Report on

Stock Price Prediction Using Machine Learning in a Volatile Market

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Chapter 1

Introduction

1.1 Introduction

The stock market refers to the collection of markets and exchanges where activities related to buying, selling, and issuing publicly-held company shares occur. It provides a platform for investors to trade stocks, bonds, and other securities. It is a crucial component of the global economy and serves several purposes:

Functions of the Stock Market

- **Facilitates Investment:**
  - Investors can buy stocks to participate in the ownership and potential profits of companies.
- **Capital Formation:**
  - Companies raise capital by issuing stocks (initial public offerings or IPOs) to fund expansion, research, and development.
- **Liquidity:**
  - Provides a platform for investors to easily buy and sell stocks, ensuring liquidity and price discovery.
- **Price Determination:**
  - Stock prices are determined by market supply and demand dynamics, reflecting investor sentiment and company performance.
- **Risk Management:**
  - Allows investors to diversify their portfolios across different sectors and asset classes to manage risk.

The Stock Market is "VOLATILE" which implies potential changes in the market trends are highly feasible. So what are the factors that influence the market?

Factors Influencing Stock Prices

- **Economic Indicators:**
  - Indicators like GDP growth, interest rates, inflation, and employment data influence stock prices making the market more volatile.
- **Company Performance:**
  - Earnings reports, profitability, management changes, product launches.
- **Market Sentiment:**
  - Investor confidence, geopolitical events, global economic conditions.

To excel in a specific domain, particularly in the "Stock Market," it is essential to have an effective prediction system. To promote growth.

Stock Price Prediction involves forecasting the future value of a company's stock using various analytical techniques. This can include historical price data analysis, statistical models, machine learning algorithms, and even sentiment analysis from news articles and social media. The goal is to predict whether a stock's price will go up or down, and by how much, over a certain period.

1.2 Why is Stock Price Prediction Important?

- **Investment Decisions**:
    - Investors use stock price predictions to make informed decisions about buying, holding, or selling stocks. Accurate predictions can lead to profitable investment strategies.
- **Risk Management**:
    - Predicting stock prices helps in managing risks. Investors and financial managers can take preventive measures to mitigate losses by anticipating potential price drops.
- **Algorithmic Trading**:
    - Automated trading systems, also known as algorithmic trading, rely heavily on accurate stock price predictions to execute high-frequency trades. These systems aim to capitalise on small price movements, and precise predictions are crucial for their success.
- **Portfolio Management**:
    - Portfolio managers use predictions to balance their portfolios by reallocating assets to maximize returns and minimize risks. Predictions help in deciding the proportion of different assets to hold.
- **Market Analysis**:
    - Companies and market analysts use stock price predictions to gauge market sentiment and economic conditions. This information can be vital for strategic planning and forecasting economic trends.
- **Hedging**:
    - Investors and companies use predictions to hedge against potential losses. For instance, if a company expects its stock to drop, it might take positions in derivatives to offset potential losses.
- **Valuation**:
    - Predictions help in valuing companies. Accurate stock price forecasts are used in discounted cash flow (DCF) models and other valuation methods to determine the fair value of a stock.[3]

1.3 The technique used in the Prediction Model:

The foundation of this project is the Long Short-Term Memory (LSTM) model, a specialized type of recurrent neural network (RNN).

Long Short-Term Memory (LSTM) is designed to effectively capture long-term dependencies and patterns in sequential data. Its unique architecture makes it particularly useful for time series forecasting, such as stock price prediction, due to its ability to maintain and recall previous data points over extended sequences.

In summary, the LSTM model's ability to handle and learn from sequential data makes it an ideal choice for predicting stock prices, capturing the underlying trends and patterns essential for accurate forecasting.

Key Characteristics:

- **Memory Cells**:
  LSTMs have memory cells that can maintain information for long periods, enabling the model to learn from both recent and distant data points.
- **Gates**:
  LSTMs use three gates (input, forget, and output gates) to regulate the flow of information, allowing the network to learn which data to keep or discard.
- **Prevention of Vanishing Gradient**:
  The structure of LSTMs helps mitigate the vanishing gradient problem, making them more effective than traditional RNNs for long sequences.

1.4 Challenges in Stock Price Prediction

- **Market Volatility**:
  - Stock markets are highly volatile and influenced by numerous unpredictable factors, making accurate predictions challenging.
- **Data Quality**:
  - The accuracy of predictions depends heavily on the quality of the data. Inaccurate or incomplete data can lead to poor predictions.
- **Overfitting**:
  - Machine learning models can sometimes overfit historical data, leading to poor generalization of new data.
- **External Factors**:
  - Economic events, political instability, natural disasters, and other external factors can significantly impact stock prices and are difficult to predict.
- **Complexity of Markets**:
  - Financial markets are influenced by a complex interplay of factors, making it difficult to model and predict stock prices accurately.

Despite these challenges, stock price prediction remains a crucial aspect of the financial industry, providing valuable insights for investors, traders, and financial analysts.[4]

Chapter 2

Literature Survey

2.1 Stock price prediction using LSTM, RNN and CNN-sliding window model

Stock markets or equity markets have a profound impact on today's economy. A rise or fall in the share price has an important role in determining the investor's gain. The existing forecasting methods make use of both linear (AR, MA, ARIMA) and non-linear algorithms (ARCH, GARCH, Neural Networks), but they focus on predicting the stock index movement or price forecasting for a single company using the daily closing price. The proposed method is a model-independent approach. Here we are not fitting the data to a specific model, rather we are identifying the latent dynamics existing in the data using deep learning architectures. In this work, we use three different deep learning architectures for the price prediction of NSE-listed companies and compare their performance. We are applying a sliding window approach for predicting future values on a short-term basis. The performance of the models was quantified using percentage error.[1]

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2.2 Stock Price Prediction Using LSTM

The prediction of stock value is a complex task that needs a robust algorithm background to compute the longer-term share prices. Stock prices are correlated within the nature of the market; hence it will be difficult to predict the costs. The proposed algorithm uses the market data to predict the share price using machine learning techniques like a recurrent neural network named Long Short Term Memory, in that process weights are corrected for each data point using stochastic gradient descent. This system will provide accurate outcomes in comparison to currently available stock price predictor algorithms. The network is trained and evaluated with various sizes of input data to urge the graphical outcomes.[2]

The proposed framework that learns online anticipating the close costs of the stock with the assistance of Long Short Term Memory (LSTM). The Long Short Term Memory (LSTM) is a counterfeit intermittent neural system (RNN) design[1] used in the field of deep learning, Unlike standard feed-forward neural systems, LSTM has input associations. Not only does the procedure not focus on single information (e.g. pictures) but also on full information arrangements, (For example, a speech or a video). For example, LSTM is material for undertakings, such as unpartitioned, associated penmanship recognition, speech recognition and recognition of peculiarities in arranged traffic or IDS (interruption location frameworks).[2]

The preparation of the model incorporates cross-approval, which is a very well-founded, projected execution of the model using the preparation information. The purpose of the tuning models is to explicitly tune the calculation training to add information to the calculation itself. The test sets are immaculate, as a model ought not to be made a decision dependent on concealed information. Scale up the information to the genuine offer costs. The final step is to draw the data using a visualization technique that helps to show the variation of data in the outcome of our algorithm.

Algorithm 1:

Stock prediction using LSTM Input: Historic stock data

Output: prediction of stock price using price variation

Step 1: Start.

Step 2: Data Preprocessing after getting the historical data from the market for a particular share.
Step 3: Import the dataset to the data structure and read the open price.

Step 4: do a feature scaling on the data so that the data values will vary from 0 and 1.

Step 5: Create a data structure with 60 timestamps and 1 output.

Step 6: Building the RNN (Recurrent neural network) for the Step 5 data set and Initialize the RNN by using sequential repressor.

Step 7: Adding the first LSTM layer and some Dropout regularization for removing unwanted values.

Step 8: Adding the output layer.

Step 9: Compiling the RNN by adding Adam optimization and the loss as mean_squared_error.
Step 10: Making the predictions and visualizing the results using plotting techniques.

The proposed algorithm can predict the share price with a very low loss and error rate, if the epoch batch rates the training will be more efficient, in the above section we have used an epoch batch size of 50 to predict the stock prices. [2]

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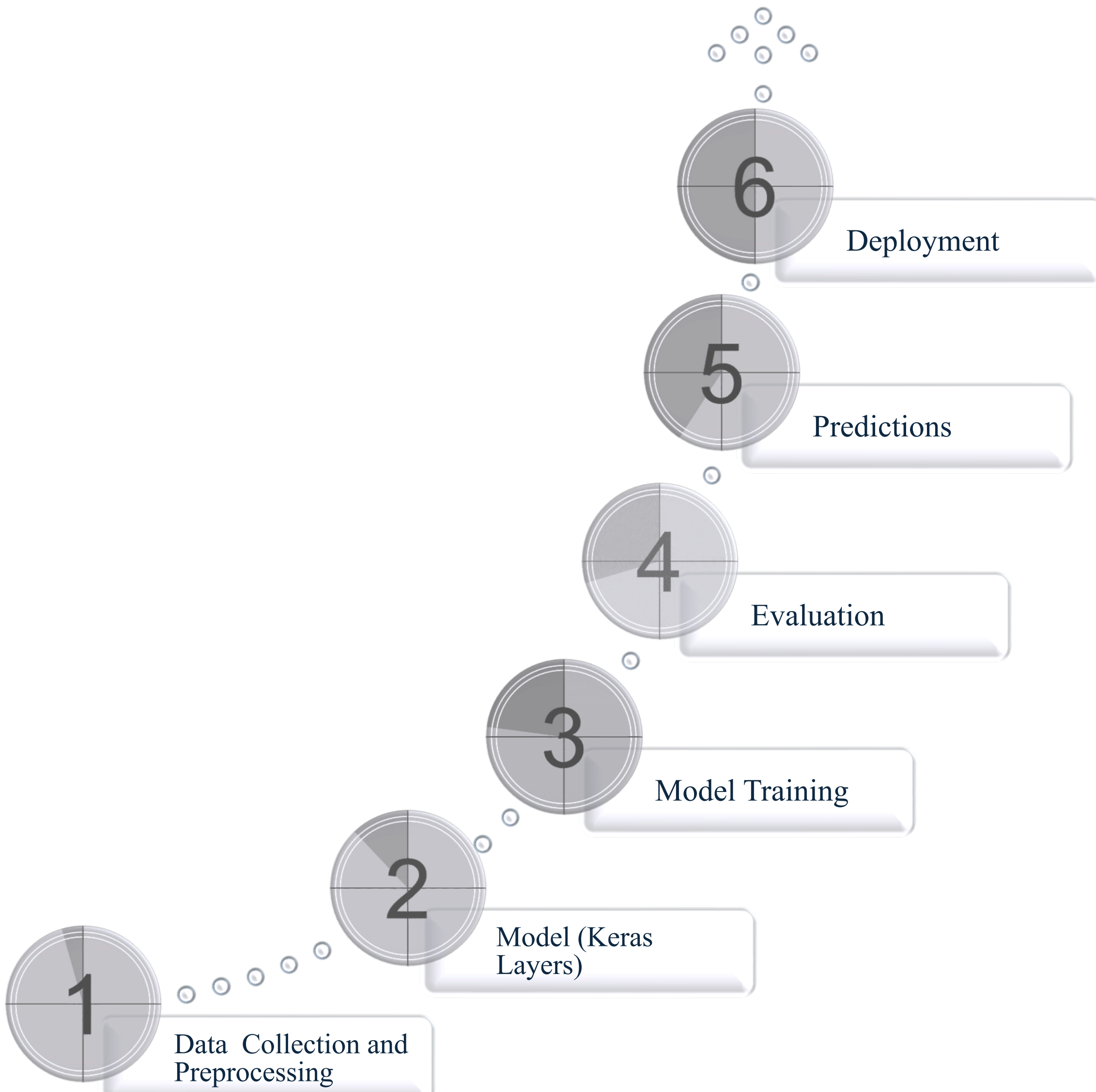
Chapter 3

Methodology



In the "Stock Price Prediction" project, the Long Short-Term Memory (LSTM) model is used. Here's an overview of the model and the methodology followed:

3.1 Data Collection and Preparation:

- **Data Source**: The historical stock prices for Apple Inc. (AAPL) were downloaded using the `finance` library, covering the period from January 1, 2015, to June 25, 2024.
- **Data Preprocessing**: The dataset was preprocessed by calculating moving averages (50-day, 100-day, and 200-day) and normalizing the closing prices using the MinMaxScaler.

3.2 Model Architecture:

A deep learning model using Keras is designed, consisting of several layers to capture the temporal dependencies in the stock price data:

- **LSTM Layers**:
  - The first LSTM layer with 50 units and ReLU activation, followed by a dropout layer with a dropout rate of 0.2.
  - The second LSTM layer with 60 units and ReLU activation, followed by a dropout layer with a dropout rate of 0.3.
  - The third LSTM layer with 80 units and ReLU activation, followed by a dropout layer with a dropout rate of 0.4.
  - The fourth LSTM layer with 120 units and ReLU activation, followed by a dropout layer with a dropout rate of 0.5.
- **Dense Layer**: A fully connected (dense) layer with a single unit to output the predicted stock price.
- **Compilation**: The model was compiled using the Adam optimizer and the Mean Squared Error (MSE) loss function.

3.3 Training:

The model was trained on the normalized training dataset with 50 epochs and a batch size of 32. During training, the model learned the patterns in the stock price data by adjusting its weights to minimize the loss function.

3.4 Evaluation:

The model's performance was evaluated using the following metrics:

- **Mean Squared Error (MSE)**
- Mean Squared Error is a common measure of the prediction accuracy of a forecasting model. It represents the average of the squares of the errors—that is, the average squared difference between the estimated values and the actual value.
- **Mean Absolute Error (MAE)**
- Mean Absolute Error measures the average magnitude of the errors in a set of predictions, without considering their direction. It is the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight.
- **Root Mean Squared Error (RMSE)**
- Root Mean Squared Error is the square root of the average of squared differences between prediction and actual observation. It gives a relatively high weight to large errors. This means the RMSE is most useful when large errors are particularly undesirable.
- **R-squared (R2)**

R-squared is a statistical measure that represents the proportion of the variance for a dependent variable that's explained by an independent variable or variables in a regression model.

Each of these metrics provides different insights into the performance of your model. For instance, lower values of MSE, MAE, and RMSE indicate a better fit of the model, while an R2 value closer to 1 indicates a higher proportion of variance explained by the model.

3.5. Predictions:

The trained model was used to make predictions on the test dataset. The predicted prices were then compared to the actual prices, and the results were visualized using Matplotlib.

3.6. Deployment:

The model was deployed using Streamlit, an open-source app framework. The app allowed users to input a stock symbol and visualize the stock prices.

Chapter 4

Result and Discussion

In this chapter, we present and discuss the results obtained from our stock price prediction model. We used Long Short-Term Memory (LSTM) neural networks to predict the closing prices of stocks present in Yahoo Finance. The performance of the model was evaluated using Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R2) metrics.

Model Performance Metrics

The performance of the LSTM model was evaluated using the following metrics:

- **Mean Squared Error (MSE)**: 42.81
- **Mean Absolute Error (MAE)**: 5.20
- **Root Mean Squared Error (RMSE)**: 6.54
- **R-squared (R2)**: 0.87

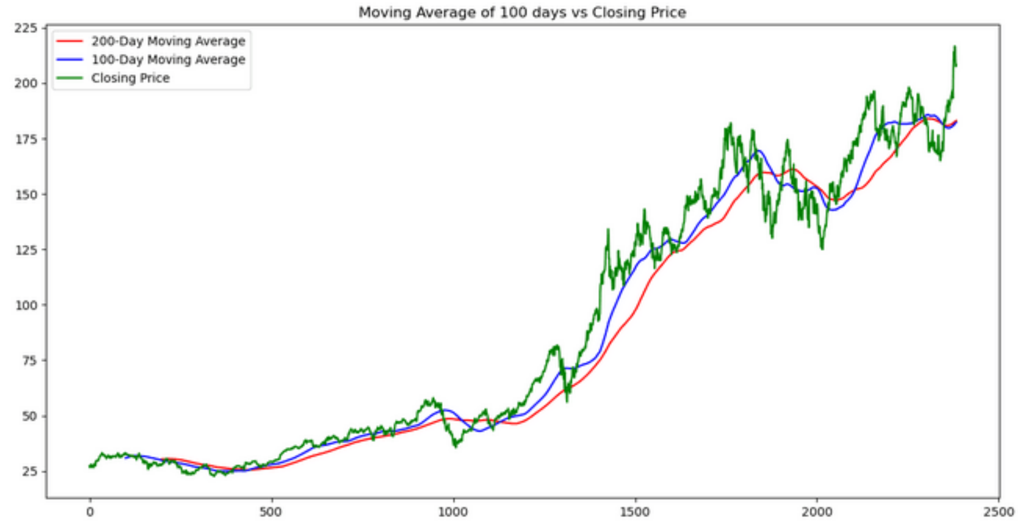
These metrics indicate that the model has a reasonably good performance in predicting the stock prices, with an R2 value of 0.87 suggesting that 87% of the variance in the stock prices is explained by the model.

Visualization of Results

The following visualizations were generated to compare the predicted stock prices with the actual stock prices:

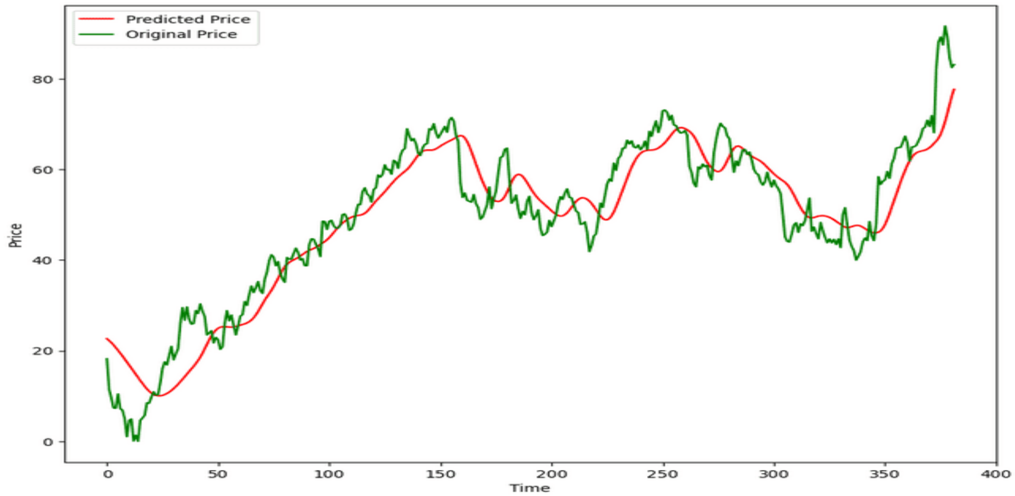
1. **200-Day Moving Average vs. Closing Price**

2. **100-Day Moving Average vs. Closing Price**



3. **50-Day Moving Average vs. Closing Price**

4. **Predicted Price vs. Original Price**



These plots demonstrate that the predicted prices closely follow the actual closing prices, indicating the model's effectiveness.

The LSTM model was able to capture the trends and patterns in the stock prices effectively, as evidenced by the high R-squared value and relatively low error metrics. The moving average plots also illustrate that the model's predictions align well with the actual closing prices, reinforcing the model's reliability.

Chapter 5

Conclusion and Future Work

The LSTM-based stock price prediction model developed in this project shows promising results, with high accuracy and low error rates. The model effectively captures the trends and patterns in stock prices, making it a valuable tool for financial forecasting.

However, there are a few areas for improvement:

- **Overfitting**: The model might be overfitting to the training data, as indicated by the relatively high number of epochs (50). Regularization techniques such as dropout were used, but further tuning might be required.
- **Data Scaling**: MinMaxScaler was used for data normalization, which is effective, but exploring other scaling techniques could potentially improve model performance.
- **Hyperparameter Tuning**: The model's hyperparameters (number of LSTM units, dropout rates, etc.) were chosen based on general best practices. A more thorough hyperparameter optimization could yield better results.

Future improvements could include:

- **Enhanced Feature Engineering**:
    - Explore additional technical indicators or alternative data sources (e.g., news sentiment analysis) to further improve prediction accuracy.
- **Model Optimization**:
    - Fine-tune hyperparameters and consider alternative neural network architectures to potentially enhance model performance.
- **Real-time Prediction**:
    - Implement real-time data processing and prediction capabilities to enable live forecasting in dynamic market conditions.

By leveraging LSTM and other machine learning techniques along with effective data preprocessing and model evaluation strategies, you've laid a solid foundation for stock price prediction. Continuously refining these aspects will likely yield further insights and improvements in predictive accuracy.

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[2] Hiba Sadia, Aditya Sharma, Adarrsh Paul, SarmisthaPadhi, Saurav Sanyal- “Stock Market Prediction Using Machine Learning Algorithms”, IJEAT, 2019. [3] T. H. Cormen, C. E. Leiserson, R. L. Rivest and C. Stein, “Introduction to Algorithms”, 2nd ed., The MIT Press, McGraw-Hill Book Company, 2001 **(Example: Text Book/ Magazine)**

[3] ChatGPT, prompt "Stock Market Price Prediction", July 9, 2024, OpenAI, https://chatgpt.com.

[4] ChatGPT, prompt "Stock Market and its Importance", July 9, 2024, OpenAI, https://chatgpt.com.