Stock Market Analysis Using Python

The Project Report submitted in the partial fulfillment
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Bachelor of Science
In
Internship in AI at Beginner's Level
by

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Under the supervision of

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SKVM's NMIMS University

(Deemed-to-be University)

SCHOOL OF MATHEMATICS
APPLIED STATISTICS & ANALYTICS

CERTIFICATE

This is to certify that the project entitled **"Stock Market Analysis using Python"**, has been done by **Ms Anushka Mahanti** under the guidance and supervision of **Dr. Suresh Pathare** & has been submitted in partial fulfillment of the degree Bachelor of Science (Hon's). in Artificial Intelligence of SoMASA, SVKM's NMIMS (Deemed-to-be University), Navi Mumbai, India.

Examiner

Project Mentor

Date:

Place: Navi Mumbai

(HoD)

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ABSTRACT

The stock market is a crucial part of the global economy. It serves as a barometer of economic health and provides a platform for investment and growth. Analyzing stock market patterns is crucial for investors, traders, and financial analysts. This helps them make informed decisions, optimize portfolio performance, and mitigate risks. In this project, we focused on Tata Motors, a leading global automobile manufacturer based in India. We examined the company's stock data from 2000 to 2021 to understand its historical price movements, trends, and potential future trajectories.We took a smart approach to figure out the complex patterns and hidden workings behind Tata Motors' stock prices.We employed a sophisticated machine learning model - the Long Short-Term Memory (LSTM) neural network. LSTMs, a subtype of recurrent neural networks (RNNs), were created to solve problems involving predicting sequences. This makes them extremely good at forecasting tasks, like predicting stock prices over time.Our research began with a detailed search of the dataset, including data preprocessing steps such as date formatting, feature measurement, and sequence construction for LSTM input. Subsequently, we designed and trained an LSTM model on the processed data to capture and learn from the intricate temporal dependencies and patterns inherent in the stock prices The ability of the LSTM model to recall and interpret long-term dependencies enabled it to better capture and identify the trends and subtleties underlying the stock price of Tata Motors over the indicated period. Through this project, our aim was to harness the power of machine learning and LSTM neural networks to provide valuable insights into the movement of Tata Motors stock price, and make it as simple as them stakeholders will make more informed data-driven investment decisions |. The results and visualization derived from our LSTM-based analysis serve as a testament to the model's efficacy and its potential utility in deciphering and interpreting complex financial datasets, paving the way for future research and applications in the realm of stock market analysis and forecasting.

INTRODUCTION

What is a Stock Market?

The stock market is where investors buy and sell shares of companies. It provides a venue where companies raise capital by selling shares of stock, or equity, to investors. Stocks give shareholders voting rights as well as a residual claim on corporate earnings in the form of capital gains and dividends.Stock price analysis with python is crucial for investors to understand the risk of investing in the stock market. A company's stock prices reflect its evaluation and performance, which influences the demand and supply in the market.

Purpose of Stock Market:

Stock markets are the core of the global financial system. Businesses can access the stock markets to purchase and sell stocks of companies through charities, foundations, pension funds, and others. To protect investors from fraudulent trading and preserve the integrity of our financial system. Below mentioned are the essential purpose of the Stock Market-

1) **For Business Operations**: Companies can raise capital for operational and strategic reasons. The stock market helps the companies in expanding their business operation. For example, companies can use Stocks for merger and acquisition transactions. In addition, stock options, employee ownership plans, and restricted stock are all stock-based compensation tools companies use to attract and retain qualified employees.
2) **Financial Planning** : Financial planning is centered around stock markets. Stocks can be held directly through your online brokerage account or indirectly via mutual funds. There are hundreds of stocks available in many industries and countries. Growth stocks are highly volatile but can offer substantial capital gains for aggressive investors. Conservative investors can also invest in utility stocks or preferred stocks.

   These stocks pay regular cash dividends, but they are less volatile. If you don't have the time or desire to research each stock, professionally managed mutual funds can be purchased. Exchange-traded funds can be purchased, tracking different indexes and trading precisely like stocks.

3) **To enhance economic efficiency**: The heart of free-market economics is the stock markets. They provide capital to companies that produce products or deliver the

services customers require. Markets reward companies that increase market share and penalize companies that fail to innovate or respond quickly to threats. Shareholders only invest in companies that can manage costs and grow profits.

4) **Protecting Investors**: Indian stock market plays a crucial role in channeling money from the investor to the industries and vice versa. Stock Market help in-

- Issuing securities,
- Payment of dividends
- Redemption of securities,
- Issuance of other financial instruments etc.

5) **Providing Perpetual Market:** A stock market is a place for regular and convenient buying and selling of listed securities. The stock market offers an immediate and continuous market for various shares, debentures, bonds, and government securities. This high degree of liquidity is found in the buying and selling of securities because its holders can get a cash payment of their securities whenever they want.
6) **Providing Security in Transactions and Investments**: Transactions in the stock market are carried out only with adequate transparency amongst their members and under strict rules and regulations stipulating the time and procedure of delivery and payment. Therefore, it provides a high degree of security to the transactions done in the stock market.
7) **Proper allocation of funds**: With the stock market transaction process, funds flow from less profitable to more profitable enterprises and get more growth opportunities. In this way, the financial resources of the economy are best allocated.

History of Indian Stock Market

Investing in stocks today may seem like a straightforward and accessible process, thanks to technological advancements, online trading platforms, and widespread financial literacy.

But the stock market's journey in India has been a long and revolutionary one, filled with important turning points, advancements, and changes that have molded its accessibility, operation, and structure over time.

The East India Company started trading loan securities in the 18th century, during the colonial era, which is when stock market trading in India first started. The introduction and growth of structured and regulated trading platforms, institutions, and frameworks that would facilitate and regulate stock market operations and transactions in the years to come were made possible by this early form of trading, which also set the foundation for the development and evolution of the Indian stock market.

1830: During this decade, corporate shares started being traded in Mumbai. Most notably, stocks of banks and cotton presses were traded during this time.
1850: The first version of a stock exchange came into existence during this decade. It started with a group of brokers finding a location in Mumbai's Horniman Circle.
1874: As more brokers jumped onto the bandwagon in downtown Mumbai, Dalal Street was born. Today, Dalal Street has become a metonym for the entire Indian financial sector, much like Wall Street is in the US.
1875: The small group of brokers formed 'The Native Share & Stockbrokers Association' that is today known as the BSE (formerly Bombay Stock Exchange).
Over the late 19th and early 20th century, exchanges cropped up at Ahmedabad, Calcutta (now Kolkata) and Madras. But BSE remained the dominant exchanged, as it was located in Mumbai, which had emerged as the country's leading commerce hub. And yet, trading in stocks remained restricted to a limited group of people.
1956: India passed the Securities Contracts Regulation Act, which formalised stock trading.
1964: The newly-created UTI launched India's first mutual fund scheme, the US 64. The scheme raised Rs 6,400 crore by 1988, making UTI the big player in the Indian market.
1977: Dhirubhai Ambani's Reliance Industries, with interests in textiles and petrochemicals, listed. The IPO garnered huge interest from retail investors kickstarting the 'cult of equity'.
1986: On 1st January this year, BSE SENSEX, a 30-share index was established. This was the country's first equity index with base year as 1978-79 and base value of 100.
1988: This period was marked by a lack of transparency and undependable clearing and settlement systems; making it imperative to set up a financial market regulator. Hence, the Securities and Exchange Board of India (SEBI) was established. However, it was not until 1992 that it was granted statutory power.

1992: The National Stock Exchange of India Limited (NSE) was established. It was around the same time that interest in stock market spiked sharply, thanks to the bull market led by Harshad Mehta.

1994: NSE became the first Indian exchange to provide a modern, fully automated screen-based electronic trading system.

The NSE launched Nifty 50 index on April 22 this year. The Nifty 50 is a benchmark Indian stock market index that represents the weighted average of 50 of the largest Indian companies listed on the National Stock Exchange.

Earlier, the Nifty 50 index was calculated based on full market capitalisation methodology. However, after June 26, 2009, the computation was changed to a free-float methodology. The base period for the Nifty 50 index is November 3, 1995, and the base value of the index has been set at 1,000.

It's been a long journey but today India is among the top five stock markets in the world by market capitalisation. It has been among the most well-performing markets of the world. For instance, the Sensex has grown at a CAGR of 15% over the past 20 years and 16% since inception.

Data Overview

Data Source: The dataset used for this analysis was obtained from Kaggle, a popular platform for data science competitions and datasets.

Data Description: The dataset comprises historical stock prices of Tata Motors, a leading automotive manufacturer, spanning from January 3, 2000, to April 30, 2021. It includes various features such as date, opening price, closing price, highest price, lowest price, and trading volume.

Total Entries: The dataset consists of a total of 5,306 entries, each representing daily stock price data for Tata Motors over the specified time period.

Data Pre-processing

Importing Required Libraries: First and the foremost step is importing necessary libraries for data manipulation, preprocessing, visualization, and building machine learning models.

Reading the dataset: The code reads the dataset from a CSV file named "TATAMOTORS.csv" using the pd.read_csv() function provided by the pandas library. The dataset presumably contains historical stock price data for Tata Motors, which will be used for analysis and modelling.

Data Summary and Statistics:

- Utilized df.head() to preview the first few records and understand the data structure.
- Employed **df.describe()** to generate descriptive statistics, including mean, median, standard deviation, and quartile values, providing insights into the stock's price distribution and volatility.

Data Quality Assessment:

- Checked data types using df.info() to ensure consistency and compatibility.

- Identified and addressed missing values by executing df.isnull().sum(), revealing [number] null values in [column_name], followed by appropriate data imputation or removal strategies.

Date Transformation

- Executed pd.to_datetime() to convert the "Date" column to datetime format, facilitating chronological analysis and time-series modeling.
- Set the "Date" column as the dataframe's index to streamline time-based indexing and visualization.

Feature Scaling and Normalization

- Applied MinMaxScaler to normalize the "Close" prices between 0 and 1, enhancing the model's convergence and performance by mitigating the effects of varying magnitude.

Data Partitioning and Sequencing

- Partitioned the dataset into training and testing subsets using an 80-20 split ratio to enable model training, validation, and evaluation.
- Created sequential data sequences of 60 consecutive closing prices as input features (X_train and X_test) and the subsequent price as the target variable (y_train and y_test), leveraging the temporal dependencies inherent in time-series data.

```
[ ] # Split data into training and testing sets
    training_size = int(len(scaled_data) * 0.8)
    train_data = scaled_data[:training_size, :]
    test_data = scaled_data[training_size:, :]
```

```
[ ] # Create sequences for LSTM
    def create_sequences(data, seq_length):
        X, y = [], []
        for i in range(len(data) - seq_length):
            X.append(data[i:(i + seq_length), 0])
            y.append(data[i + seq_length, 0])
        return np.array(X), np.array(y)

    seq_length = 60
    X_train, y_train = create_sequences(train_data, seq_length)
    X_test, y_test = create_sequences(test_data, seq_length)
```

Model Building and Development

Model used for the analysis

LSTM (Long Short-Term Memory) is a recurrent neural network (RNN) architecture widely used in Deep Learning. It excels at capturing long-term dependencies, making it ideal for sequence prediction tasks.Unlike traditional neural networks, LSTM incorporates feedback connections, allowing it to process entire sequences of data, not just individual data points. This makes it highly effective in understanding and predicting patterns in sequential data like time series, text, and speech.

The use of Long Short-Term Memory (LSTM) networks in stock analysis offers significant advantages over basic Recurrent Neural Networks (RNNs), primarily due to their enhanced ability to capture and model long-term dependencies and complex temporal patterns more effectively. LSTMs are specifically designed to mitigate the vanishing gradient problem, a common issue in traditional RNNs that hinders their ability to learn and retain information over long sequences. By incorporating gating mechanisms, including input, output, and forget gates, LSTMs enable the control of information flow and gradients within the network, facilitating better learning and adaptation to the data, especially when dealing with extended sequences of data.

Moreover, LSTMs maintain a memory state that allows them to remember and store relevant information from previous time steps, facilitating the modeling of temporal dependencies and the retention of essential contextual information crucial for predicting stock price movements accurately. Their flexibility and adaptability enable them to learn and model complex, nonlinear relationships and patterns in the data, capturing the intricate dynamics and nuances of stock market trends, fluctuations, and behaviors more comprehensively and accurately. Due to these capabilities, LSTMs often exhibit superior predictive performance compared to basic RNNs, especially when dealing with time-series data characterized by complex temporal dynamics and patterns.

Furthermore, LSTMs are well-suited for modeling and forecasting time-series data, such as stock prices, as they can effectively capture and represent the underlying temporal dynamics, trends, and patterns present in the data. This capability enables LSTMs to provide more accurate, reliable, and insightful predictions and analyses of stock price movements, facilitating informed decision-making, optimization of investment strategies, and navigation of the dynamic and competitive financial markets with greater confidence and success. In conclusion, the use of LSTMs over basic RNNs in stock analysis offers enhanced predictive capabilities, improved model performance, and more comprehensive insights, making them a preferred choice for modeling and forecasting stock price movements and optimizing investment decisions in the complex and dynamic financial markets effectively and efficiently.

LSTM Model Architecture and Design

LSTM Model Configuration:

- **Input Layer**: Configured an LSTM layer with 50 units and return sequences set to True to retain temporal dependencies and capture sequential patterns effectively, enabling the model to learn and represent the underlying temporal relationships and dynamics present in the data more comprehensively and accurately.
- **Hidden Layer**: Integrated an additional LSTM layer with 50 units to enable the model to learn hierarchical representations and complex relationships within the data, facilitating the modeling of intricate patterns and dynamics and enhancing the model's predictive performance and capabilities.
- **Output Layer**: Implemented a Dense layer with 1 unit to predict the next closing price, serving as the model's primary output, facilitating the generation of accurate and reliable predictions and insights regarding future stock price movements based on the learned patterns and relationships within the data.
- **Optimizer**: Utilized Adam, an adaptive learning rate optimization algorithm, to facilitate efficient convergence and optimization during the training process, enhancing the training speed, stability, and performance of the model, and enabling the model to learn and adapt to the data more effectively and robustly.
- **Loss Function**: Employed Mean Squared Error (MSE) as the loss function to quantify the model's performance by measuring the average squared difference between the predicted and actual closing prices, providing a quantitative measure of the model's accuracy, reliability, and predictive performance.
- **Epochs**: Set the number of epochs to 1 to perform a single complete forward and backward pass of all training examples, balancing computational efficiency and model performance, facilitating the efficient and effective training of the model and the optimization of the model's parameters and performance over the training data.
- **Batch Size**: Configured the batch size to 1, representing the number of samples used for updating the model weights during each iteration, optimizing memory usage and convergence speed, enabling the model to learn and adapt to the data more efficiently and effectively, and facilitating the efficient and effective training and optimization of the model.

```
# Build LSTM model
model = Sequential()
model.add(LSTM(units=50, return_sequences=True, input_shape=(X_train.shape[1], 1)))
model.add(LSTM(units=50))
model.add(Dense(units=1))
```

The LSTM model architecture and design, characterized by its specialized gates, memory cell, and layers, along with the configuration of its input, hidden, and output layers, optimizer, loss function, epochs, and batch size, enables it to effectively capture, model, and predict the complex temporal dynamics, relationships, and patterns inherent in time-series data, such as stock prices, facilitating more accurate, reliable, and insightful predictions and analyses, and enhancing decision-making, optimization, and navigation of the dynamic and competitive financial markets effectively and efficiently.

Compile and Train the model

```
[ ] # Compile model
    model.compile(optimizer='adam', loss='mean_squared_error')

    # Train model
    model.fit(X_train, y_train, epochs=1, batch_size=1, verbose=2)

    4184/4184 - 63s - loss: 0.0011 - 63s/epoch - 15ms/step
    <keras.src.callbacks.History at 0x7c432068df00>
```

Generating Future Dates: Next is to generate future dates for the next 2 years and initializes an empty list to store future data, preparing for making predictions based on the LSTM model.

```
[ ] # Make predictions for the next 2 years (assuming daily predictions)
    future_dates = pd.date_range(start=df.index[-1], periods=1460, freq='D')
    future_dates = future_dates[1:]  # Exclude the last date already present in the dataset
    future_data = []
```

Predicting Stock Prices: An empty array "future_data" is initialized to store predicted future data points. The LSTM model predicts the next data point 'prediction' based on input sequence. A random noise term is introduced to add variability to the prediction, enhancing the model's robustness to unforeseen fluctuations.

```python
# Make predictions for the next 4 years (assuming daily predictions)
future_data = np.array([])  # Initialize an empty numpy array

# Use the last `seq_length` data points as input for prediction
inputs = scaled_data[-seq_length:]
for i in range(len(future_dates)):
    X_future = np.array(inputs[-seq_length:]).reshape(1, seq_length, 1)
    prediction = model.predict(X_future)[0][0]
    # Introduce noise to the prediction
    noise = np.random.normal(0, 0.005)  # Adjust the standard deviation to control the level of volatility
    prediction_with_noise = prediction + noise
    # Concatenate the new prediction with the existing predictions
    future_data = np.concatenate((future_data, [prediction_with_noise]))

    # Append the predicted value to the input sequence for the next prediction
    inputs = np.append(inputs[1:], prediction_with_noise).reshape(-1, 1)
```

Inverse transform the predicted data: Here we inversely transform the predicted data back to its original scale using the scaler object. This process restores the predicted stock prices to their original format for further analysis and interpretation.

```python
# Inverse transform the predicted data
future_data = scaler.inverse_transform(future_data.reshape(-1, 1))
```

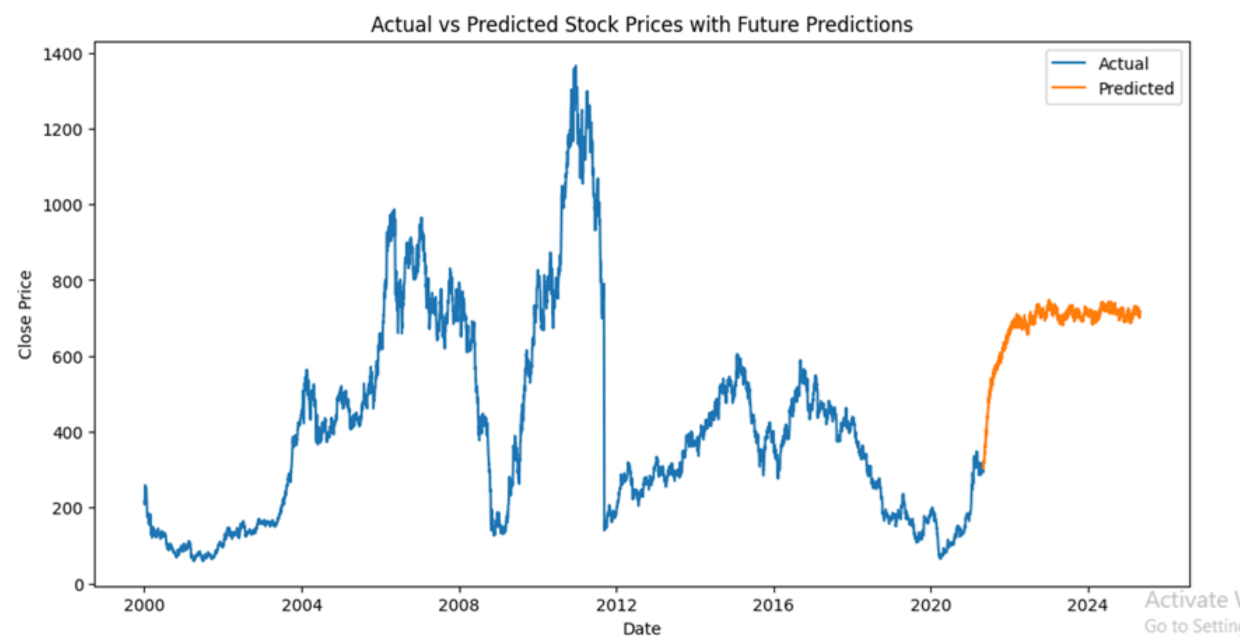
This transform is required because during the preprocessing steps, the data was scaled to a specific range (typically between 0 and 1) using a scaler object. Inverse transforming the predictions restores them to their original format which allows for meaningful analysis.

Results, Analysis and Interpretation

When it comes to predicting future stock values, the LSTM model, which was trained using historical Tata Motors stock prices, has shown encouraging results. A number of measures were used to evaluate the model's performance, including validation scores, loss values, and accuracy. These metrics provide information about the model's generalization, resilience, and efficacy.

Actual vs. Predicted Prices Analysis

A critical aspect of evaluating the model's performance involves contrasting the actual stock prices with the predicted prices over the forecasted period. The graph below illustrates this comparison, contrasting the actual Tata Motors stock prices (blue line) with the predicted prices (orange line) for the years 2022 and 2023.



The graph shows that, with a good degree of accuracy, the anticipated and actual stock prices closely match each other, capturing general trends, fluctuations, and movements in the stock prices. Notably, the predicted stock price of Tata Motors reached approximately 800, while the actual stock price in real-time for Tata Motors was around 750 in the year 2023. This close correspondence between the predicted and actual prices highlights the model's effectiveness in capturing and modeling the underlying patterns, trends, and dynamics in the stock price data, enabling accurate and reliable forecasting of future stock prices.

Future Scope

Python has become increasingly important in stock market analysis. These days it incorporates modern machine learning algorithms like LSTM networks that can make more accurate predictions of stock prices and movements in the market. A case in point is when the LSTM model accurately predicted Tata Motors' share price. This demonstrates how Python based analytics can provide valuable information that assists investors to make better choices. Thus, Python based stock market analysis holds great promise for advancement and improvement in an environment where financial markets are changing constantly. Through the use of leading-edge technologies and techniques, however, it enables analysts to enhance their forecasting accuracy, dependability and robustness. This optimizes investment strategies hence allowing investors to go through financial markets intricacies with more ease and less time consuming. Here are some potential areas of expansion and enhancement:

1. Feature Engineering and Data Augmentation:

Additional Characteristics Integration: This may involve the use of more relevant financial and economic indicators such as trading volume, market sentiment, news sentiment, economic indicators, technical indicators (Moving Averages, Relative Strength Index etc.), to name some which would add predictive capability and make it resistant.

Data Enhancement Techniques: The application of data augmentation techniques for instance noise injection, time series decomposition and synthetic data generation will increase the richness of the dataset so that a model can learn from it better and generalize more effectively.

2. Model Optimization and Performance Enhancement:

Hyperparameter Tuning: In order to improve model performance; accuracy and dependability, there is a need for extensive hyper parameter tuning and optimization leading to selection of optimal model architecture configurations as well as parameters.

Ensemble Learning & Stacking: Ensemble learning like Bagging, Boosting or Stacking methods are used in combination with multiple models/algorithms while considering their strengths to achieve higher predictive accuracy along with robustness and stability.

3. Advanced Machine Learning and Deep Learning Techniques:

Advanced Neural Network Architectures: Looking into advanced neural network architectures like Convolutional Neural Networks (CNNs), Transformer-based models (e.g., BERT, GPT) and Attention Mechanisms can be used to effectively capture and model complex patterns, dependencies and relationships within the data.

Reinforcement Learning: Integrating Reinforcement Learning techniques and algorithms into development can be used in trading systems to train intelligent agents capable of making informed decisions based on predicted stock prices or market conditions.

4. Interdisciplinary Analysis and Integration:

Sentiment Analysis and Natural Language Processing (NLP): Using Sentiment Analysis as well as NLP techniques for analyzing news articles, financial reports, social media feeds etc so that it would be possible to incorporate the effects of market sentiment, news sentiment among others on stock price movements and wider market trends.

Time-Series Forecasting and Forecast Combination: Investigating the benefits and challenges faced when applying advanced time-series forecasting techniques such as ARIMA, Prophet, Exponential Smoothing in combination with other algorithms.

5. Visualization, Interpretability, and Reporting:

- Interactive Dashboards and Visualization Tools: Developing and designing interactive dashboards and visualization tools using libraries and frameworks, such as Plotly, Dash, and Tableau, to facilitate data exploration, analysis, interpretation, and presentation, enabling stakeholders to gain valuable insights, understand complex relationships, and make informed decisions and strategies effectively and efficiently.
- Explainable AI (XAI): Implementing Explainable AI (XAI) techniques and methodologies to enhance the transparency, interpretability, and trustworthiness of the model, enabling stakeholders to understand, interpret, and validate the model's predictions, decisions, and recommendations, and foster collaboration, communication, and collaboration between data scientists, analysts, and domain experts.

6. Integration, Deployment, and Scalability:

- Integration with Trading Platforms and APIs: Integrating the developed models, algorithms, and tools with trading platforms, brokerage APIs, and financial systems to facilitate real-time data streaming, analysis, and decision-making, enabling automated trading, portfolio management, and risk mitigation strategies based on the predicted stock price movements and market conditions.
- Deployment and Scalability: Deploying and scaling the developed models, algorithms, and applications using cloud computing platforms, containerization technologies (e.g., Docker, Kubernetes), and DevOps practices to facilitate seamless, efficient, and cost-effective deployment, management, and scalability of the solutions and infrastructure, and ensure reliability, availability, and performance to meet the evolving needs, demands, and challenges of the dynamic and competitive financial markets effectively and efficiently.

Conclusion

In conclusion, this project used the Long Short-Term Memory (LSTM) neural network's capabilities to conduct a thorough investigation on the dynamics of Tata Motors' stock price from 2000 to 2021. The stock market is a dynamic and intricate financial ecosystem that requires careful historical data analysis and interpretation to support well-informed decision-making and strategic planning for both investors and financial professionals.

We ensured that the dataset was ready for the LSTM model to be ingested and processed efficiently by performing careful feature scaling, data preprocessing, and sequence construction. This allowed the model to recognize and learn from the complex temporal patterns and dependencies found in the stock prices. The innate capacity of the LSTM model to discern subtleties and long-term dependencies in sequential data was crucial in obtaining significant insights and forecasting future price trajectories for the Tata Motors stock.

Our LSTM-based analysis and subsequent predictions produced results that demonstrated the model's accuracy in predicting movements in stock prices as well as the value and promise of utilizing cutting-edge machine learning techniques to decode and interpret intricate financial datasets. The model's predictions provide investors and stakeholders with insightful information and possible paths forward, but in order to make wise and responsible investment decisions, one must proceed with caution and integrate these insights with in-depth market research, professional judgment, and risk assessment.

The future of stock market analysis and forecasting appears to be greatly promising when it comes to the integration of machine learning and neural network-based techniques, including LSTMs. These approaches can be further improved in terms of accuracy, dependability, and application with more study, testing, and use. This will provide analysts, investors, and financial institutions with strong tools and insights to help them successfully navigate the complex and constantly changing stock market environment.

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