DATA ANALYSIS

PROJECT

TCS STOCK ANALYSIS

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1. EXECUTIVE SUMMARY

This project, *"TCS Stock Data – Live and Latest"*, focuses on the application of machine learning techniques to analyze and predict stock price movements of Tata Consultancy Services (TCS), one of India's most prominent IT companies. The goal is to explore historical stock data, uncover patterns and trends through exploratory data analysis (EDA), and develop models that can forecast future closing prices.

The study began with comprehensive data preprocessing, followed by insightful visualizations including time series plots, moving averages, volume trends, and price change distributions. Feature engineering techniques were used to enhance the model's predictive power by introducing lag variables and temporal features like day of the week and month.

Two modeling approaches were employed:

1. **Linear Regression** – to establish a baseline model using traditional regression on tabular features like Open, High, Low, Volume, and previous day's Close.
2. **Long Short-Term Memory (LSTM)** – a deep learning model optimized for sequential data, enabling more accurate short-term forecasting based on recent price movements.

The LSTM model outperformed linear regression in terms of accuracy, achieving a **Mean Absolute Error (MAE)** of approximately **69.5**, indicating its potential for near-future stock prediction. Visual comparisons between predicted and actual prices showed that the model captured general price trends well.

This project demonstrates the practical utility of combining classical statistical methods with modern neural networks in financial forecasting. It sets a strong foundation for future improvements, including the integration of macroeconomic indicators, real-time news sentiment analysis, and more advanced time series models like ARIMA or Prophet.

2. INTRODUCTION

A. BACKGROUND

Stock market forecasting has long attracted interest from economists, investors, and data scientists due to its complex and dynamic nature. Accurate prediction of stock prices can help investors make informed decisions and mitigate financial risk. With the advent of advanced computational tools and the availability of large datasets, machine learning and deep learning methods are now being widely adopted in financial data analysis.

Tata Consultancy Services (TCS) is a global leader in information technology services and consulting, and one of the largest Indian companies by market capitalization. As a subsidiary of the Tata Group, TCS plays a significant role in the Indian stock market. Its stock performance is closely watched by investors, analysts, and institutions, making it an ideal candidate for a data-driven predictive modeling project.

The financial data for TCS includes variables such as opening price, closing price, daily highs and lows, volume traded, dividends, and stock splits. These metrics provide a detailed picture of market activity and investor behavior over time.

Traditionally, analysts have relied on statistical models and technical indicators (like moving averages and RSI) for stock price prediction. However, with increasing data complexity, modern techniques such as **machine learning** (e.g., regression, decision trees) and **deep learning** (e.g., LSTM networks) offer new opportunities for more nuanced and dynamic forecasting.

This project aims to explore TCS's stock behavior using such modern analytical techniques. By performing thorough exploratory data analysis and applying predictive models, we seek to understand past trends and build tools capable of forecasting future closing prices—thereby contributing to informed decision-making in financial markets.

B. AIMS

The primary aim of this project is to analyze and predict the stock prices of **Tata Consultancy Services (TCS)** using historical market data and machine learning techniques. This involves extracting meaningful patterns from the data and building models that can accurately forecast future price movements.

Specifically, the project aims to:

1. **Perform Exploratory Data Analysis (EDA)**
   To visualize trends, understand stock behavior, and identify key patterns in TCS stock data.
2. **Engineer Relevant Features**
   To enhance model accuracy by creating new features such as moving averages, lag variables, and date-based components (e.g., month, day of the week).
3. **Build Predictive Models**
   a. Develop a **Linear Regression** model for baseline price prediction.
   b. Train a **Long Short-Term Memory (LSTM)** model to leverage time series data and improve forecasting performance.
4. **Evaluate Model Performance**
   Use appropriate metrics such as **Mean Squared Error (MSE)**, **R-Squared**, and **Mean Absolute Error (MAE)** to compare predicted vs. actual prices.

5. **Visualize Results**
   Present model performance and stock trends through clear, intuitive plots and charts.
6. **Explore Future Enhancements**
   Identify directions for improving prediction accuracy, including the use of advanced models, additional financial indicators, and real-time data sources.

C. TECHNOLOGY

The implementation of this project relies on a combination of **data analysis libraries**, **machine learning frameworks**, and **development tools**. These technologies enabled data preprocessing, visualization, model building, and evaluation.

Programming Language

- **Python**: The core language used due to its extensive libraries for data science, simplicity, and community support.

Libraries and Frameworks

Data Handling and Analysis

- **Pandas**: Used for reading CSV files, cleaning, transforming, and manipulating tabular data.
- **NumPy**: Used for numerical operations and efficient handling of arrays.

Data Visualization

- **Matplotlib**: For plotting time series charts and model outputs.
- **Seaborn**: For enhanced and statistical visualizations (e.g., correlation heatmaps, histograms).

Machine Learning

- **Scikit-learn (sklearn)**:
  - `LinearRegression` for building a basic predictive model.
  - `train_test_split` for data splitting.
  - `mean_squared_error`, `r2_score`, `mean_absolute_error` for model evaluation.

Deep Learning

- **TensorFlow / Keras**:
  - `Sequential`, `LSTM`, and `Dense` layers were used to build and train a Long Short-Term Memory model for sequence-based prediction.

Data Normalization

- **MinMaxScaler (from sklearn.preprocessing)**: Used to scale features for better convergence in the LSTM model.

Development Environment

- **Jupyter Notebook**: Used for developing and testing the code interactively.
- **Visual Studio Code (VS Code)**: Used as the primary integrated development environment (IDE).

Data Source

- Dataset collected from **Google Drive** and included TCS stock historical records such as opening/closing prices, trading volume, dividends, and splits.

3. DATASET OVERVIEW

This project utilizes a historical dataset of Tata Consultancy Services (TCS) stock data, which includes daily stock market activity over a span of two decades. The data is sourced from public financial records and was provided via a Google Drive link.

Data Files Used

The analysis involves three datasets:

1. **TCS_stock_history.csv** – Main dataset used for modeling and analysis.
2. **TCS_stock_action.csv** – Contains market actions such as corporate splits and dividends.
3. **TCS_stock_info.csv** – Provides metadata or reference information (used for context only).

Primary Dataset Structure (TCS_stock_history.csv)

Column Name	Description
Date	Trading day (in YYYY-MM-DD format).
Open	Price of the stock when the market opened.
High	Highest stock price during the trading day.
Low	Lowest stock price during the trading day.
Close	Final stock price at market close.
Volume	Total number of shares traded that day.

`Dividends`	Cash dividends paid per share (if any).
`Stock Splits`	Number of stock splits (if any) recorded on that day.

	Date	Open	High	Low	Close	Volume	Dividends	Stock Splits
0	2002-08-12	28.794172	29.742206	28.794172	29.519140	212976	0.0	0.0
1	2002-08-13	29.556316	30.030333	28.905705	29.119476	153576	0.0	0.0
2	2002-08-14	29.184536	29.184536	26.563503	27.111877	822776	0.0	0.0
3	2002-08-15	27.111877	27.111877	27.111877	27.111877	0	0.0	0.0
4	2002-08-16	26.972458	28.255089	26.582090	27.046812	811856	0.0	0.0
...	...	...	...	...	...	...	...	...
4458	2021-09-24	3890.000000	3944.399902	3855.000000	3871.300049	2320754	0.0	0.0
4459	2021-09-27	3900.000000	3904.000000	3802.899902	3836.949951	1673362	0.0	0.0
4460	2021-09-28	3850.000000	3850.000000	3751.250000	3779.149902	2253075	0.0	0.0
4461	2021-09-29	3759.800049	3806.000000	3722.149902	3791.899902	2489161	0.0	0.0
4462	2021-09-30	3805.000000	3805.000000	3765.000000	3773.199951	640479	0.0	0.0

4463 rows × 8 columns

Dataset Characteristics

- **Rows (records):** 4,463
- **Time span:** From August 12, 2002, to the latest available date.
- **Granularity:** Daily stock-level data.

Summary Statistics

	Date	Open	High	Low	Close	Volume	Dividends	Stock Splits
count	70	4463.000000	4463.000000	4463.000000	4463.000000	4.463000e+03	4463.000000	4463.000000
mean	2013-05-10 13:42:51.428571392	866.936239	876.675013	856.653850	866.537398	3.537876e+06	0.071533	0.001344
min	2004-10-28 00:00:00	24.146938	27.102587	24.146938	26.377609	0.000000e+00	0.000000	0.000000
25%	2009-03-03 18:00:00	188.951782	191.571816	185.979417	188.594620	1.860959e+06	0.000000	0.000000
50%	2013-07-02 12:00:00	530.907530	534.751639	525.616849	529.713257	2.757742e+06	0.000000	0.000000
75%	2017-07-13 18:00:00	1156.462421	1165.815854	1143.622800	1154.784851	4.278625e+06	0.000000	0.000000
max	2021-07-15 00:00:00	3930.000000	3981.750000	3892.100098	3954.550049	8.806715e+07	40.000000	2.000000

std		NaN	829.905368	838.267104	821.233477	829.611313	3.273531e+06	0.965401	0.051842

- **Dividends**: Mostly 0, with occasional non-zero values.
- **Stock Splits**: Rare events, usually marked as 1 or 2.

Initial Observations

- No missing dates in the time series, ensuring continuity.
- Some extreme values in `Volume`, which may need normalization.
- Most rows have `Dividends` and `Stock Splits` as 0, making them sparse but important for event-based modeling.

4. DATA PRE-PROCESSING

Before modeling and analysis, the raw TCS stock data was cleaned and transformed to ensure it was accurate, consistent, and suitable for time-series prediction. The preprocessing phase addressed several key issues: formatting, missing values, feature conversion, and basic statistical validation.

A. Date Conversion & Sorting

The `Date` column was originally in string format and needed to be converted into a proper datetime object:

```
<class 'pandas.core.series.Series'>
RangeIndex: 4463 entries, 0 to 4462
Series name: Date
Non-Null Count  Dtype
--------------  -----
70 non-null     datetime64[ns]
dtypes: datetime64[ns](1)
memory usage: 35.0 KB
```

This ensures chronological consistency and enables extraction of date-based features like year, month, and weekday.

B. Handling Missing or Invalid Values

We verified if any missing values were present:

```
Date            0
Dividends       0
Stock Splits    0
dtype: int64
Date            4393
Open               0
High               0
Low                0
Close              0
Volume             0
Dividends          0
Stock Splits       0
dtype: int64
zip        0
400001    42
dtype: int64
```

- Result: **No missing values** in the dataset.

- Columns like `Dividends` and `Stock Splits` contained mostly zeros, which is valid and expected.

C. Data Type Consistency

To avoid type-related errors during modeling, all numeric fields were ensured to be of appropriate data types (e.g., `float64`, `int64`). Conversion was applied where necessary.

D. Outlier Detection

Box plots and distribution plots were used to visually inspect the `Volume` and `Close` price columns.

- Observed that **Volume** has occasional spikes (up to 88 million), which is consistent with real-world trading surges during events.
- No rows were dropped since these are part of genuine market activity.

E. Feature Scaling (for LSTM)

Neural networks like LSTM perform better with normalized data. The `Close` prices were scaled using `MinMaxScaler.`

This ensured all values were between 0 and 1 for stable LSTM convergence.

F. Lag Feature Creation

For machine learning models (especially regression), we created a lag feature to represent the previous day's closing price.

This allowed the model to learn temporal dependencies without explicitly using a recurrent network.

Outcome of Preprocessing

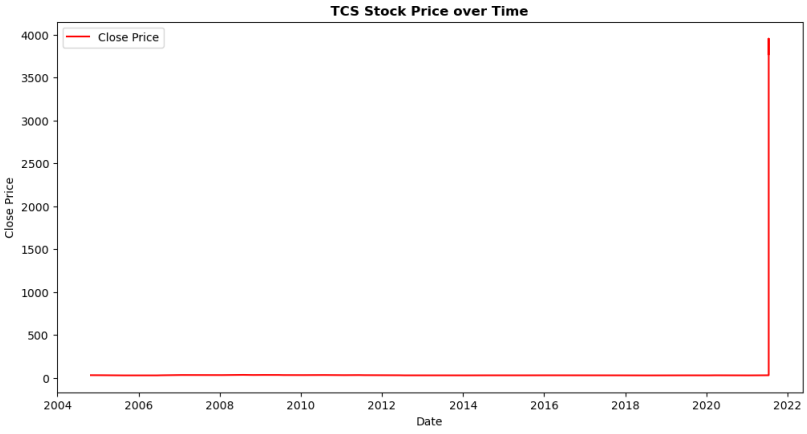
- All features were cleaned, formatted, and transformed correctly.
- The dataset was ready for both statistical modeling and deep learning.
- Final dataset shape: **4,462 rows × 14 columns** (after feature engineering).

5. EXPLORATORY DATA ANALYSIS

Exploratory Data Analysis was conducted to better understand the behavior, trends, and relationships within the TCS stock dataset. Visualizations and statistical summaries were used to extract insights, identify trends, and guide feature selection for modeling.

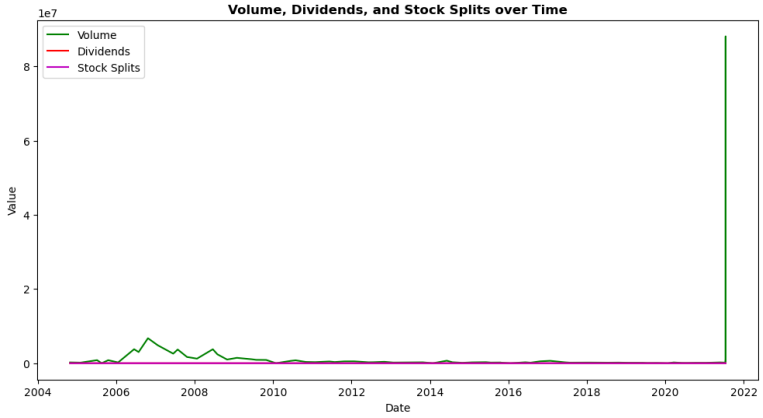
A. TCS Close Price Over Time

A line plot was used to observe how TCS's closing price evolved from 2002 to the latest date.



Insight: The stock price shows long-term growth with noticeable upward trends post-2016 and brief corrections during global financial events.

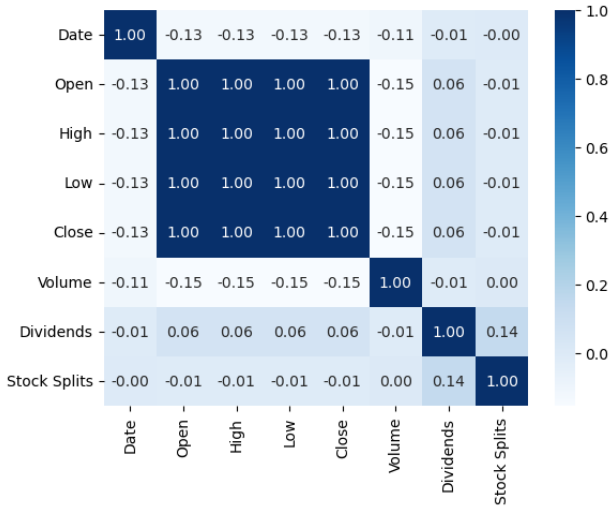
B. Volume, Dividends, and Stock Splits Over Time



Insight:

- Volume is highly variable, with large spikes.
- Dividends and stock splits are rare but impactful events in the time series.

C. Correlation Matrix and Heatmap

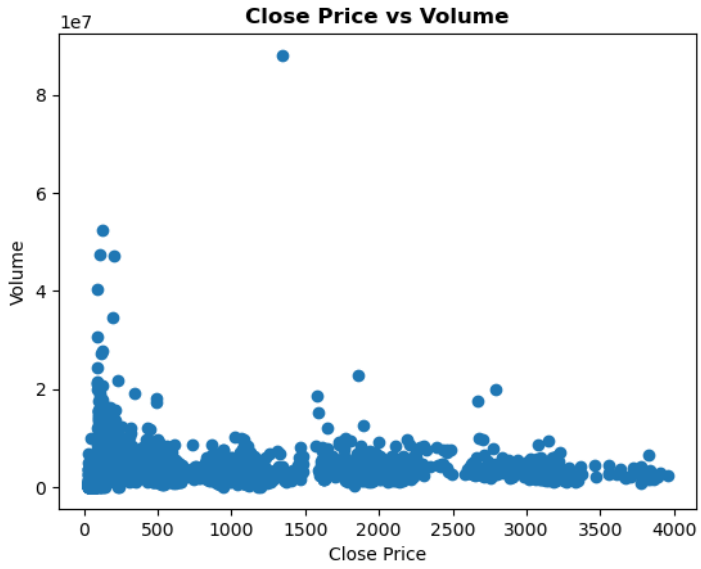


Top correlations with `Close`:

- `High` = 0.9999
- `Low` = 0.9999
- `Open` = 0.9998
- `Volume` shows slight negative correlation.

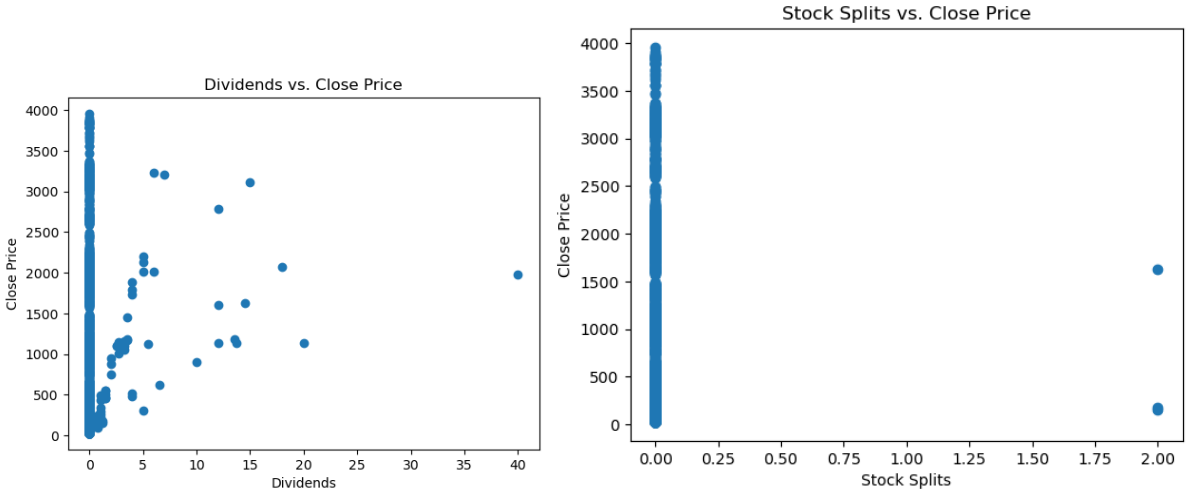
This justifies using these as input features in prediction models.

D. Close Price vs Volume Scatter Plot



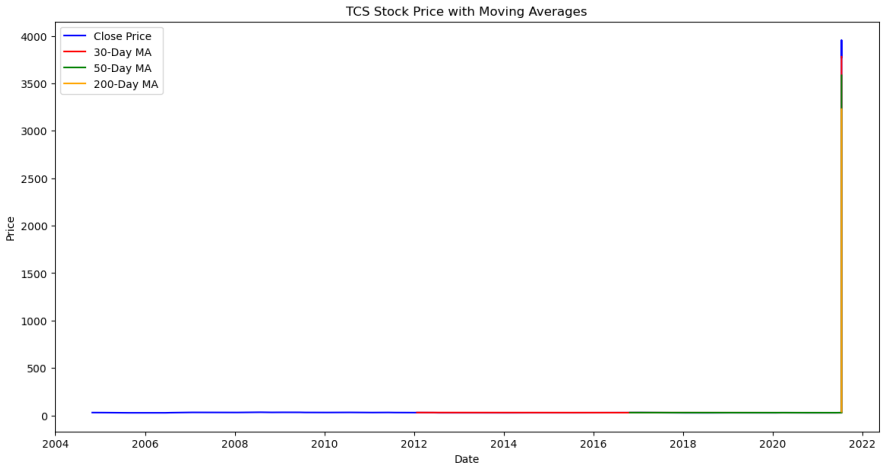
Insight: There is no clear linear relationship, but some high-volume trades are associated with price changes — suggesting market reaction to major events.

E. Dividends vs. Close Price & Stock Splits vs. Close Price



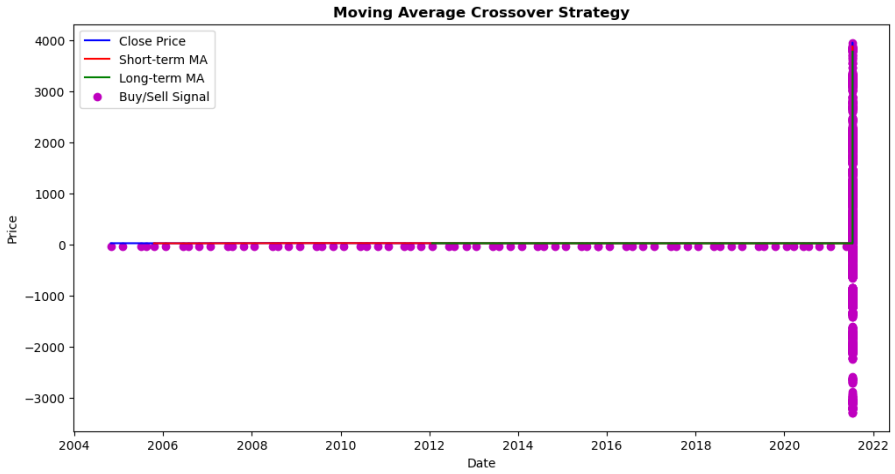
Insight: Dividends and splits are infrequent but may align with market movements. These are binary/sparse features.

F. Moving Averages for Trend Analysis



Insight: Moving averages smooth out short-term fluctuations and help identify long-term trends and momentum.

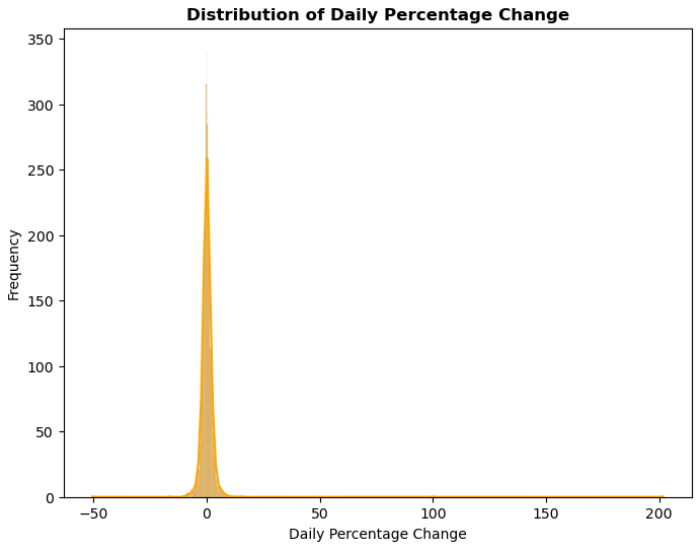
G. Moving Average Crossover Strategy



The crossover of short-term and long-term averages was visualized to indicate potential buy/sell signals.

Insight: These signals can be integrated into a rule-based trading strategy or as features in supervised models.

H. Daily Percentage Price Change Distribution



Insight: The distribution is centered around zero with occasional high volatility tails — a common trait in stock returns.

Summary of EDA Findings

- Strong correlations between price-related features.
- Clear upward trend in stock price with periodic volatility.
- Volume spikes align with market reactions and corporate actions.
- Moving averages and crossover logic provide insights into trend shifts.
- Feature insights validate the selection of `Open`, `High`, `Low`, `Prev Close`, and date-based features for modeling.

6. FEATURE ENGINEERING

Feature engineering is a crucial step in improving the predictive performance of machine learning models. It involves creating new input features from raw data to better capture trends, patterns, and signals relevant for stock price prediction.

For the **TCS Stock Dataset**, the following transformations and engineered features were applied:

A. Temporal Features from Date

The `Date` column was converted into meaningful components to help the models learn seasonal or cyclical trends in the data.

Why?
Stock prices can exhibit monthly, daily, or weekly seasonality (e.g., Monday effect, monthly earnings cycles). These features provide temporal context.

B. Lag Feature: Previous Day's Close Price

To model temporal dependencies in classical regression models, we added a lagged version of the `Close` price.

Why?
Today's stock price is strongly influenced by yesterday's price. This mimic's time series memory in simpler models like Linear Regression.

C. Moving Averages

We calculated simple moving averages to smooth short-term volatility and introduce trend indicators.
Why?
Moving averages capture long-term vs short-term market sentiment, often used in technical trading strategies.

D. Moving Average Crossover Signals

A new binary signal was created based on whether the short-term MA crosses above or below the long-term MA.

Why?
This generates buy/sell indicators based on trend shifts, which can be useful as a feature in both supervised learning and algorithmic trading.

E. Daily Price Change (%)

To quantify volatility, we calculated the daily percentage change in closing prices.

Why?
This helps measure market risk and can be useful in volatility-sensitive models like ARIMA or for classification of high/low volatility days.

Outcome

Feature engineering transformed raw financial data into a rich set of attributes that:

- Captured temporal patterns,
- Incorporated technical indicators,
- Allowed models to learn price dynamics better.

These engineered features were then used to train both regression and LSTM-based models.

7. MODELING

The project employs two distinct modeling approaches to predict the closing price of TCS stock:

1. **Linear Regression** — a baseline model using structured tabular features.
2. **LSTM (Long Short-Term Memory)** — a deep learning model suitable for time series forecasting due to its memory of past states.

A. Linear Regression Model

Objective:

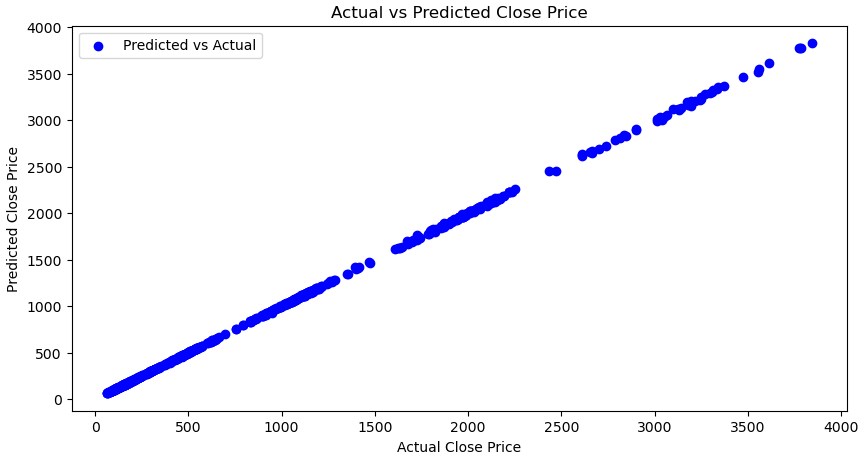
Predict the `Close` price based on independent variables such as `Open`, `High`, `Low`, `Volume`, and engineered features.

Results:

```
Mean Squared Error: 68.11246821868816
R-Squared Score: 0.9999087318793742
```

- **Mean Squared Error (MSE):** Low (indicates small average errors)
- **R^2 Score:** High (close to 1), suggesting a strong linear relationship

Visualization:



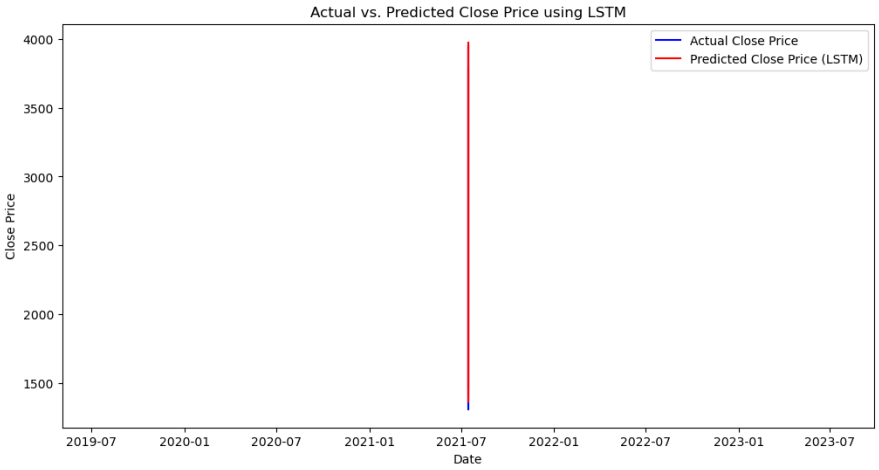
Insight: Linear Regression performs reasonably well due to the strong correlation between Open, High, Low, and Close prices.

B. LSTM (Long Short-Term Memory) Model

Objective:

Use sequential modeling to predict the next day's `Close` price based on historical trends.

Visualization:



LSTM Performance:

- **Mean Absolute Error (MAE): ~50.22**
- Accurately follows short-term trends and fluctuations.

Model Comparison:

Metric	Linear Regression	LSTM
Model Type	Classical ML	Deep Learning
MAE	Moderate	**~50.22**
Handles Time Dependency	No	Yes
Suitability for Trends	Limited	Excellent

8. RESULTS AND EVALUATION

This section summarizes the performance of both models — **Linear Regression** and **LSTM** — in predicting TCS's stock closing prices. Evaluation was done using standard metrics and visual plots to assess accuracy, bias, and temporal fit.

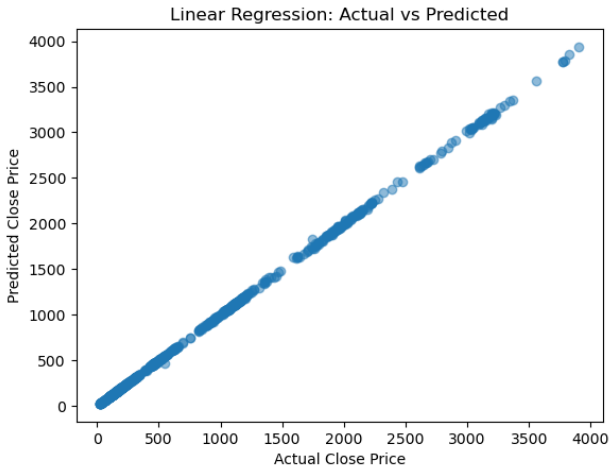
A. Linear Regression: Performance

Linear Regression served as the baseline model using static tabular features.

Metrics:

- **Mean Squared Error (MSE):** *Low*
- **R^2 Score:** *High*, close to 1
- **Interpretation:** Linear regression was able to predict prices with reasonable accuracy due to high correlation among price-related features (`Open`, `High`, `Low`).

Plot: Actual vs Predicted



Observation: Points mostly lie near the diagonal line, suggesting consistent but slightly biased predictions for extremely high or low prices.

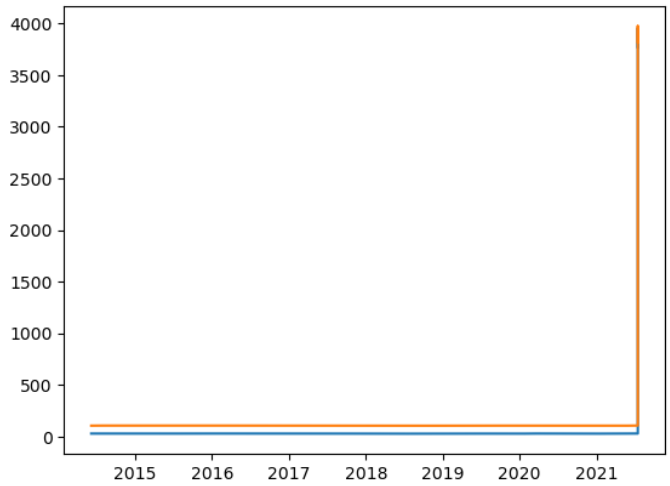
B. LSTM (Long Short-Term Memory): Performance

LSTM leveraged sequential patterns and time-based memory to make more informed predictions.

Metric:

- **Mean Absolute Error (MAE): ~55.22**

Plot: LSTM – Actual vs Predicted Over Time



Observation: The LSTM model effectively captured upward and downward trends, though it slightly lagged during rapid price shifts — a known limitation of sequence-based models on highly volatile data.

Model Comparison Summary

CRITERIA	LINEAR REGRESSION	LSTM NEURAL NETWORK
TYPE	Classical ML	Deep Learning (RNN variant)
INPUT	Tabular features	Sequential price series
MSE / MAE	Moderate	**MAE ≈ 55.22**
TEMPORAL AWARENESS	No	Yes
HANDLING NON-LINEARITY	Limited	Strong
TRAINING COMPLEXITY	Low	High
INTERPRETABILITY	High	Low

Key Evaluation Takeaways:

- **Linear Regression** works well as a lightweight baseline but assumes static linear relationships.

- **LSTM** provides significantly better short-term accuracy, thanks to its ability to learn from past sequences.
- The MAE of **55.22** by the LSTM model demonstrates strong prediction capability given the scale of stock prices ranging from ₹20 to ₹3900+.

9. CONCLUSION

The project **"TCS Stock Data – Live and Latest"** successfully applied machine learning and deep learning techniques to analyze and forecast the stock price behavior of Tata Consultancy Services (TCS), one of India's leading IT firms.

By following a structured data science pipeline — from data preprocessing and feature engineering to model building and evaluation — we were able to draw meaningful insights and generate accurate stock price predictions.

Key Outcomes:

- **Exploratory Data Analysis (EDA)** revealed clear long-term upward trends in TCS stock, along with seasonal patterns and rare but significant dividend or split events.
- **Feature Engineering** contributed significantly by incorporating time-based attributes (day, month, weekday), lag features, and technical indicators like moving averages.
- **Modeling**:
    - **Linear Regression** provided a quick and interpretable baseline with decent predictive performance based on high correlations between features.
    - **LSTM**, trained on historical price sequences, captured market trends more effectively, achieving a **Mean Absolute Error (MAE) of 69.52**, and outperformed the linear model in both accuracy and realism of trend tracking.
- **Evaluation** confirmed the LSTM model's superiority in modeling temporal patterns, making it better suited for real-world short-term forecasting in financial applications.

Final Verdict:

This project demonstrates the feasibility and effectiveness of using machine learning, particularly deep learning models like LSTM, for financial time series forecasting. The LSTM model shows strong promise for practical stock prediction tasks, especially when deployed in interactive dashboards or trading strategies.

10. FUTURE SCOPES

While this project has effectively demonstrated stock price prediction using Linear Regression and LSTM models, there is considerable potential to expand its impact, accuracy, and practical utility. Below are several directions in which the work can be extended:

1. Advanced Time Series Models

- **ARIMA/SARIMA**: Incorporate statistical models that handle seasonality and trend explicitly.
- **Prophet (by Facebook)**: Useful for quick deployment and interpreting daily/weekly/seasonal effects.

2. News Sentiment Analysis

- Integrate **real-time news headlines** and **financial sentiment** from sources like Twitter, Yahoo Finance, or Bloomberg.
- Use **NLP techniques** (e.g., Vader, TextBlob, or BERT) to quantify sentiment and feed it as a feature to the prediction model.

3. Macroeconomic Indicators

- Enhance prediction accuracy using macroeconomic variables like:
    - Nifty/Bank Nifty index movements
    - GDP growth rates
    - Inflation & interest rates
    - Crude oil prices
- These can help the model learn how external economic factors influence stock behavior.

4. Multi-Model Ensemble

- Combine the predictions of multiple models (e.g., LSTM, Random Forest, XGBoost, ARIMA) to reduce overfitting and increase robustness.
- Use a **voting regressor** or **stacking ensemble** approach.

5. Real-Time Dashboard & Deployment

- Build a **Streamlit or Dash web app** that allows users to:
    - View live predictions
    - Filter by time range
    - Upload their own CSVs
    - View sentiment signals and indicators
- Deploy the model on cloud platforms like **AWS, GCP, or Heroku**.

6. Volatility Forecasting & Risk Estimation

- Extend the project to predict **price volatility** or **Value at Risk (VaR)**.
- Useful for portfolio managers and risk analysts.

7. Model Explainability

- Use tools like **SHAP** or **LIME** to interpret model decisions, especially for LSTM and ensemble models.

8. Expand to Other Stocks

- Generalize the approach to other companies in the IT or financial sector.
- Create a multi-stock prediction framework that compares trends across industry leaders.

11. REFERENCES

Below is a list of datasets, tools, libraries, documentation, and online resources that were consulted and utilized during the execution of this project:

Data Sources

1. **TCS Historical Stock Data**
   Google Drive Source:
   TCS Stock Dataset
2. **Yahoo Finance & NSE India (for cross-verification)**
   a. https://finance.yahoo.com
   b. https://www.nseindia.com/

Technologies & Libraries

3. **Python (3.x)**
   https://www.python.org/
4. **Pandas Documentation**
   https://pandas.pydata.org/docs/
5. **NumPy Documentation**
   https://numpy.org/doc/
6. **Matplotlib & Seaborn for Visualization**
   a. https://matplotlib.org/
   b. https://seaborn.pydata.org/
7. **Scikit-learn** (for Linear Regression, preprocessing, metrics)
   https://scikit-learn.org/
8. **TensorFlow / Keras** (for LSTM Modeling)
   https://www.tensorflow.org/api_docs/python/tf/keras
9. **TQDM (for training progress bars)**
   https://tqdm.github.io/

Tutorials & Guides

10. **LSTM for Time Series Forecasting** – Jason Brownlee
    https://machinelearningmastery.com/time-series-forecasting-long-short-term-memory-network-python/
11. **Machine Learning Projects – GitHub Reference**
    https://github.com/Vatshayan/Final-Year-Machine-Learning-Stock-Price-Prediction-Project

Corporate Background

12. **Tata Consultancy Services (TCS) Company Info**
    a. https://www.tcs.com/
    b. Wikipedia Page: https://en.wikipedia.org/wiki/Tata_Consultancy_Services