# AUTO TRADING USING DEEP LEARNING

*This project report is submitted to*

*Silicon Institute of Technology, Bhubaneswar*

*in partial fulfillment of the requirements for the award of the degree of*

**Master of Science**
**in**
**Data Science**

*Submitted by*

**Debashish Mohapatra (**2111209003)

**Visakha (**2111209001)

**Group No.: MSDS03**

*Under the Esteemed Supervision of*

**Dr. Satyananda Champati Rai**


**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**
**SILICON INSTITUTE OF TECHNOLOGY**

**SILICON HILLS, BHUBANESWAR – 751024, ODISHA, INDIA**

**Jan, 2023**

# CERTIFICATE

This is to certify that the work contained in the project entitled **"Auto Trading using Deep Learning ."**, submitted by **Debashish Mohapatra (Regd. No.: 2111209003)** and **Visakha (Regd. No.: 2111209001**) is a record of bonafide works carried out by them under my supervision and guidance. The contents embodied in the project is being submitted as a part of 3rd semester project for the postgraduate curriculum and have not been submitted for the award of any other degree or diploma in this or any other university.

Date: 21/01/2023

Place: Bhubaneswar, Odisha

**Dr. Satyananda Champati Rai**

Professor

Department of Computer Science & Engineering

**External Examiner**


**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**
**SILICON INSTITUTE OF TECHNOLOGY**
**BHUBANESWAR – 751024**

# DECLARATION

We hereby certify that:-

a. The work contained in the project is original and has been done by ourselves under the supervision of our supervisor.

b. The work has not been submitted to any other Institute for any degree or diploma.

c. We have conformed to the norms and guidelines given to us by the Project Review Committee of our department.

d. Whenever we have used materials (data, theoretical analysis and text) from other sources, we have given due credit to them by citing them in the text of the project and giving their details in the references.

Date: 21/01/2023

Place: Bhubaneswar, Odisha

**Debashish Mohapatra** (2111209003)

**Visakha** (2111209001)


**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**
**SILICON INSTITUTE OF TECHNOLOGY**
**BHUBANESWAR – 751024**

# ACKNOWLEDGEMENTS

In the accomplishment of this project successfully, many people have bestowed upon us their blessing and heart pledged support, this time we are utilizing to thank all the people who have been concerned with the project.

Primarily we would thank God for being able to complete this project with success. We are deeply indebted to our supervisor and mentor Dr. Satyananda Champati Rai whose valuable guidance has been the ones that helped us patch this project and make it full proof success. His suggestions and instructions have served as the major contributor towards the completion of the project.

We would like to thank our head of the department Dr Pradyumna Kumar Tripathy and all the faculty members who have helped us with their valuable suggestions and their feedback has been very helpful in various phases of the completion of the project.

Finally, we would like to wind up by paying our heartfelt thanks to our parents and friends who have helped a lot finalizing this project within the limited time frame.

**Debashish Mohapatra**

**Visakha**


**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**
**SILICON INSTITUTE OF TECHNOLOGY**

**BHUBANESWAR – 751024**

# ABSTRACT

Machine learning-based algorithmic trading has been the subject of more and more research in recent years. Getting a precise picture of the stock market environment from many types of data is one of the challenges. The majority of currently available algorithmic trading research use a single data source to examine the stock market. There are still issues to be resolved regarding how to obtain the temporal features of various types of data and integrate them to obtain a deeper representation of the stock market environment. This is due to the complicated stock market environment, which causes different types of data to reflect changes in the stock market from different perspectives. To tackle these problems, in this study, we combine deep learning and reinforcement learning (RL) and propose a model that integrates stock data can reduce the impact of noise in stock data. The work done here is concentrated on accurately forecasting stock price and trying to maximize investment profit based on current data so that in the future it will be able to accurately estimate future forecasted stock trend.

***Keywords:*** *Investment, Prediction, Model, Deep learning, Stock.*

# LIST OF ABBREVIATIONS

| Abbreviation | Description |
|---|---|
| ML | Machine learning |
| DL | Deep learning |
| ATS | Automated Trading System |
| AI | Artificial intelligence |
| MSc | Master of science |
| RMSE | Root Mean Square Error |
| RL | Reinforcement Learning |
| MSE | Mean Square Error |
| LSTM | Long short-term memory |
| MDP | Markov Decision Process |
| Wrt | with respect to |
| RNN | Recurrent Neural Network |
| ES | Evolution Strategy |

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## CONTENT DETAILS

# CHAPTER 1

## INTRODUCTION

The stock market has attracted more investors in recent years, and their goal is to make the most money possible. The price of stocks, however, is highly erratic and non-stationary as a result of the impact of outside circumstances like emergencies and natural catastrophes. The secret to successful stock trading is to create a trading plan that works for you. A smart trading strategy results in higher earnings and stops losses early. Investors typically base their trading decisions on their own assessments of the stock market; yet they are sometimes influenced by their own emotions when trading, which causes the ultimate gains to frequently fall short of expectations. For each share issued by a corporation that is publicly traded, a stock price is a given. The price, or what the public is prepared to pay for a share of the company, is a reflection of the company's value. The stock price is extremely difficult to forecast. It can and will fluctuate in value depending on a range of external and internal company-related factors. It might be difficult and tiring to decide which stocks to buy out of the numerous options on the market. Every stock has a certain amount of risk. The return is larger when the risk is higher, but you could lose everything. We used Long Short-Term Memory(LSTM) and Reinforcement Learning(RL) to forecast the future trend of stocks and depending on that when to buy a stock and how much money to invest. LSTM is a special kind ofrecurrent neural network capable of handling long-term dependencies. It is very much efficient to implement in financial data, especially in stock data which varies too much. The sequential decision-making problem can be solved via reinforcement learning, which can then be used in stock trading to create dynamic trading strategies. In our work used different types of stocks dataset based on different sectors of India which includes daily stock data from 2022 to 2023.

## 1.1. BACKGROUND

Automated trading platforms keep emotions to a minimum while trading. Traders often have an easier time sticking to the plan by controlling their emotions. Trade orders are automatically executed after the trade rules are satisfied, so traders cannot pause or second-guess the trade. Automated trading can restrain traders who are inclined to overtrade, buying and selling at every apparent opportunity, in addition to assisting those who are hesitant to "pull the trigger". Predicting stock priceis very challenging and it needs best accuracy. Because stock price varies too much and it depends on many factors. Depending upon the risk of the stock, return is also associated. Simply we can say that, high risk stocks returns more but there is no certainty that one can always get high return. Sometimes the loss is high too. So, the risk associated with the stocks is a concern too. LSTM is a special kind of recurrent neural network capable ofhandling these stocks data. We forecast the future trend of stocks using this model.

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## 1.2. PROBLEM STATEMENT

To design and develop an efficient deep learning algorithm for giving auto alert during trading.

## 1.3. OBJECTIVE AND MOTIVATION

*"The objective of this project is to analyze the stock trends and to give alert to the user when to buy or sell the stocks for maximizing profit".*

The pay or income is used across a wide range of sectors. The individual continues to spend excessively in one industry since they are unaware of the financial information. Which yields relatively little savings. The primary goal of our project is to demonstrate to a person how to enhance savings and current financial insights. Stock forecasting is not a novel concept. However, it is a recent development in this industry to use deep learning to predict stocks accurately. Compared to the current machine learning stock prediction methods, it improves stock forecast accuracy.] So, analyzing the stocks and their risk is our second objective. Our first priority is to give best possible suggestions on buying and selling the stocks so that an user can make maximum profit and doesn't feel fear to take risk in stock market.

We would like to introduce the issues and challenges in ML based stock prediction system:

a) *It is not accurate and efficient as compared to DL models.*
b) *As stock data vary too much, ML model has low accuracy predicting the stocks*

In this work we proposed a model which will take input from different stock based on their sectors and help the users to maximize their profit through investing.

## 1.4. PROPOSED METHOD

### 1.4.1. Selecting stocks from different sectors

We choose the daily datasets that contain data for the years 2022–2023 from among the many datasets based on various industries in India. The datasets were then evaluated, and the real trend of the dataset was visualized. Then, based on the trend, we attempted to develop a model that would, as nearly as possible, forecast the future trend, and for that, we presented the Root Mean Squared Error (RMSE). We made an effort to keep the RMSE below 5. Then, based on that model, we proposed an Evolution Strategy Agent based on RL, which takes into account prior behavior and makes recommendations regarding when to buy and sell stocks.

### 1.4.2. Classifying Stock Risk

In terms of investment, a stock's risk is crucial. Investors contend that the stock's risk is influenced by how it fluctuates in the market. It is dangerous if the stock deviates too far from its opening price. We divided the equities into three risk categories—low, medium, and high—based on this theory.

### 1.4.3. Forecasting Stock Price

Here, we utilized an LSTM model to forecast the future trend of the stocks based on the stock data we used to categorize it. In terms of financial data, LSTM is really effective. Here, we made the assumption that there are no outside factors influencing the closing price of the stock. Therefore, LSTM only predicts values based on historical data.

### 1.4.4. Giving Buying and selling alert

For a user, it's crucial to buy and sell stocks at the right time. Every user is unique, and this also holds true for their willingness to take risks. So, in this case, we set the beginning purchase amount at 10,000 in order to conduct a fair evaluation, examine how our model performs when applied to various stocks, and, ultimately, to suggest a model that can learn effectively and decide when to alert users to buy and sell stocks.

## 1.5.PROJECT ORGANIZATION

**Chapter 1** titled, *"Introduction",* presents the general overview of the requirement of this project, the objective and motivation, and to give alert to user for maximizing the profit.
**Chapter 2** titled, *"Literature review",* presents the renowned works earlier performed by well-known personalities in the area of stock prediction and financial statistics.
**Chapter 3** titled, *"Methodology",* presents our detailed work and model proposed.
**Chapter 4** titled, *"Experimental Results",* presents our experimental results.
**Chapter 5** titled, *"Conclusion",* is the summery of the complete work carried out with a miniature part given to the society.

## SUMMARY

In this chapter we discussed about:

- Necessity of Automated Trading System.
- Our objective and motivation to work on this project.
- Overview of how the work is done.

# CHAPTER 2

# LITERATURE REVIEW

## 2.1. Introduction

Data handling is really challenging. Numerous statisticians and academics employed a variety of methodologies to study the pattern. The analysis of the stock data is considerably more challenging. Many researchers have employed various methods in the past to anticipate stock prices. Here, a few of them are described. We will take some of the fundamental ideas, conclusions, and data from such work and turn them into some norms for our project.

Making predictions based on current data is not very difficult, but it is quite difficult to analyze them and inform consumers in a generic fashion. Numerous events, like as a quick market fall or a significant investment in one particular stock, could have an impact on our recommendations. The amount of money you invest determines the likelihood of a higher return, but it also increases the danger. As a result, it is difficult to grasp stock data because it depends on so many different factors. Prem Sanka C. says that stock deviates based on social media posts.

Stocks data consists of 7 features; those are date, open, high, low, close, adjusted close and volume. Most of the predictions are done with the adjusted close values of the stock.

## 2.2. Scope of the Work

Accurately predicting future stock trends across many industries will make it easier to advise investors to purchase and sell equities and maximize their total return. The prediction accuracy will be higher than that of machine learning models as more deep learning techniques can be used to time series data, such as stock data.

## SUMMARY

In this chapter we discussed about:

- The basics of stock data.
- The different models / techniques used by various researchers.
- Scope of our work.

# CHAPTER 3

# METHODOLGY

## 3.1. Introduction

In this chapter we will discuss the details of our work.

## 3.2. Forecasting Stock Price

### 3.2.1. LSTM Method

Deep learning uses the artificial recurrent neural network (RNN) architecture known as long short-term memory (LSTM). LSTM features feedback connections as opposed to typical feedforward neural networks. It can analyze whole data sequences in addition to single data points (like photos) (such as speech or video). For instance, LSTM can be used for tasks like linked, unsegmented handwriting identification, speech recognition, and network traffic anomaly detection, or IDSs (intrusion detection systems).

A cell, an input gate, an output gate, and a forget gate make up a typical LSTM unit. The three gates control the flow of information into and out of the cell, and the cell remembers values across arbitrary time intervals.

Since there may be lags of uncertain length between significant occurrences in a time series, LSTM networks are well-suited to categorizing, processing, and making predictions based on time series data. To solve the vanishing gradient issue that can arise when training conventional RNNs, LSTMs were created. The advantage of LSTM over RNNs, hidden Markov models, and other sequence learning techniques in many applications is their relative insensitivity to gap length.

## LSTM Architecture

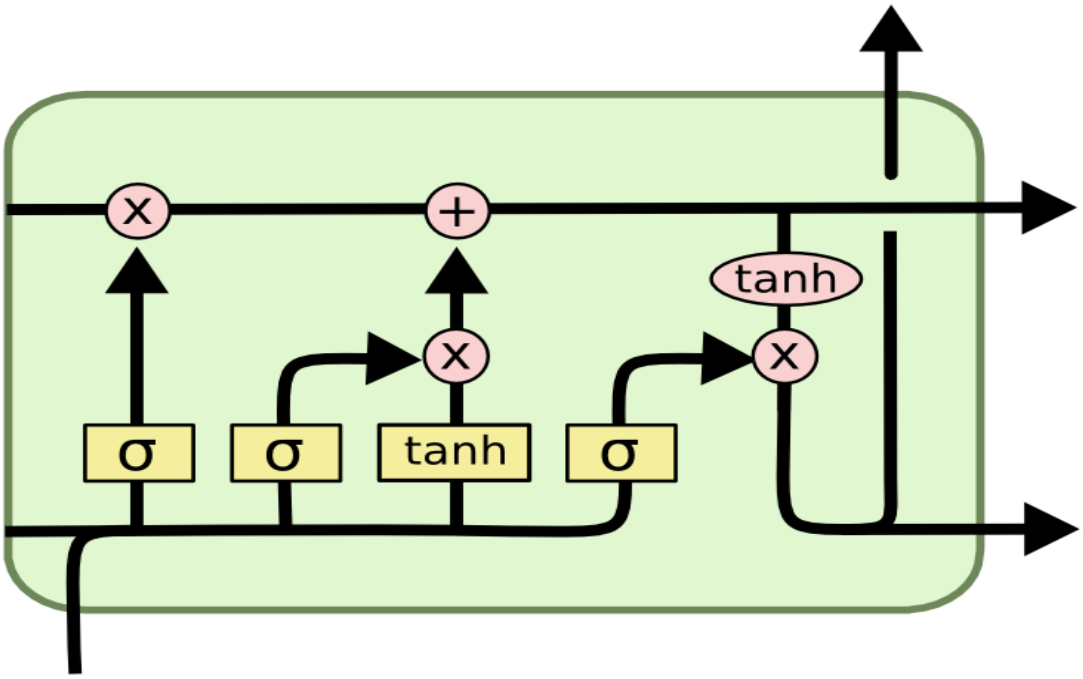


Fig:3.1: LSTM Architecture

### 3.2.2. Prediction

We divided the data in (80:20) and used 80% of this data to train the model. For the prediction accuracy, we used the ADAM optimizer and took the loss function as the mean squared error. We recorded the predicted close value at the time of testing and contrasted it with the actual close value. This had excellent results. We tested this model on all 11 stock price datasets, and the results were excellent. The future trend forecast was then saved for the user's recommendation.

We get the results as follows:

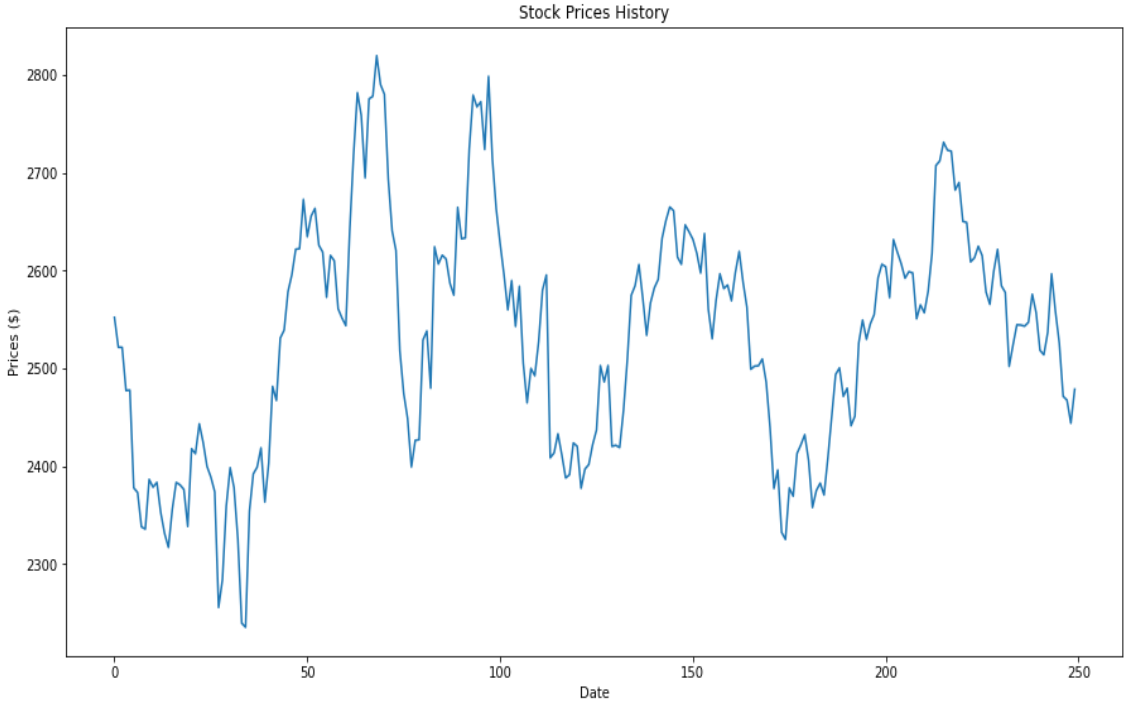


Fig:3.2: Reliance Stock Price

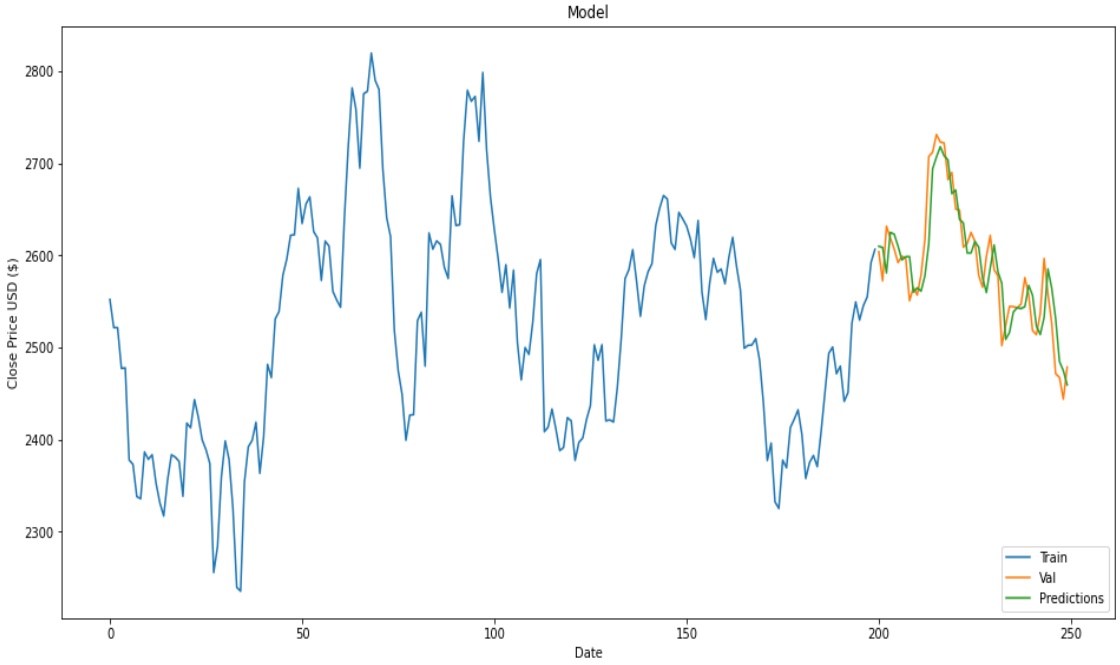


Fig:3.3: Reliance Forecasted Stock Price

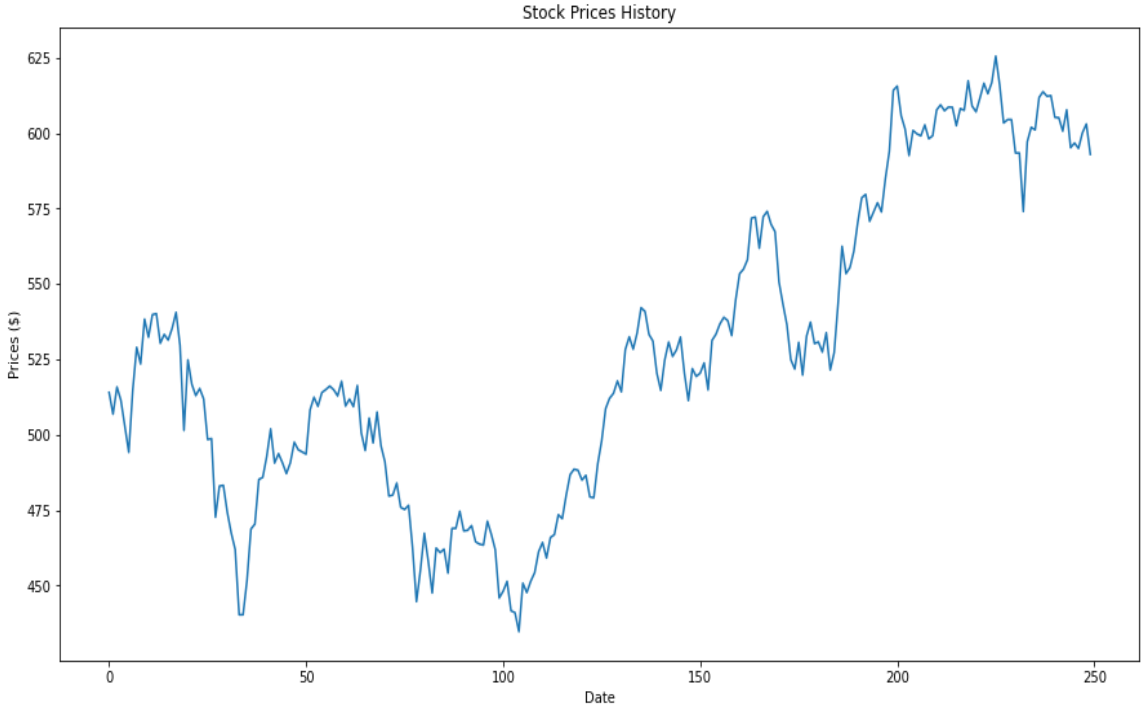


Fig:3.4: SBI Stock Price

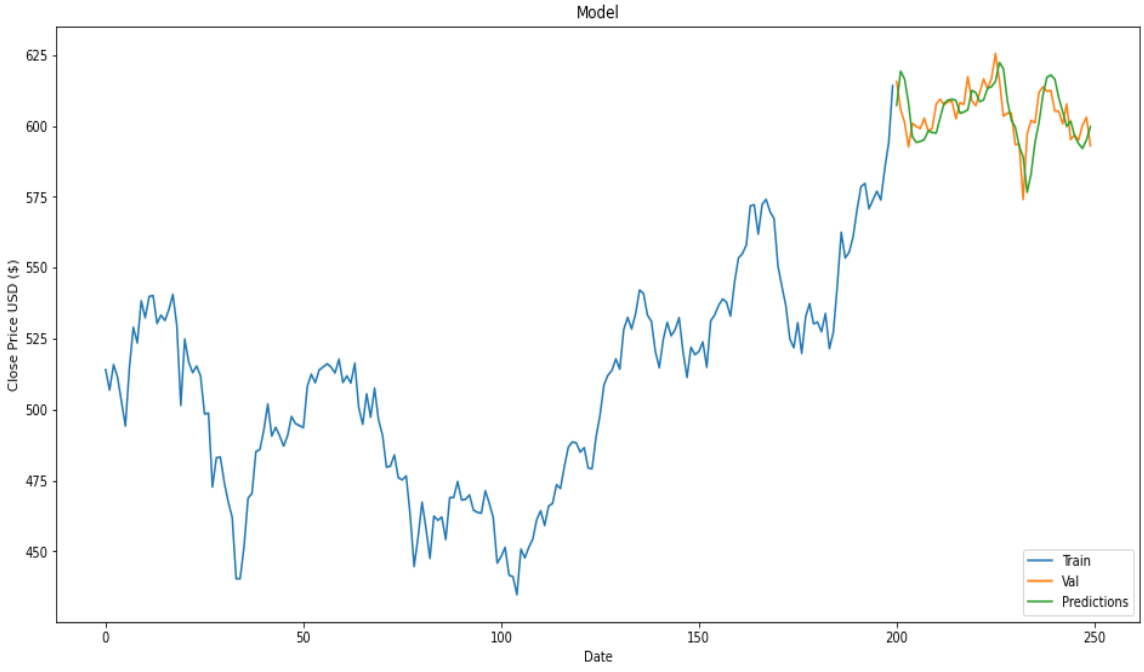


Fig:3.5: SBI Forecasted Stock Price

## 3.3. Stock Risk

Different stock datasets based on various sectors were chosen as the datasets for this. This includes data on 311 different market stocks for the years 2022 to 2023. As a result, we first segregate the stock data into directories. There are seven columns in the separated stock data. Date, Open, High, Low, Close, Adj Close, and Volume make up this list.

### 3.3.1. Beta

A stock's anticipated movement in relation to changes in the entire market is measured by the concept of beta. A stock with a beta larger than 1.0 is thought to be more volatile than the overall market, whereas one with a beta below 1.0 is thought to be less volatile.


Fig:3.6: Different sectors of Stock Market

Table 3.1: Stock Risk Table

| Stock | Sector | Beta |
|---|---|---|
| Wipro | IT | 1.11 |
| SBI | Finance | 0.90 |
| Cipla | HealthCare | 0.39 |
| BHEL | Industrial | 1.34 |
| Bajaj Auto | Customer Discretionary | 0.69 |
| Dabur | Customer Stable | 0.67 |
| Reliance | Communication Service | 1.05 |
| HP | Energy | 0.64 |
| Dalmia | Materials | 1.22 |
| NTPC | Utility | 0.63 |
| Oberoi Realty | Real Estate | 1.30 |

## 3.4. Reinforcement Learning

The field of machine learning known as reinforcement learning (RL) studies how intelligent agents should behave in a given environment to maximize the concept of cumulative reward. Along with supervised learning and unsupervised learning, reinforcement learning is one of the three fundamental machine learning paradigms.

In contrast to supervised learning, reinforcement learning does not need the presentation of labeled input/output pairings or the explicit correction of suboptimal actions. Instead, the emphasis is on striking a balance between exploitation and exploration (of undiscovered territory) (of current knowledge).

Since many reinforcement learning algorithms for this situation involve dynamic programming approaches, the environment is generally expressed as a Markov decision process (MDP). The fundamental distinction between traditional dynamic programming techniques and reinforcement learning algorithms is that the latter do not require understanding of a precise mathematical representation of the MDP and are more suitable for big MDPs than precise techniques are.

### 3.4.1. Evolution Strategy Agent

The large family of evolutionary algorithms includes evolution strategies (ES). Evolutionary algorithms refer to a subset of population-based optimization algorithms that are motivated by natural selection. The optimization goals of ES are vectors of real numbers ($X \in R^n$). Natural selection holds that people with features that help them survive can live for generations and pass on the positive attributes to the following generation. Gradually, evolution occurs through selection, and the population becomes more environmentally suited.

To choose the action to take at each stage, the agent simply does a forward pass on the neural networks constructed with the stated weights. It then adds up the benefits offered by the gym environment. So this algorithm is best suited to solve the stock market data.

RL Architecture:

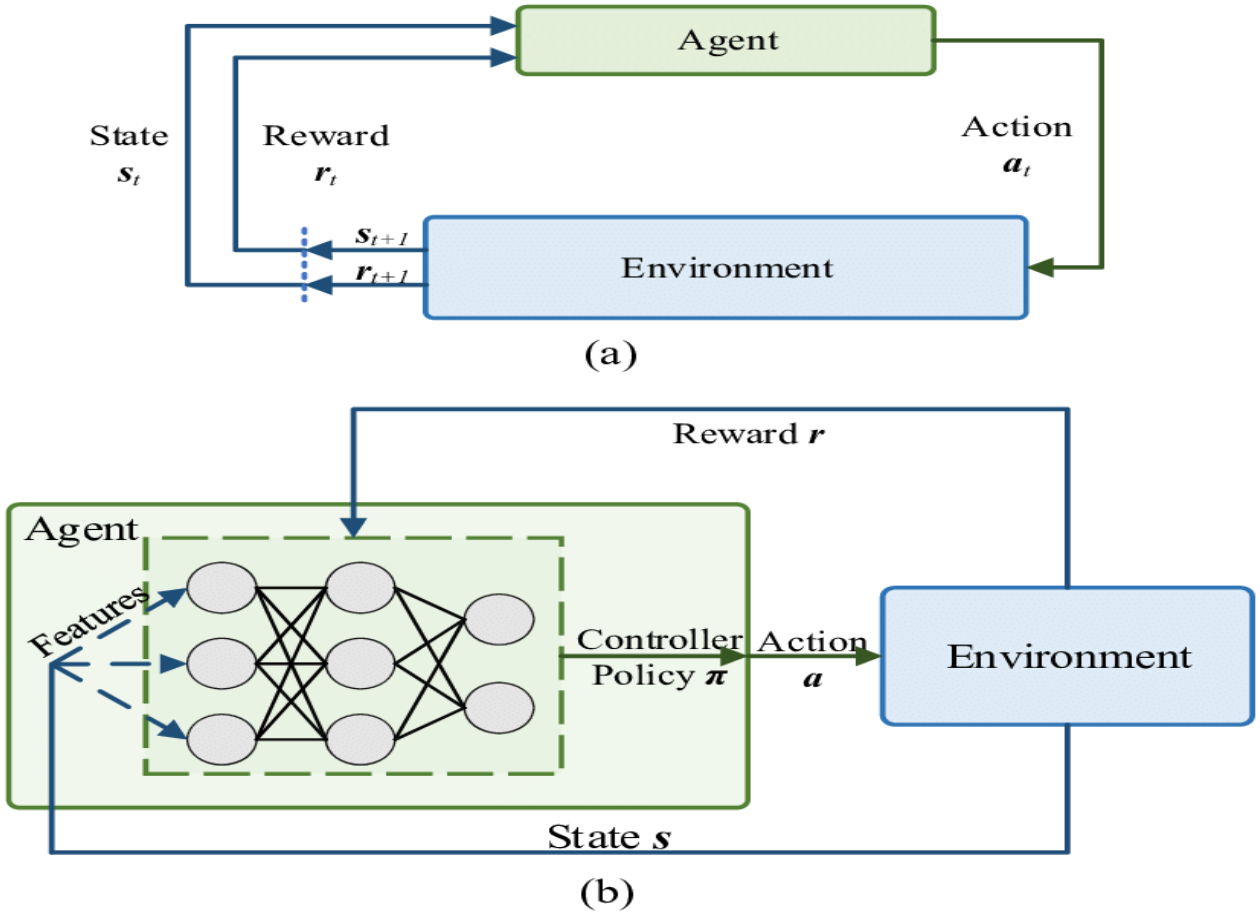


Fig:3.7: RL Architecture

## 3.5 Auto alert to user

This is the last step of our approach, when we use the purchase price to calculate the overall gain and total investment. Following receipt of these inputs, the model will propose when to purchase and sell stocks in order to optimize the profit

## SUMMARY

In this chapter we discussed about details of methods we used for this project. We can summarize them as follows

- Forecasting stock price
- What is LSTM
- What is Stock Risk
- Reinforcement learning and Evolution Strategy
- Auto alert to user

# CHAPTER 4

## Experimental Results

### 4.1. Introduction

In this chapter we will discuss about the Results obtained through training and testing of different stock datasets.

### 4.2. Results and Discussions

#### 4.2.1. Stock Prediction

We randomly selected one dataset from each sector, after which we visualized the stock's actual trend. After that, we projected and showed the stock's trend using the LSTM approach. We implemented RMSE for this reason in order to gauge how well our model predicts.

Showing the actual and Forecasted Stock Price.

i) IT Sector Stock:

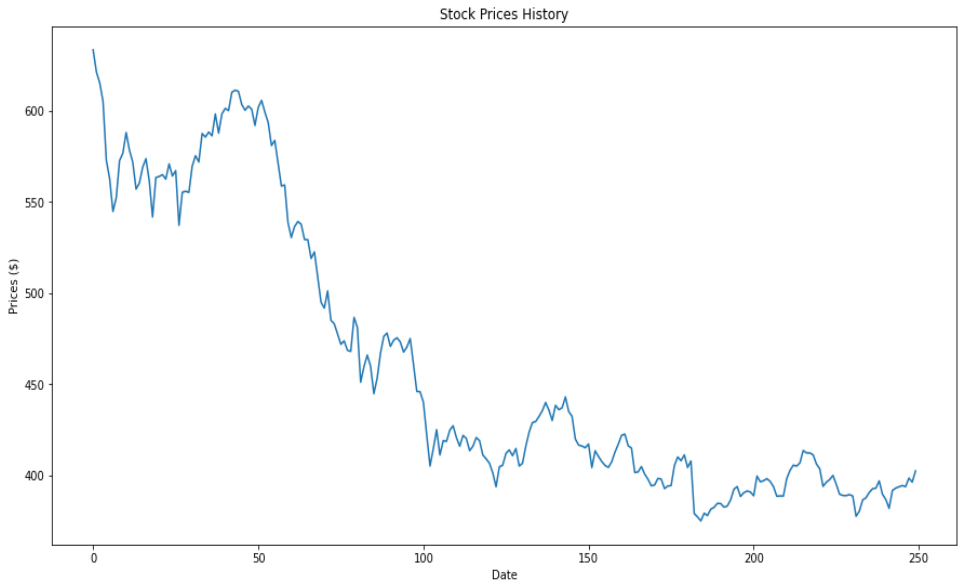


Fig:4.1: Wipro Stock Price

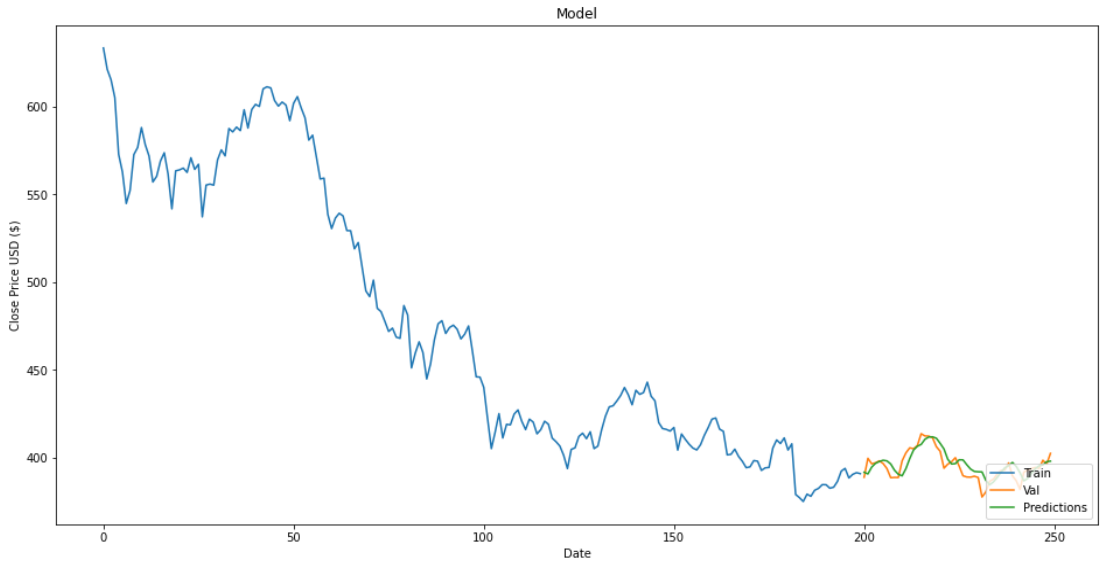


Fig:4.2: Wipro Forecasted Stock price

ii) Real Estate Sector

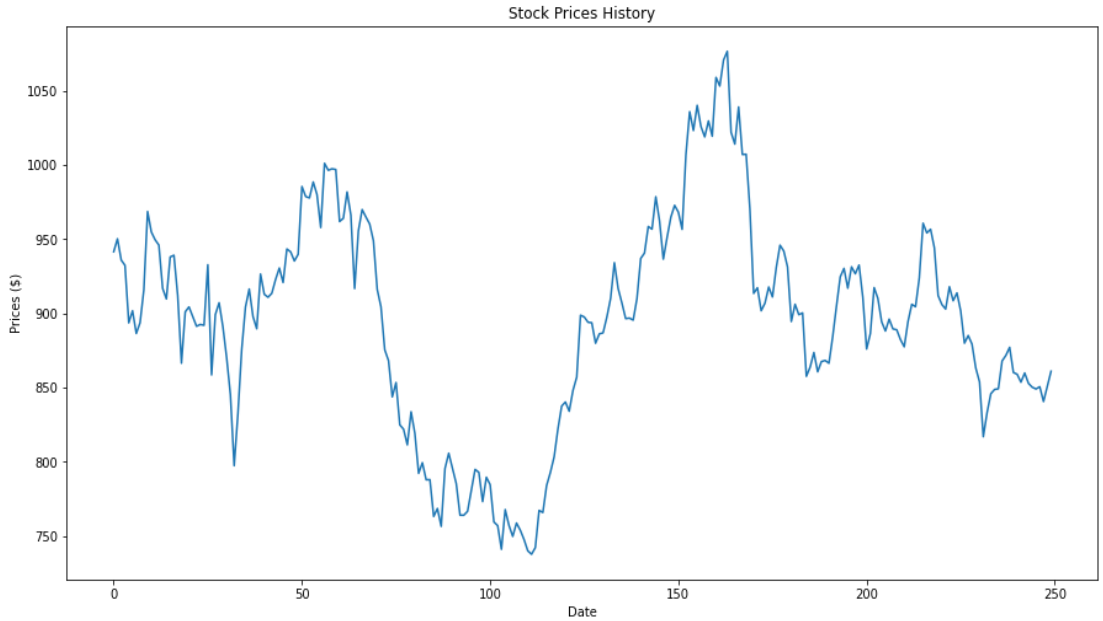


Fig:4.3: Oberoi Realty Stock price

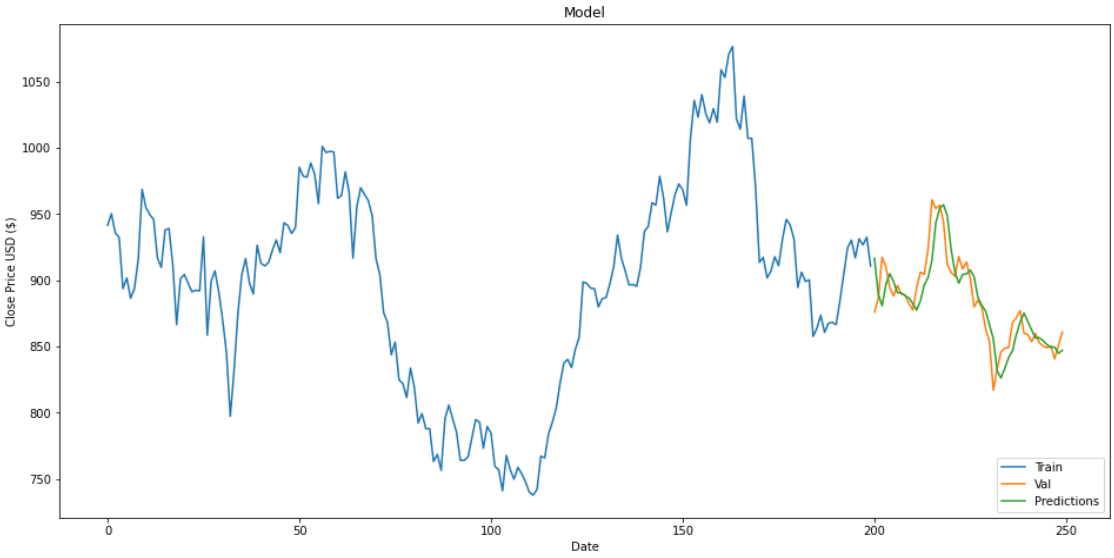

Fig:4.4: Oberoi Realty Forecasted Stock Price

### 4.2.2. Summarization of Forecasted Results

With regard to obtaining a low RMSE value and a quick execution time, setting the epoch size and batch size is crucial.

The batch size is a hyper-parameter that specifies how many samples must be processed before the internal model parameters are updated. One or more batches can be created from a training dataset. The learning algorithm is known as batch gradient descent when all training data are combined into a single batch. Stochastic gradient descent is the name of the learning algorithm when the batch size is one sample. The learning algorithm is known as mini-batch gradient descent when the batch size is greater than one sample and less than the size of the training dataset.

A hyper-parameter called "epochs" determines how many times the learning algorithm will run over the whole training dataset.

Every sample in the training dataset has had a chance to update the internal model parameters once during an epoch. One or more batches make up an epoch. The batch gradient descent learning algorithm, for instance, is used to describe an epoch that only contains one batch.

Table: 4.1: Batch, Epoch, RMSE and Stock

| Batch Size | Epoch | RMSE | Stock |
|---|---|---|---|
| 1 | 10 | 0.98 | Wipro |
| 1 | 10 | 0.50 | SBI |
| 1 | 10 | 0.82 | Cipla |
| 1 | 10 | 0.61 | BHEL |
| 1 | 10 | 3.70 | Bajaj Auto |
| 1 | 10 | 3.96 | Dabur |
| 1 | 10 | 0.55 | Reliance |
| 1 | 10 | 2.97 | HP |
| 1 | 10 | 1.92 | Dalmia |
| 1 | 10 | 0.92 | NTPC |
| 1 | 10 | 0.63 | Oberoi Realty |

We've experimented with other batch sizes and epochs, and we've found that this number produces superior results to others.

### 4.2.3. Buying and Selling Units

We have developed an improved model using the RL algorithm that can learn when to buy and sell stock units as well as how many units should be purchased or sold in order to maximize profit.

The goal of this algorithm is to win over the trust of various users who are willing to take financial risks and so demonstrate their interest in ATS.

The outcome of buying and selling units is displayed below.

```
day 0: buy 5 units at price 4707.999880, total balance 5292.000120
day 1, sell 5 units at price 4751.499940, investment 0.923961 %, total balance 10043.500060,
day 4: buy 5 units at price 4468.250120, total balance 5575.249940
day 6: buy 5 units at price 4432.500000, total balance 1142.749940
day 8: buy 5 units at price 4578.999940, total balance -3436.250000
day 9, sell 5 units at price 4843.500060, investment 8.398141 %, total balance 1407.250060,
day 10, sell 5 units at price 4774.500120, investment 7.715739 %, total balance 6181.750180,
day 12: buy 1 units at price 946.049988, total balance 5235.700192
day 13, sell 5 units at price 4584.500120, investment 0.120117 %, total balance 9820.200312,
day 14: buy 5 units at price 4548.750000, total balance 5271.450312
day 15, sell 5 units at price 4690.249940, investment 395.771894 %, total balance 9961.700252,
day 16, sell 1 units at price 939.200012, investment -79.352569 %, total balance 10900.900264,
day 18: buy 5 units at price 4332.250060, total balance 6568.650204
day 19, sell 5 units at price 4505.249940, investment 3.993303 %, total balance 11073.900144,
day 22: buy 1 units at price 891.349976, total balance 10182.550168

                                    .
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                                    .
day 240, sell 5 units at price 4294.750060, investment -0.145315 %, total balance 21436.800104,
day 241: buy 5 units at price 4268.250120, total balance 17168.549984
day 242, sell 5 units at price 4299.249880, investment 0.726287 %, total balance 21467.799864,
day 245: buy 1 units at price 849.049988, total balance 20618.749876
day 246, sell 1 units at price 850.599976, investment 0.182556 %, total balance 21469.349852,
day 247: buy 5 units at price 4202.999880, total balance 17266.349972
day 248, sell 5 units at price 4253.999940, investment 1.213420 %, total balance 21520.349912,

total gained 11520.349912, total investment 115.203499 %
```

Fig:4.5:Oberoi Realty Investment Result

### 4.2.4 Visualizing the result

To make the concept easier to understand, we have created a graph where the purchasing and selling locations are indicated. To test the consistency of our model, we applied the algorithm to stocks from a variety of industries. We also noted the cumulative gain for each stock.

Here, we present a number of stock-related results.

I) Healthcare Sector


Fig:4.6: Cipla Stock

II) Utility Sector


Fig:4.7: NTPC Limited Stock

III) Energy Sector

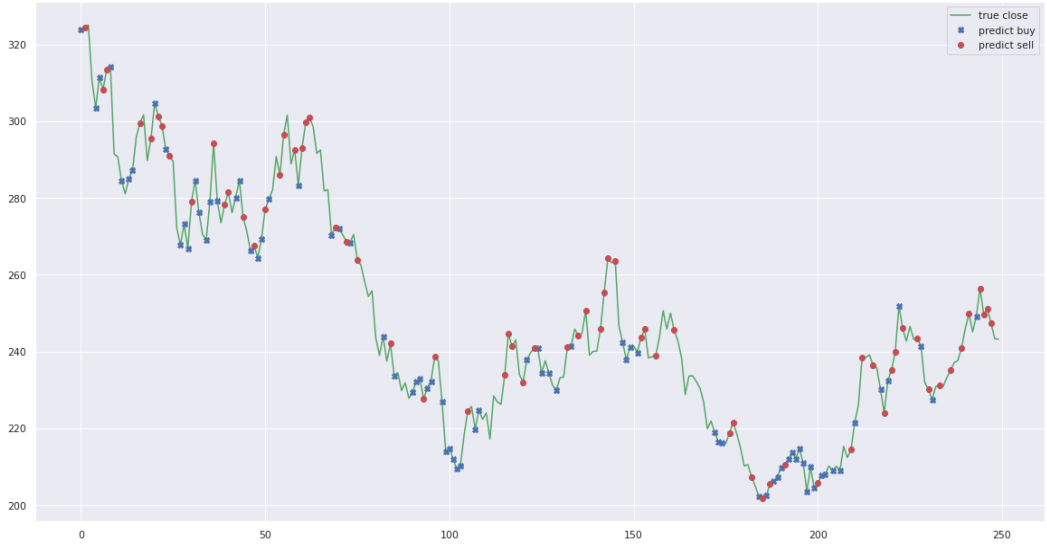


Fig: 4.8: HP Stock

IV) Communication Service Sector


Fig:4.9: Reliance Stock

V) Materials Sector

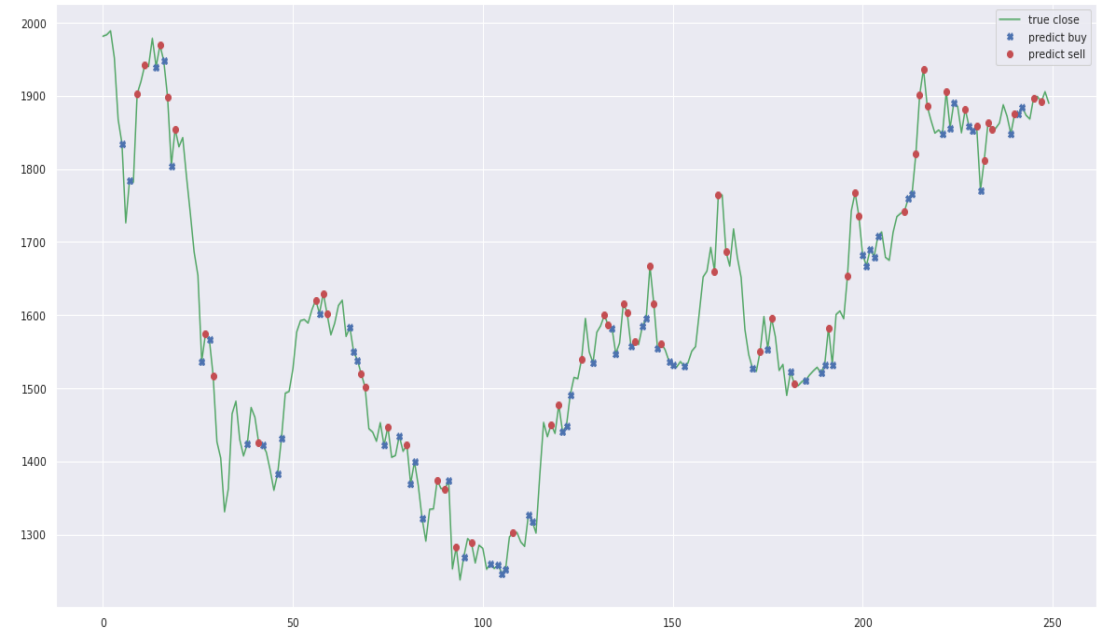


Fig:4.10: Dalmia Stock

### 4.2.5 Total Gain and Total Investment

Here, we present the total return from each company depending on several sectors that we obtain using our model in tabular style.

Table 4.2: Total gain and investment

| Stock | Sector | Purchase Amount | Total Gain |
|---|---|---|---|
| Wipro | IT | 10,000 | 3615.55 |
| SBI | Finance | 10,000 | 8120.24 |
| Cipla | Healthcare | 10,000 | 9536.14 |
| BHEL | Industrial | 10,000 | 5872.54 |
| Bajaj Auto | Consumer Discretionary | 10,000 | 15704.14 |
| Dabur | Consumer Stable | 10,000 | 6330.94 |
| Reliance | Communication Service | 10,000 | 14125.19 |
| HP | Energy | 10,000 | 4444.79 |
| Dalmia | Materials | 10,000 | 18961.85 |
| NTPC | Utilities | 10,000 | 4186.80 |
| Oberoi Realty | Real Estate | 10,000 | 11520.34 |

## SUMMARY

This chapter covered the experimental findings from the training and testing of several stocks.

# CHAPTER 5

# CONCLUSION AND FUTURE SCOPE

## 5.1. Conclusion

With regard to root mean square errors, the technique of forecasting a stock's future trend using LSTM has produced trustworthy outcomes for both the opening and closing prices . The fundamental consequence of this work is the creation of a trading algorithm based on reinforcement learning, which, from an economic standpoint, has the potential to be lucrative and enticing for investors and, with little modification, can produce good results and returns.

In this work, we have illustrated an application of evolution strategy agent learning while retaining the fundamentals of reinforcement learning based on deep learning. And solutions to the monetary difficulty of deciding on a successful stock trading strategy A detailed image of the buy and sell points for stocks is presented to the user, enabling him to make profitable trading decisions.

## 5.2. Future Scope

We are working to develop an effective algorithm that can inform users and automatically assess prospective trends in the future by enhancing trading algorithms to anticipate the stock's buy, sell, and hold points for a given period of time and the sort of investment a user wants to make, such as long- or short-term. In the future, investigate the application of additional reinforcement learning strategies to stock trading to obtain an improved and more effective auto trading algorithm.

## Summary

In this chapter we discussed about the conclusion and future scope of Stocks in different areas.

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# APPENDIX – A

## LIST OF FORMULAS USED

1. Mean Square Error: $$\mathbf{MSE} = \frac{\mathbf{1}}{\boldsymbol{n}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} (\boldsymbol{Y_i} - \boldsymbol{\hat{Y}_i})^{\mathbf{2}}$$

2.Root Mean Square Error: $$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}}$$

3.Reinforcement Learning: $$P_a(s, s') = \Pr(s_{t+1} = s' \mid s_t = s, a_t = a)$$

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Department of Computer Science and Engineering
Silicon Institute of Technology,
Silicon Hills, Bhubaneswar –751024,
Odisha, India
Jan, 2023