AUTO TRADING USING DEEP LEARNING:

Visakha
Regd No.: 2111209001
3rd Sem, M.Sc. Data Science,
Section: A

Debashish Mohapatra
Regd No.: 2111209003
3rd Sem, M.Sc. Data Science,
Section: A

Supervised by: Dr. Satyananda Champati Rai

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

I. 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 of recurrent neural network[4] 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.

II. 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 price is 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 of handling these stocks data. We forecast the future trend of stocks using this model.

III. METHODOLOGY

We select the daily datasets for the years 2022-2023 from a large pool of datasets based on different Indian sectors. Following an evaluation of the datasets, the true trend of the dataset was visualized. Then, based on the trend, we tried to create a model that would fairly predict the future trend. To that goal, we produced the Root Mean Squared Error (RMSE). The goal was to keep the RMSE at or below 5. Then, based on that model, we proposed an Evolution Strategy Agent based on RL, which considers previous behavior and offers suggestions for when to buy and sell stocks.

A. 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.

B. Predicting the trend of stocks

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.

C. Beta: A measure of volality

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.

D. Classification of stock rick

Regression analysis is used to compute beta. In terms of numbers, it shows how responsive a security's returns are to market fluctuations.

A stock with a beta above 1.0 fluctuates more than the market over time. A stock's beta is less than 1.0 if it moves less than the market. Low-beta stocks carry less risk but have lower potential returns while high-beta stocks are considered to carry greater risk but have larger potential returns.

E. Description about the dataset

Here, a total of 11 datasets from various industries are used, each of which has a unique risk factor attached to it. Each dataset contains data for the one-year period from 2022 to 2023. The stock data contains 7 columns. Those are date, open, high, low, close, adj close and volume.

All the files have the following columns:

Date - in format: yy-mm-dd.

Open - price of the stock at market open.

High - Highest price reached in the day.

Low – Lowest price reached in the day.

Close - Lowest price reached in the day.

Adj close – Gives the better/overall idea about the stock.

Volume - Number of shares traded.

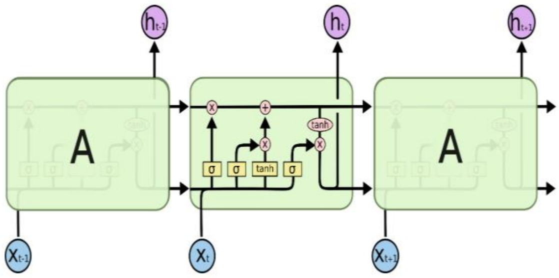
F. Forecast the stock price

To handle models like image classification, sequential data like audio and video, timeseries forecasting, etc., we employ LSTM , a type of recurrent neural network.

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.LSTM are explicitly design to avoid long term dependency problem, remembering their behavior for a long period of time is practically very difficult task.

The vanishing gradient issue is avoided. Recurrent gates referred to as "forget gates" are typically added to LSTM. Backpropagated errors are kept from disappearing or blowing up thanks to LSTM. Errors can instead travel backwards through an infinite number of virtual layers that are spread out in space.

As a result, LSTM can be trained to perform tasks that need memories of past events that occurred hundreds or even millions of discrete time steps ago. Long time intervals between important events don't affect the performance of LSTM, and it can handle signals that combine low- and high-frequency components.



The repeating module in an LSTM contains four interacting layers.

G. 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.

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 ($X € R^n$). 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 network constructed with the stated weights. It then adds up the benefit offered by the environment. So this algorithm is best suited to solve the problem of when to alert user to buy and sell stocks.

H. Total gain for the alerts generated

Based on the risk-taking appetite of the user and amount of money the user wants to invest. After getting these inputs from the user, the model will recommend the stocks which has the forecasted close value equal or lower than the amount.

I. Figures and Tables

a) Table-1

Sector and Beta values

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

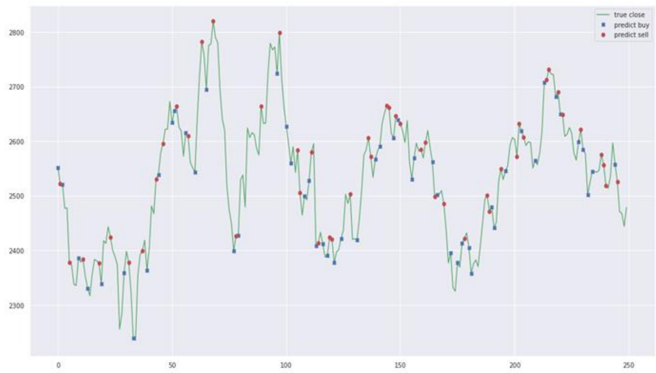
b) Table-2

Stock RMSE and Total Gain

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

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

Fig-1(Model taking input and showing the buy and sell points for oberio realty stock)

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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

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 %
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Fig -3(CIPLA Stocks Price)

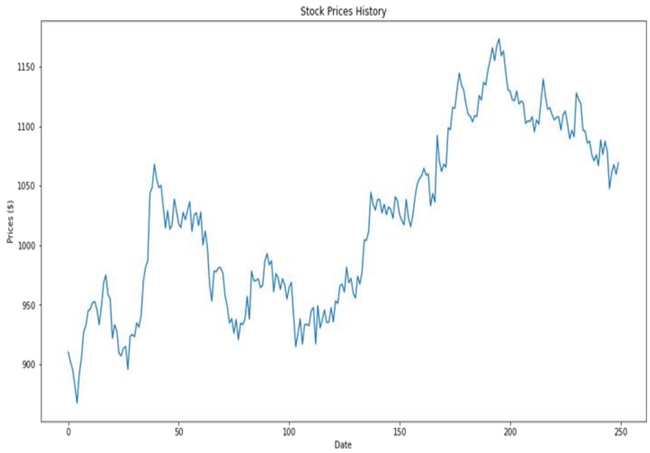


Fig- 4(CIPLA forecasted Stocks Price)

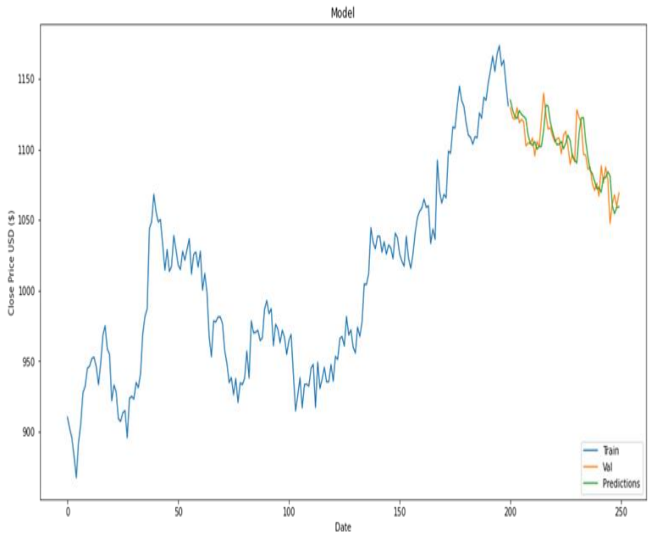


FIG -5(UDEMY STOCKS PRICE)

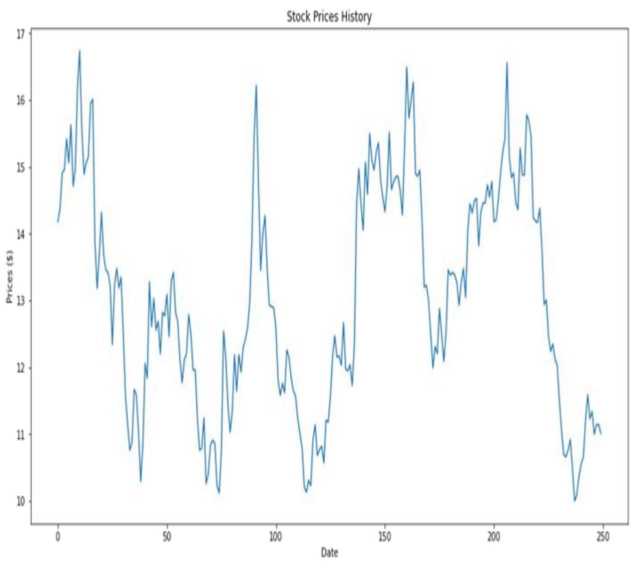
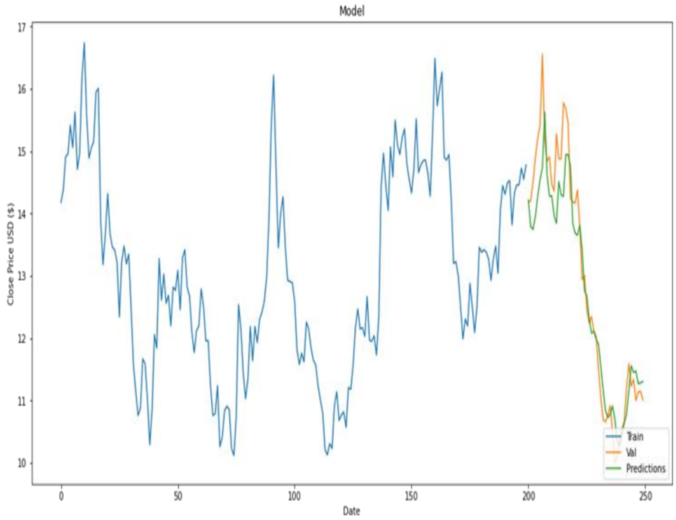


FIG -6(UDEMY FORECASTED STOCKS PRICE)



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CONCLUSION

Using LSTM, the method of predicting a stock's future trend has produced reliable results for both the opening and closing prices with regard to root mean square errors(RMSE).The main outcome of this work is the development of a reinforcement learning-based trading algorithm. Which, from an economic perspective, has the potential to be profitable and appealing for investments and, with minimal change, can yield good results and returns.

While recalling the principles of reinforcement learning, we have demonstrated an application of evolution stratey agent learning in this study.And solutions to the monetary difficulty of deciding on a successful stock trading strateg y. The depiction of the buy and sell points for stocks provides the trader with a clear picture that will help him make profitable investments during trading

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