Risk Analysis & Predictive Modelling of Stocks

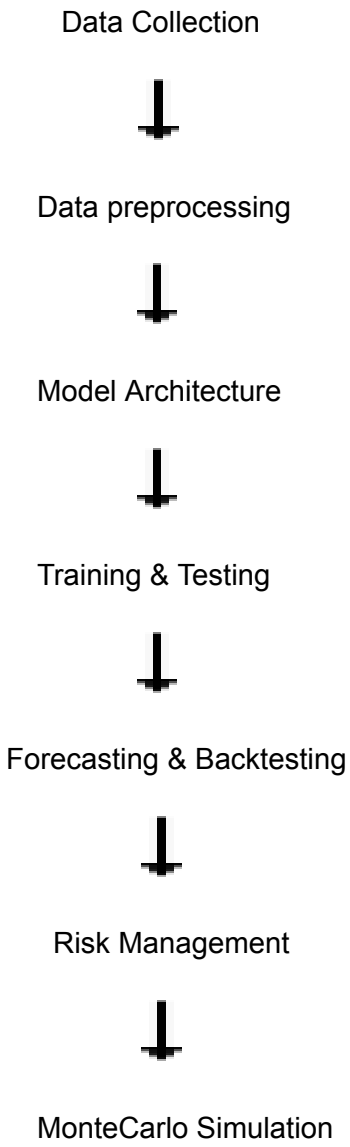
Introduction

In today's fast-paced financial markets, accurately predicting stock prices is crucial for investors seeking to make informed decisions. This project aims to develop a robust stock price forecasting model using historical data and advanced machine learning techniques. Specifically, we implemented a Long Short-Term Memory (LSTM) neural network to analyze stock price trends and generate future price predictions.

To enhance the forecasting model, we incorporated Monte Carlo simulation to assess potential future price scenarios and their probabilities. Additionally, we utilized 100-day and 200-day moving averages as technical indicators to identify long-term trends. The model is equipped with a user-friendly interface that allows users to select stocks, specify forecast durations, and receive actionable buy or sell recommendations based on the predicted trends.

By leveraging the power of data-driven analysis, this project contributes to the growing field of quantitative finance, offering tools that can help investors navigate the complexities of stock market investments.

Methodology



1. Data Collection:

The stock data was sourced using the Yahoo Finance API (`yfinance`), fetching historical closing prices for selected stock. The data was gathered from January 1, 2010, to December 7, 2024.

2. Data Preprocessing:

The closing price data was normalized using MinMaxScaler to scale the values between 0 and 1, ensuring that the model could efficiently handle the variations in stock price. Sequences of stock price data were created for model input, with each sequence containing 60 days of historical data used to predict the next day's price.

3. Model Architecture:

A Long Short-Term Memory (LSTM) neural network was used for forecasting. LSTMs are well-suited for time-series prediction due to their ability to capture long-term dependencies in sequential data. The model consisted of two LSTM layers with dropout for regularization and a Dense layer for outputting predicted prices. The model was trained using the Adam optimizer and mean squared error as the loss function.

4. Training and Testing:

The dataset was split into 80% training data and 20% testing data. The model was trained for 100 epochs with batch sizes of 32, and a 10% validation split was used during training to monitor performance and prevent overfitting.

5. Backtesting

Backtesting involves simulating the performance of a trading strategy using historical data. This allows for a rigorous evaluation of the strategy's potential profitability, risk exposure, and overall effectiveness before real-world implementation.

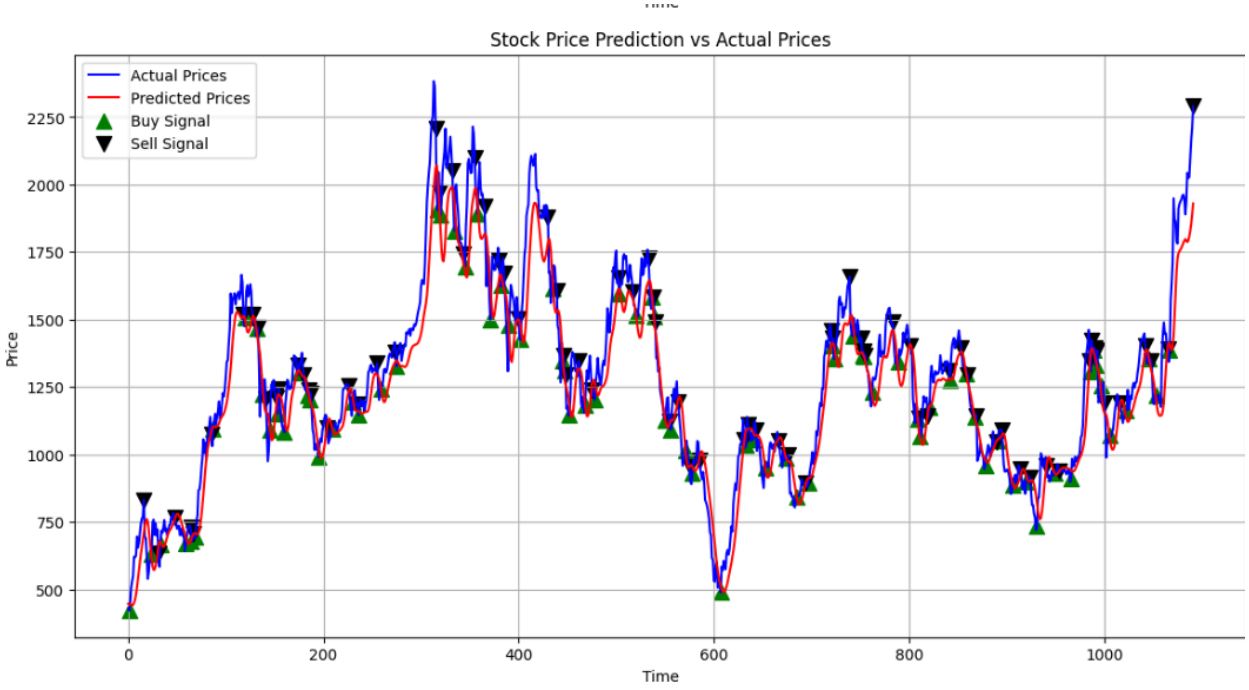
6. Risk Management

Risk management is the systematic process of identifying, assessing, and mitigating threats or uncertainties that can affect [1] an organization. It involves analyzing risks' likelihood and impact, developing strategies to minimize harm, and monitoring measures' effectiveness. [2] By proactively addressing potential risks, organizations can protect their assets, reputation, and overall success.

7. Monte Carlo Simulation

Monte Carlo simulation is a computational technique that uses random sampling to model uncertainty and risk. By running multiple simulations with different random inputs, it provides a probabilistic range of possible outcomes, helping decision-makers assess potential risks and rewards.

Result

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Final portfolio value: $637343041.16 from an initial investment of $100000
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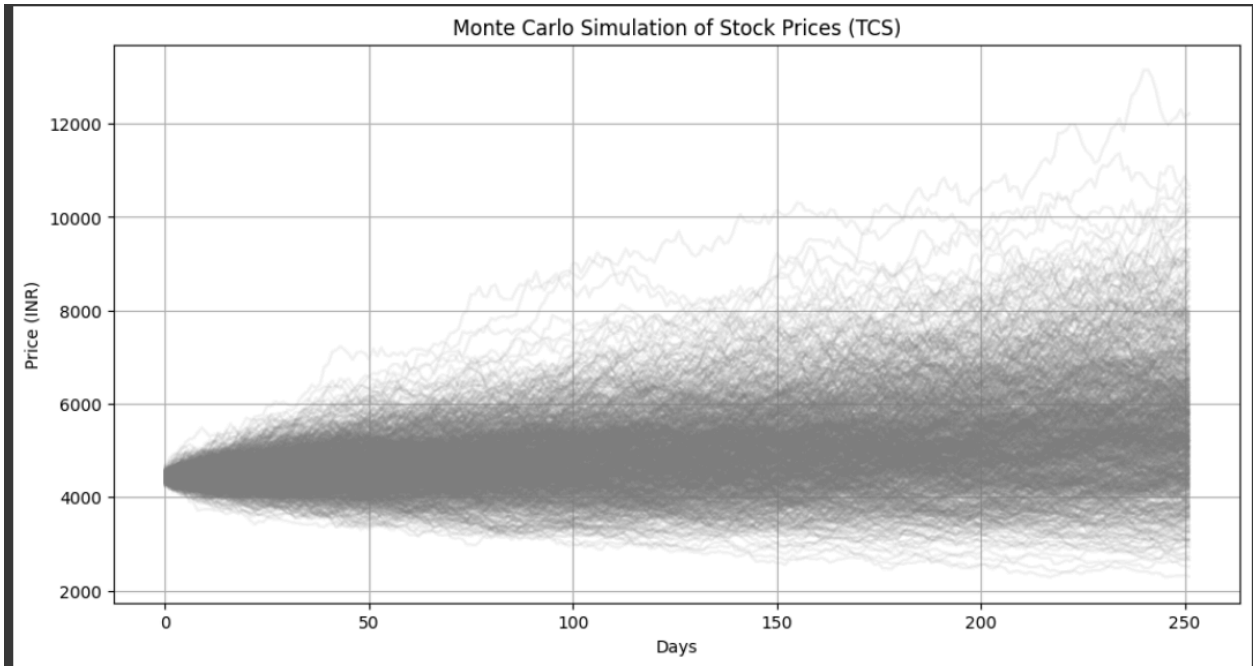

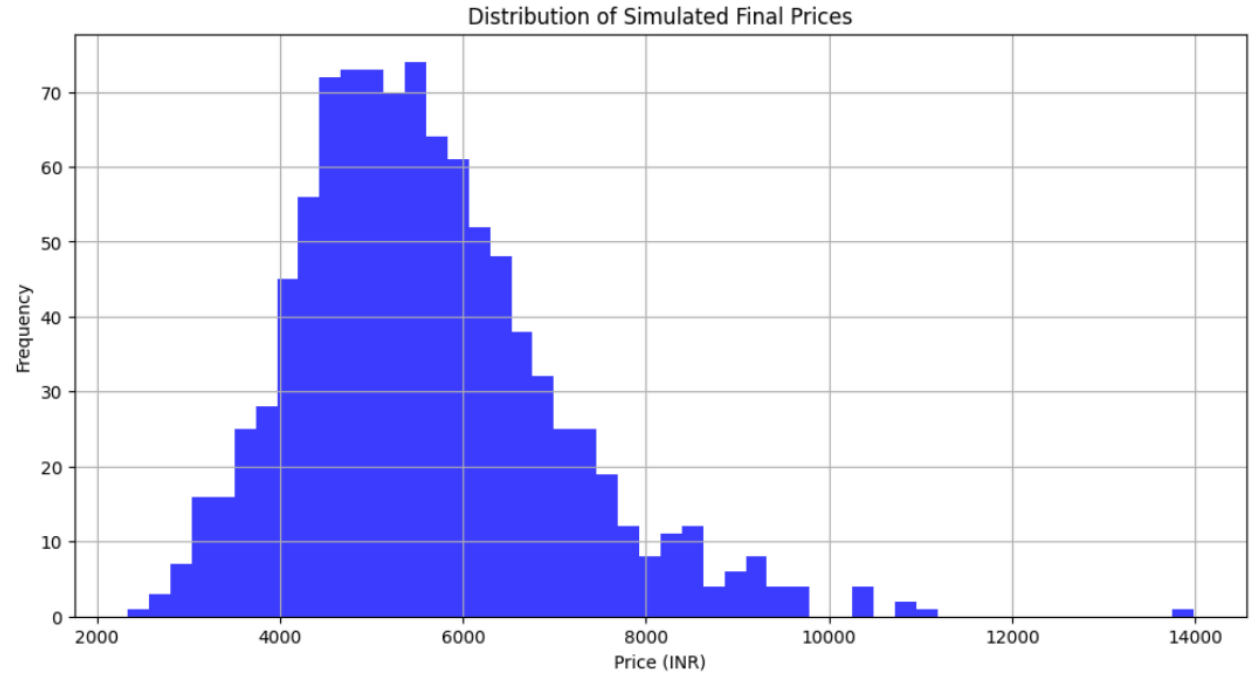


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Expected Price after 252 days: ₹5588.45
Value at Risk (5% worst-case scenario): ₹3557.71
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Conclusion

In this project, I built an LSTM-based stock price prediction model that forecasts short-term trends and generates buy/sell signals using backtesting. To enhance the analysis, I integrated Monte Carlo simulation to assess potential future price scenarios and their probabilities.

While the model showed promising results, it's important to note that stock market predictions are inherently uncertain. Future improvements could involve incorporating more indicators and refining the model's architecture. This project demonstrates the potential of machine learning and probabilistic techniques in aiding informed investment decisions.