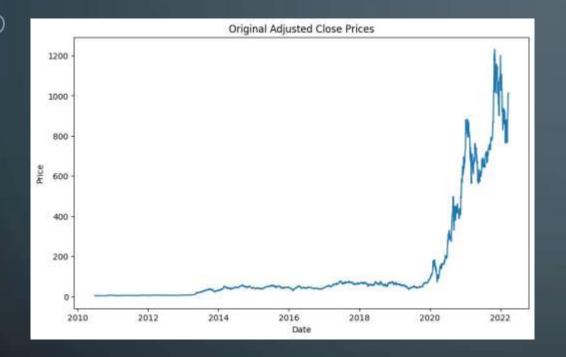


Fig 4: Working of Output Gate

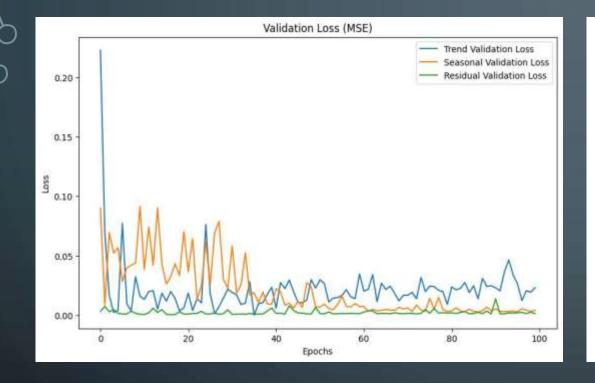
# VISUALIZING MULTIPLE ASPECTS OF DATA



— Seasonal 1.25 0.75 0.50 

Fig 5: Original Closing Price Graph

Fig 6: Seasonal Decomposition of the Data Graph



| Epoch | Trend Validation Loss | Seasonal Validation L | oss Residual Validation Loss |
|-------|-----------------------|-----------------------|------------------------------|
| 1     | 0.222865              | 0.090186              | 0.003251                     |
| 11    | 0.013341              | 0.038465              | 0.000555                     |
| 21    | 0.018600              | 0.036452              | 0.000927                     |
| 31    | 0.019068              | 0.058189              | 0.000704                     |
| 41    | 0.005907              | 0.022225              | 0.001524                     |
| 51    | 0.029744              | 0.006909              | 0.001336                     |
| 61    | 0.020337              | 0.007389              | 0.002611                     |
| 71    | 0.016771              | 0.006152              | 0.001600                     |
| 81    | 0.023774              | 0.003589              | 0.001872                     |
| 91    | 0.023108              | 0.005301              | 0.013828                     |
|       |                       |                       |                              |

Fig 7: Validation Loss Graph

Table 2: Validation Loss in Tabular Form

# FINAL RESULT

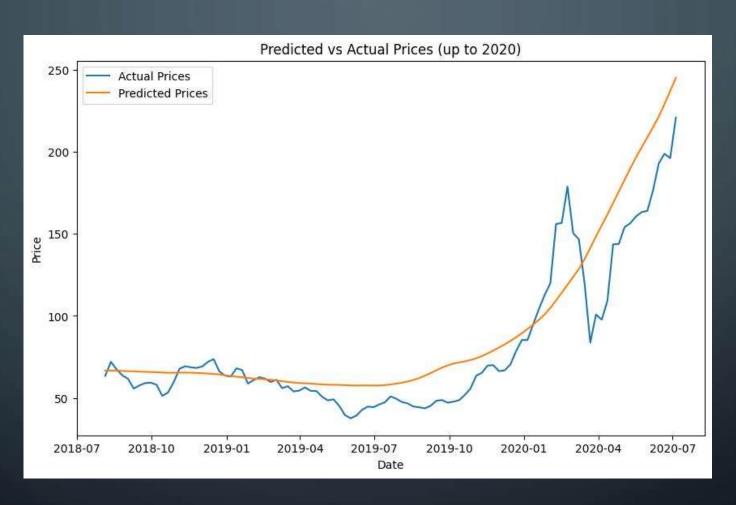


Fig 8: Actual vs Predicted Graph

### CONCLUSION

- □ Challenges in Stock Market Prediction: No model can guarantee successful predictions due to the complexity and numerous influencing factors.
- ☐ Importance of Preprocessing Techniques: Effective preprocessing, like decomposing and differencing for stationarity, enhances model performance.
- □ LSTM's Strengths: LSTM models capture long-term dependencies, making them effective for sequential data in time series forecasting.
- ☐ Component-wise Model Training: Training LSTM on decomposed components (trend, seasonal, residual) allows for detailed and accurate forecasting.
- □ Comparative Analysis for Better Decisions: Comparing various time series models is crucial for making informed stock trading decisions to minimize losses and maximize profits.

# FUTURE SCOPE

- ☐ Focus on Public Sentiments: Integrate sentiment analysis from social media and financial news to enhance stock price predictions.
- ☐ **Hybrid Model Development:** Develop a hybrid model combining historical data with sentiment analysis for more accurate forecasting.
- □ Incorporate Environmental Factors: Include environmental factors like floods and storms in prediction models to improve accuracy.
- □ **Expand to Cryptocurrency:** Extend the application to predict cryptocurrency trading using time series and sentiment analysis.
- **Enhance Predictive Models:** Continuously refine predictive time series models for higher accuracy in stock market forecasting.

