A Comprehensive Approach to Stock Trading using Machine Learning

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Statement by the Candidates

We wish to state that work embodied in this dissertation titled ”A Comprehensive Approach to Stock Trading using Machine Learning” forms our own contribution to the work carried out under the supervision of Dr. R. D. Daruwala and Prof. Rizwan Ahmed at Veermata Jijabai Technological Institute. This work has not been submitted for any other Degree or Diploma of any University/Institute. Wherever, references have been made to previous works of others, it has been clearly indicated.

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Certificate

This is to certify that **Husain Kapadia, Sameer Karode, Suraj Maniyar**, **Tanay Shah** and **Shubhankar Borse** students of Electrical Engineering department, have completed the dissertation," **A Comprehensive Approach to Stock Trading using Machine Learning**" to our satisfaction.

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Abstract

This thesis presents an approach to maximally increase profits for stock trading. Both Fundamental and Technical analysis are used in the portrayed approach. A large number of companies from various sectors were considered, and sector wise grouping of these companies is done. First, the best companies to invest in each sector are found by doing a fundamental analysis of the stock. Next, portfolio optimization is done to figure out how much cash should be allocated to each company at any amount of time. Once this is done, the technical factors are used to figure out buying and selling points, and set up a daily routine to optimize the current price in hand. This can either be implemented using a branching model or by various Machine Learning models such as Reinforcement Learning or Neural Networks. Each of these models is used and the trader is encouraged to rely on the one which gives the best results according to the comparisons made in the thesis.

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Chapter 1

Introduction

1.1 Motivation

There are several motivations for trying to predict stock market prices. The most basic of these is financial gain. Any system that can consistently pick winners and losers in the dynamic market place would make the owner of the system very wealthy. Thus, many individuals including researchers, investment professionals, and average investors are continually looking for this superior system which will yield them high returns.

There is a second motivation in the research and financial communities. It has been proposed in the Efficient Market Hypothesis (EMH) that markets are efficient in that opportunities for profit are discovered so quickly that they cease to be opportunities. The EMH effectively states that no system can continually beat the market because if this system becomes public, everyone will use it, thus negating its potential gain. There has been an on-going debate about the validity of the EMH, and some researchers attempted to use neural networks to validate their claims. There has been no consensus on the EMH's validity, but many market observers tend to believe in its weaker forms, and thus are often unwilling to share proprietary investment systems.

While traditional approach focuses on Time series analysis [25], recently, Neural networks are used to predict stock market prices because they are able to learn nonlinear mappings between inputs and outputs. Contrary to the EMH, several researchers claim the stock market and other complex systems exhibit chaos. Chaos is a nonlinear deterministic process which only appears random because it can't be easily expressed. With the neural networks' ability to learn nonlinear, chaotic systems, it may be possible to outperform traditional analysis and other computer-based methods.

In addition to stock market prediction, neural networks have been trained to perform a variety of financial related tasks. There are experimental and commercial systems used for tracking commodity markets and futures, foreign exchange trading, financial planning, company stability, and bankruptcy prediction. Banks use neural networks to scan credit and loan applications to estimate bankruptcy probabilities, while money managers can use neural networks to plan and construct profitable portfolios in real-time. As the application of neural networks in the financial area is so vast, this work will focus on net price maximization.

Finally, although neural networks are used primarily as an application tool in the financial environment, several research improvements have been made during their implementation. Notable improvements in network design and training and the application of theoretical techniques are demonstrated by the examination of several example systems.

In hindsight, a bunch of methods are available for optimizing portfolios and a bunch of methods are available for technical analysis. A combination of the two would significantly improve profits. Also, a comparative study involving each method is essential to find out which methods we can use in different situations.

1.2 Problem Definition

To develop a comprehensive algorithm for stock market investment by incorporating fundamental analysis, portfolio optimization and daily returns maximization using various models, and comparing the outcomes obtained by different models.

1.3 Prerequisites and Libraries used

The entire simulation, data acquisition, visualization and modelling was done on Python 2.7 using various libraries such as pandas, keras tensorflow, matplotlib, numpy, scipy optimize and scikit-learn toolkit.

1.4 Organization of Report

Chapter 1 gives an introduction to the thesis work presented here and defines its motivation, aim and proposed idea. Finally, it also presents an overview of the entire thesis.

Chapter 2 will critically review the previous work done on stock trading. It explains the historical work done with different models, and talks about how the thesis will build on this work.

Chapter 3 gives a basic idea of stocks, and the information regarding the stock market which is required to implement and develop the algorithm.

Chapter 4 is based on fundamental analysis of stocks. It gives detailed information regarding all fundamental factors, and how they are used to score companies. It also compares the recommended high scored companies to the financial time recommendations.

Chapter 5 gives an explanation to various methods of portfolio optimization, and how these methods are implemented to achieve optimal resource sharing.

Chapter 6 is based on technical analysis of the daily stock returns. A detailed explanation of every technical factor is provided, and the implementation of the branching model is explained.

Chapter 7 introduces the concept of Unsupervised Reinforcement Learning using a Q-learning algorithm. The implementation of this algorithm is then explained.

Chapter 8 gives a detailed explanation for a Neural Network based training model, and shows the results after simulating the same.

Chapter 9 concludes the thesis with details of accomplishments, challenges faced and limitations of the approach.

Chapter 2

Literature Review

This report examines a refined investment strategy based on both the technical and fundamental factors of a company. Just like in [5], which used a 9 variable F-score, we too employ a pass and a fail score to each of the companies under consideration. A total of 18 criteria are considered to assign a score to a company based on which the user decides whether to invest in the company or not. As stated in ‘Machine Learning applications in financial markets’ [7], the Efficient Market Hypothesis, it is assumed that the price of a security reflects all of the information available and that everyone has some degree of access to the information. Fama’s theory further breaks EMH into three forms: Weak, Semi-Strong, and Strong. In Weak EMH, only historical information is embedded in the current price. The Semi-Strong form goes a step further by incorporating all historical and currently public information into the price. The Strong form includes historical, public, and private information, such as insider information, in the share price. From the tenets of EMH, it is believed that the market reacts instantaneously to any given news and that it is impossible to consistently outperform the market.

Both fundamentalists and technicians have developed certain techniques to predict prices from financial news articles. ‘Mittal and Goel, Stock Prediction Using Twitter Sentiment Analysis’ [2] has employed similar strategy by using Twitter for Sentiment Analysis. In addition, ‘Bala and Dixit, Predicting Market Volatility Using Semantic Vectors and Google Trends’ [9] have employed Google Trends to predict market volatility. While Sentiment analysis classifies as a reasonable approach, we have focused on technical analysis for Stock trading.

‘Joseph D. Piotroski, Value investing: The use of Historical Financial Statement Information to Separate Winners from Losers’ [4] focuses on predictions of behavioural models based on the ability to predict the future performance and examines a refined investment strategy based on a company’s Book-to-Market (BM) ratio. ‘Shen, Ziang and Zheng’ [13] employs SVM and Reinforcement Learning that exploits the temporal correlation among global stock markets. ‘Molina, Stock Trading with Recurrent Reinforcement Learning (RRL)’ [10] uses Recurrent Reinforcement Learning to predict the asset prices before they occur. The Sharpe’s ratio is commonly used metric in financial engineering which traders look to maximize.

‘A. Kar, “Stock Prediction using Artificial Neural Networks’ [12] gives a glimpse of the use of Artificial Neural Networks to predict stock market indices. It examines the influence of various parameters like activation functions, number of hidden layers and the variation in data length. We have employed the same strategy of using Neural Networks where the technical indicators are fed as inputs and the outputs are used as classifiers to take actions like buy, sell and hold. So the problem is treated as a classification problem.

‘Markowitz’ [16] in his pioneering paper on optimizing portfolios, published in 1952, for the first time gave the concept of efficient portfolios. Since than many researchers ‘Freyembya’ [19] have made improvements in the method. Recently many improved techniques that incorporate many more factors apart from the traditional risk and return have been proposed [20],[21]. We propose to automate Black Litterman optimization method using fundamental analysis techniques.

While many papers emphasis on fundamental analysis and Sharpe’s ratio, our aim is focused on extracting information from various technical factors and incorporating it along with fundamental data to maximize the portfolio.

Chapter 3
Basic Concepts of Stock market

3.1 Stocks

Stocks are “a type of security that signifies ownership in a corporation and represents a claim on part of the corporation’s assets and earnings”.

However, stock holders do not own corporations; they own shares issued by corporations. But corporations are a special type of organization because the law treats them as legal persons. In other words, corporations file taxes, can borrow, can own property, can be sued, etc. The idea that a corporation is a “person” means that the corporation *owns its own assets*. A corporate office full of chairs and tables belong to the corporation, and *not* to the shareholders.

What shareholders own are shares issued by the corporation; and the corporation owns the assets. So if you own 33% of the shares of a company, it is incorrect to assert that you own one-third of that company; it is instead correct to state that you own 100% of one-third of the company’s shares. Shareholders cannot do as they please with a corporation or its assets. However, owning stock gives you the right to vote in shareholder meetings, receive dividends (which are the company’s profits) if and when they are distributed, and it gives you the right to sell your shares to somebody else.

3.2 The Stock market

Once a company completes an initial public offering (IPO), its shares become public and can be traded on a stock market. Stock markets are venues where buyers and sellers of shares meet and decide on a price to trade. Some exchanges are physical locations where transactions are carried out on a trading floor, but increasingly the stock exchanges are virtual, composed of networks of computers where trades are made and recorded electronically.

Stock markets are secondary markets, where existing owners of shares can transact with potential buyers. It is important to understand that the corporations listed on stock markets do not buy and sell their own shares on a regular basis (companies may engage in stock buybacks or issue new shares, but these are not day-to-day operations and often occur outside of the framework of an exchange). So when you buy a share of stock on the stock market, you are not buying it from the company, you are buying it from some other existing shareholder. Likewise, when you sell your shares, you do not sell them back to the company – rather you sell them to some other investor.

The prices of shares on a stock market can be set in a number of ways, but the most common way is through an auction process where buyers and sellers place bids and offers to buy or sell. A bid is the price at which somebody wishes to buy, and an offer (or ask) is the price at which somebody wishes to sell. When the bid and ask coincide, a trade is made.

A company's total valuation is determined by multiplying the number of shares available by the current market price per share. This is referred to as the company's market capitalization. For example, if a company has 1000 shares available at a price of Rs.10.00 per share, the company is valued by the market at Rs.10,000. One important use for market capitalization is how the major indexes are weighted. The Nifty50, for example, indexes the 50 stocks weighted by a diversified range of market capitalization, and uses that price as an indicator of the performance of industry as a whole.

Notice that the word "value" is never used in the absolute sense here: the idea is that no asset has an intrinsic value independent of offers to pay for it. The valuation is what the market is willing to pay.

3.3 Analyzing the market

Stock analysis is a term that refers to the evaluation of a particular trading instrument, an investment sector or the market as a whole [2]. Stock analysts attempt to determine the future activity of an instrument, sector or market. There are two basic types of stock analysis: fundamental analysis and technical analysis. Fundamental analysis concentrates on data from sources including financial records, economic reports, company assets and market share. Technical analysis focuses on the study of past market action to predict future price movement.

Fundamental analysis is the process of evaluating businesses, projects, budgets and other finance-related entities to determine their performance and suitability. Typically, financial analysis is used to analyse whether an entity is stable, solvent, liquid or profitable enough to warrant a monetary investment. When looking at a specific company, a financial analyst conducts analysis by focusing on the income statement, balance sheet and cash flow statement.

Technical analysis (sometimes referred to as trend analysis) tries to predict the future movement of a stock based on past data. Trend analysis is based on the idea that what has happened in the past gives traders an idea of what will happen in the future. There are three main types of trends: short-term, intermediate-term and long-term.

Technical analysis and fundamental analysis are often seen as opposing approaches to analysing securities, but combining the two techniques can be successful. For example fundamental analysis can be used to identify an undervalued stock and technical analysis to find a specific entry and exit point for the position

3.4 Stock Data Appearance

A stock quote, which is commonly used for representing data somewhat looks like Table 3.1.

Table 3.1: Generic Stock Data frame

Date	**Open**	**High**	**Low**	**Close**	**Adj. Close**	**Volume**
18-04-17	341.1	343.5	336.35	338.55	338.55	1273125
19-04-17	340	341.6	333.25	340	340	73656
20-04-17	340	343.7	338.05	342.6	342.6	72382
21-04-17	343	346.15	340.7	342.85	342.85	93490
24-04-17	343	347	339	343.25	343.25	112466
25-04-17	342.5	359.85	341.6	354.15	354.15	271401
26-04-17	350.1	359.95	350.1	357.95	357.95	165187
27-04-17	356.45	361.35	353.8	357.95	357.95	146713
28-04-17	356.4	357.85	350.55	354	354	129146
02-05-17	354	355.3	346.15	347.5	347.5	111019
Date	**Open**	**High**	**Low**	**Close**	**Adj. Close**	**Volume**

03-05-17	347.5	350.1	344.05	346.45	346.45	71284
04-05-17	347.75	351.3	343.8	345.9	345.9	72364
05-05-17	345.95	348.75	343	344.65	344.65	80561
08-05-17	344.75	355.25	344.7	351.25	351.25	121032
09-05-17	350	350.5	343.4	345.5	345.5	148963
10-05-17	337	380.05	336.95	372.7	372.7	1635184
11-05-17	371.7	371.7	362.65	366.1	366.1	557720
12-05-17	362.15	370.55	361.55	364.9	364.9	279225

The chart is the historical representation of Airtel stock obtained from yahoo finance. The data frame shows us daily values of the opening and closing stock price, the stock volume and daily highs and lows. These terms are explained below:

1. Trading Volume - This figure shows the total number of shares traded for the day, listed in hundreds. To get the actual number traded, add "00" to the end of the number listed.
2. Day High and Low - This indicates the price range at which the stock has traded at throughout the day. In other words, these are the maximum and the minimum prices that people have paid for the stock.
3. Close - The close is the last trading price recorded when the market closed on the day. If the closing price is up or down more than 5% than the previous day's close, the entire listing for that stock is bold-faced. Keep in mind, you are not guaranteed to get this price if you buy the stock the next day because the price is constantly changing (even after the exchange is closed for the day). The close is merely an indicator of past performance and except in extreme circumstances serves as a ballpark of what you should expect to pay.

Chapter 4

Fundamental Analysis

4.1 The need for fundamental analysis

The stocks of MRF are trading at a whopping Rs. 65000 per stock while those of Apollo Tyres are trading at just Rs.235. Does this mean that as a company MRF is doing much better than Apollo tyres?

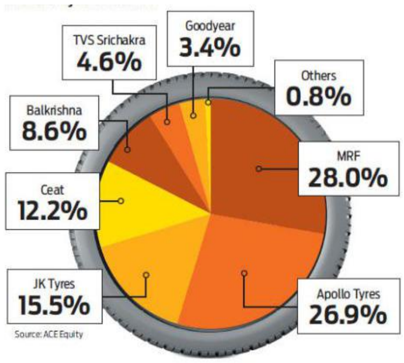


Figure 4.1: Split up of Market share of tyre brands[11]

Consider the market shares of both the companies at the end of Q4 2015. It is seen that while MRF is the market leader with 28 % market share, Apollo tyres comes in a close second with 26.9 % share (source : Outlook India). This definitely does not endorse the huge difference in stock prices which are often misleading.

Hence, an in depth analysis of the company's working, its management and financial dealings is required to understand its future growth prospects. And investing in a company with a brighter future is always better. This approach of studying a company's fundamentals to pick good stocks is called fundamental analysis.

4.2 The Fundamental Analysis theory:

The final goal of fundamental analysis [8] is to find the true value or the intrinsic value of the stock and it is assumed that the stock is worth only as much as the company while the company is worth all its future profits added together discounted for the time value of money. One of the implicit assumptions of the theory is that people are rational that is they will not buy something for an amount greater than its valuation. However, some people view stocks as just tools of speculation to make profit without any regard for the company's fundamentals. This approach is called the greater fools theory that is the person who can sell off his stock to a greater fool wins. In such cases fundamental analysis fails.

However, it still gives a good starting point for investment in a majority of cases. We use this theory to rank companies based on how strong their fundamentals are, and then select the best stocks to invest in. The actual investment is then done by observing the price trends of the stocks based on another theory called technical analysis which is discussed later.

Now, a lot of stress has been given on the fundamentals of a company. What exactly are these fundamentals? These are various factors like revenues, earnings, future growth, return on equity, profit margins, debt, cash flows and other data used to determine a company's underlying value and potential for future growth.[15]

Every company releases all this data on a regular basis mostly quarterly or some annually in form of reports. These report contains various statements namely Income statement, Balance sheet and cash flow statement which are of utmost importance. As we aim to automate the process of stock selection, manually getting data from the quarterly reports was not feasible.

4.3 Data acquisition:

Yahoo finance regularly uploads the income statements, balance sheets and the cash flow statements of all companies whose stocks are traded on either BSE or NSE.

We use web scraping to extract the data from yahoo finance website and then clean the extracted data to create 3 CSV files for a company one each for income statement , balance sheet and cash flow. For scraping 'selenium' python library is used. The code and explanation is provided in Appendix A.

Once the data is acquired we get a file having various company fundamentals as follows

Table 4.1: Annual Balance Sheet of JSW Energy

Period Ending	**3/31/2016**	**3/31/2015**	**3/31/2014**	**3/31/2013**
Current Assets				
Cash And Cash Equivalents	3949000	3515000	5675000	3990000
Short Term Investments	753000	13861000	6342000	5757000
Net Receivables	28783000	12205000	12895000	20169000
Inventory	6494000	5483000	4158000	4415000
Other Current Assets	1417000	1021000	3534000	3046000
Total Current Assets	42512000	36457000	32603000	37377000
Long Term Investments	1932000	2327000	2535000	2714000
Property Plant and Equipment	-	-	-	-
Goodwill	831000	97000	106000	280000
Intangible Assets	-	-	-	-
Accumulated Amortization	-	-	-	-
Other Assets	-	-	-	-
Deferred Long Term Asset Charges	-	-	-	-
Total Assets	281373000	194200000	192444000	203781000
Current Liabilities				
Accounts Payable	25632000	16395000	16405000	25678000
Short/Current Long Term Debt	155231000	92941000	101065000	103766000
Other Current Liabilities	6925000	4962000	5896000	9348000
Total Current Liabilities	63151000	34442000	34645000	50916000
Long Term Debt	125592000	80624000	89323000	88527000
Other Liabilities	-	-	-	-
Deferred Long Term Liability Charges	615000	615000	615000	615000
Minority Interest	-	-	-	-
Negative Goodwill	-	-	-	-
Total Liabilities	195464000	118473000	126229000	141291000
Stockholders' Equity				
Misc. Stocks Options Warrants	-	-	-	-

Period Ending	3/31/2016	3/31/2015	3/31/2014	3/31/2013
Redeemable Preferred Stock	-	-	-	-
Preferred Stock	-	-	-	-
Common Stock	40209000	40209000	40209000	40209000
Retained Earnings	39698000	25152000	20343000	17386000
Treasury Stock	5452000	9819000	5160000	4443000
Capital Surplus	-	-	-	-
Other Stockholder Equity	-	-	-	-
Total Stockholder Equity	-	-	-	-
Net Tangible Assets	-	-	-	-

Table 4.2 Annual Cash flow statement of JSW Energy

Period Ending	3/31/2016	3/31/2015	3/31/2014	3/31/2013
Net Income	13955000	13495000	7547000	9037000
Operating Activities Cash Flows Provided By or Used In				
Depreciation	9471000	7884000	8086000	6601000
Adjustments To Net Income	-	-	-	-
Changes In Accounts Receivables	-11971000	240000	6503000	-7848000
Changes In Liabilities	-	-	-	-
Changes In Inventories	-703000	-1575000	257000	3244000
Changes In Other Operating Activities	-39000	2381000	-1584000	-1958000
Total Cash Flow From Operating Activities	35674000	33943000	22691000	17246000
Investing Activities Cash Flows Provided By or Used In				
Capital Expenditures	-35899000	-6772000	-4940000	-9783000
Investments	-	-	-	-
Other Cash flows from Investing Activities	-	-	-	-
Total Cash Flows From Investing Activities	-34657000	-4222000	-3625000	-9441000
Financing Activities Cash Flows Provided By or Used In				
Dividends Paid	-	-	-	-

Period Ending	3/31/2016	3/31/2015	3/31/2014	3/31/2013
Sale Purchase of Stock	-	-	-	-
Net Borrowings	-	-	-	-
Other Cash Flows from Financing Activities	1237000	2445000	1265000	274000
Total Cash Flows From Financing Activities	-15982000	-23272000	-18591000	-6844000
Effect Of Exchange Rate Changes	-	-	-	-
Change In Cash and Cash Equivalents	-13374000	6449000	476000	961000

Table 4.3: Annual Income statement of ONGC

Revenue	3/31/2016	3/31/2015	3/31/2014	3/31/2013
Total Revenue	1314979000	1612117000	1744771000	1624025000
Cost of Revenue	726331000	959051000	964794000	868869000
Gross Profit	588647000	653066000	779976000	755156000
Operating Expenses				
Research Development	-	-	-	-
Selling General and Administrative	-	-	-	-
Non Recurring	-	-	-	-
Others	-	-	-	-
Total Operating Expenses	1078669000	1359030000	1407420000	1280527000
Operating Income or Loss	236310000	253087000	337351000	343499000
Income from Continuing Operations				
Total Other Income/Expenses Net	-	-	-	-
Earnings Before Interest and Taxes	236310000	253087000	337351000	343499000
Interest Expense	-13039000	-9235000	-5188000	-3882000
Income Before Tax	-	-	-	-
Income Tax Expense	84170000	96974000	127604000	127519000
Minority Interest	-	-	-	-
Net Income From Continuing Ops	-	-	-	-
Non-recurring Events				

Revenue	3/31/2016	3/31/2015	3/31/2014	3/31/2013
Discontinued Operations	-	-	-	-
Extraordinary Items	-	-	-	-
Effect Of Accounting Changes	-	-	-	-
Other Items	-	-	-	-
Net Income				
Net Income	141238000	183335000	265065000	242196000
Preferred Stock And Other Adjustments	-	-	-	-
Net Income Applicable To Common Shares	-	-	-	-

Also, various statistical factors like current ratio, P/E ratio, Earnings per share, PEG ratio etc. are either calculated from the scraped data or are scraped from yahoo finance [22] website where they are listed for all stocks under the header key stats.

Table 4.4: Some statistics directly scraped from yahoo finance

Ticker	DE Ratio	Trailing P/E	Price/ Sales	Price/ Book	Profit Margin	Op. Margin	Return on Assets	Return on Equity	Revenue Per Share	Market Cap	Enterprise Value
SUNTECK	59.19	7.13	1.58	1.29	22.17	33.49			240.15	22820000000	324300000000
SUNTV	24.03	34.11	12.11	8.84	35.52	49.68	20.38	25.53	65.26	3.1132E+11	3.1133E+11
SUVEN	14.13	31.55	4.2	3.54	13.36	15.7	6.29	11.56	39.24	19480000000	194800000000
SUZLON	14.13	222.09	0.88	3.54	0.4	14.47	6.29	11.56	21.81	96220000000	2.0959E+11
TAKE	25.22	12.5	1.27	1.92	9.79	13.26	-0.56	-40.55	104.21	16490000000	170300000000

Ticker	DE Ratio	Trailing P/E	Price/ Sales	Price/ Book	Profit Margin	Op. Margin	Return on Assets	Return on Equity	Revenue Per Share	Market Cap	Enterprise Value
TANLA	0.06	18.71	0.96	0.74	5.09	6.18	4.02	4.26	50.88	4960000000	4200000000
TBZ	129.92	-18.77	0.31	1.19	-1.66	2.21	1.77	-6.12	247.99	5150000000	7190000000
TCI	88.85	21.76	0.71	3.14	3.24	5.55	7.8	13.75	332.05	17860000000	19960000000
TCS	0.31	18.4	4.1	5.86	22.3	25.67	20.72	35.34	592.63	4.79E+12	4.41E+12

We give a pass score if a stock passes the test for a factor and a fail score if the test fails.

This test is done for various factors which are discussed below. Then the cumulative pass and fail score is used for further analysis.

4.4 Various fundamentals and factors considered for fundamental analysis

4.4.1 Return on Assets:

Return on assets is an indicator of how profitable a company relative to its total assets. ROA gives an idea at how efficient the management is at using its assets to generate earnings. It is calculated as:

The higher the value it is better. To give a quantitative result we give a pass score if ROA of the company increases in successive years. If it decreases it can be assumed that the new management is not as efficient as the previous one and that does not auger well for the future of the company hence, we give a fail score.

4.4.2 Operating Cash Flow:

Every company publishes a cash flow statement to support its income statement and balance sheet.

The statement of cash flows reveals how a company spends its money (outflows) and from where does it come (inflows). There are three distinct sections, each of which relates to a particular component – operations, investing and financing – of a company's business activities.

Cash flow from operations is the key source of a company's cash generation. It is the cash that the company produces internally as opposed to funds coming from outside investing and financing activities. A positive value signifies that the main business of the company is profitable. Also, an increasing value over the past few years shows that the company is doing well in its core business.

Hence, for both these case we give a pass score else if the conditions are not met we give a fail score. Also, the cash flow from operations should be greater than the Return on assets.

4.4.3 Long-term Debt:

A company takes on long-term debt in order to acquire immediate capital. For example, start-up ventures require substantial funds to get off the ground and pay for basic expenses, such as research expenses, Insurance, License and Permit Fees, Equipment and Supplies and Advertising and Promotion. All businesses need to generate income, and long-term debt is an effective way to get immediate funds to finance and operations.

A decreasing long-term debt signifies that the company is becoming self sustaining and is also able to repay its original debts. This is a good sign hence we assign a pass score if the condition holds true. However, if the long-term debt is increasing over the past few years then there may be two possibilities,

1. That the company is not performing well and cannot repay its debts, also it needs to borrow to keep up its operations. Such a company would not be an ideal investment hence, we give a fail score.

2. The company is performing well but is borrowing heavily to expand its operations further. This can be a good investment as in future the business is likely to take off. To identify such a case we check whether the rate of increase of profits is greater than the rate of increase in borrowings. If so, we give a pass score.

4.4.4 Current ratio:

The current ratio is a liquidity ratio that measures a company's ability to pay short-term and long-term obligations. To gauge this ability, the current ratio considers the current total assets of a company (both liquid and illiquid) relative to that company's current total liabilities.

The formula for calculating a company's current ratio, then, is:

A ratio under 1 indicates that a company's liabilities are greater than its assets and suggests that the company in question would be unable to pay off its obligations if they came due at that point and a fail score is given. If the ratio is higher than 1 then we compare it to the previous year. An increasing trend signifies that the financial health of the company is improving and it is a good sign so a pass score is given. Else, a fail score is given.

4.4.5 Asset Turnover ratio:

The asset turnover ratio is an efficiency ratio that measures a company's ability to generate sales from its assets by comparing net sales with average total assets. In other words, this ratio shows how efficiently a company can use its assets to generate sales.

The total asset turnover ratio calculates net sales as a percentage of assets to show how many sales are generated from each dollar of company assets.

It is quite similar to return on assets however, asset turnover ratio is more industry specific as different industries require different assets to generate the same sales.

So, we calculate the industry average asset turnover ratio and if a specific company beats the average, then a pass score is give otherwise a fail score is given

4.4.6 Revenue:

Revenue is the amount of money that a company actually receives during a specific period, including discounts and deductions for returned merchandise. It is the "top line" or "gross income" figure from which costs are subtracted to determine net income.

We keep a strict condition on revenue that it should be increasing for the past three years to get a pass score; else, a fail score is given.

4.4.7 Return on Equity:

ROE gives us a glimpse into how efficiently company management is producing a return for the owners of the company based on the amount of equity in the company.

An increasing trend gets a pass score while a decreasing one gets a fail score.

4.4.8 Earnings Growth (for 3-year period):

The earnings growth for a k year period is given as

Where, EPS is Earnings per share which itself is a measure of the profitability of buying a share. EPS is given by

Looking at the past 3 years data earnings growth helps to estimate the potential growth in earnings for the next 3 years. If this is greater than an arbitrarily set threshold (we take it as 5 %) then a pass score is given. However, no fail score is given irrespective of the earnings growth.

4.4.9 P/E ratio:

PE ratio is one of the most widely used tools for stock selection. It is calculated by dividing the current market price of the stock by its earnings per share (EPS). It shows the sum of money you are ready to pay for each rupee worth of the earnings of the company. Assume there are two companies ‘A’ and ‘B’, operating in the same sector. If P/E of ‘A’ is 30 and P/E of ‘B’ is 22, then ‘B’ is considered to be a better buy, as the market price has not gone up to reveal the earnings prospects of the company. But ‘A’ is considered to show higher growth prospects as compared to ‘B’.

Stocks with low PE can be considered good bargains as their growth potential is still unknown to the market. However, it may also happen that a low P/E company may not grow as expected in the future. If the PE is high, it warns of an over-priced stock. It means the stock’s price is much higher than its actual growth potential. So these stocks are more liable to crash drastically but it also means that in the recent past the company has grown better than others in its sector.

Interpretation of PE ratio is heavily dependent on comparison of the company with its peers. Also P/E that is considered very high in certain sectors can be considered very low in other sectors.

Thus, for scoring using P/E we first calculate the industry P/E which is the weighted average of all stocks in that industry. The weights are given using the market capitalization of the stock.

If P/E of company is less than industry average and then overall cumulative pass score is greater than the cumulative fail score then an additional pass score is given. If the P/E ratio is lower and the overall financial health indicated by the difference in cumulative pass and fail scores is negative then an additional fail score is given.

4.4.10 PEG Ratio:

The price/earnings to growth ratio (PEG ratio) is the stock’s price-to-earnings (P/E) ratio divided by the growth rate of its earnings for a specified time period. The PEG ratio is used to determine a stock’s value while taking the company’s earnings growth into account, and is considered to provide a more complete picture than the P/E ratio.

The lower the PEG ratio, the more the stock may be undervalued given its earnings performance. The degree to which a PEG ratio value indicates an over or underpriced stock varies by industry and by company type; though a broad rule of thumb is that a PEG ratio below one is desirable. We also give a pass score if PEG is less than 1 otherwise we give a fail score.

4.4.11 Debt to Equity ratio:

Debt/Equity Ratio is a debt ratio used to measure a company's financial leverage, calculated by dividing a company's total liabilities by its stockholders' equity. The D/E ratio indicates how much debt a company is using to finance its assets relative to the amount of value represented in shareholders' equity.

If the D/E ratio is less than the industry average then pass score is incremented else fail score is incremented.

4.4.12 Price to Sales ratio:

It is a valuation ratio that compares a company's stock price to its revenues. The price-to-sales ratio is an indicator of the value placed on each rupee of a company's sales or revenues. A low ratio may indicate possible undervaluation, while a ratio that is significantly above the average may suggest overvaluation. Consider two companies A and B with their stocks trading at the same price. Now if A has a higher price to sales ratio than B it means that the sales of B are higher that is, in spite of performing better in business, the stock price is lower and the stock is undervalued. This makes B a better investment. Price to sales, like other ratios, also should be compared only within the same industry. Hence, for scoring we give a pass score if P/S is lower than industry average else we give a fail score.

4.4.13 EBIDTA:

EBITDA stands for earnings before interest, taxes, depreciation and amortization. EBITDA is one indicator of a company's financial performance and is used as a proxy for the earning potential of a business, although doing so has its drawbacks. Further, EBITDA strips out the cost of debt capital and its tax effects by adding back interest and taxes to earnings.

$$EBITDA = Net\ Profit + Interest + Taxes + Depreciation + Amortization \quad (4.11)$$

EBITDA is essentially net income with interest, taxes, depreciation and amortization added back to it. It can be used to analyze and compare profitability between companies and industries because it eliminates the effects of financing and accounting decisions. It is often used in valuation ratios and compared to enterprise value and revenue.
Generally a lower value of EBIDTA as compared to industry peers is considered as a good signal however to put it quantitatively we consider a value less than 10 for giving a pass score otherwise we give a fail score.

4.4.14 Price to Book ratio:

Book value per share is one of the methods for comparison in valuing of a company. Enterprise value, or firm value, market value, market capitalization, and other methods may be used in different circumstances or compared to one another for contrast. For example, enterprise value would look at the market value of the company's equity plus its debt, whereas book value per share only looks at the equity on the balance sheet.

Thus, the book value indicates the value based on the company's valuation, if the stock price falls below that then it is disastrous as it indicates the company is tending towards bankruptcy. Hence, when price to book value falls below 1, we give a fail score.
Once, a company is evaluated based on all the above factors we get a cumulative pass and fail score. Then each company is ranked on the pass score / fail score ratio.

4.5 Results

Here is a list of pass and fail scores by considering the annual financial statements of the previous 4 financial years from FY13 to FY16 and also the quarterly statements of all quarters of FY1

Table 4.5: Some companies with a very good pass/fail score ratio

TICKER	Pass Score	Fail Score	Ratio
GESHIP	17	1	17
ALLCARGO	16	1	16
LYCOS	16	1	16
PAGEIND	16	1	16
SFL	16	1	16
TANLA	15	1	15
SANDESH	15	2	7.5
EMMBI	15	2	7.5
ASIANPAINT	14	2	7
RBL	14	2	7

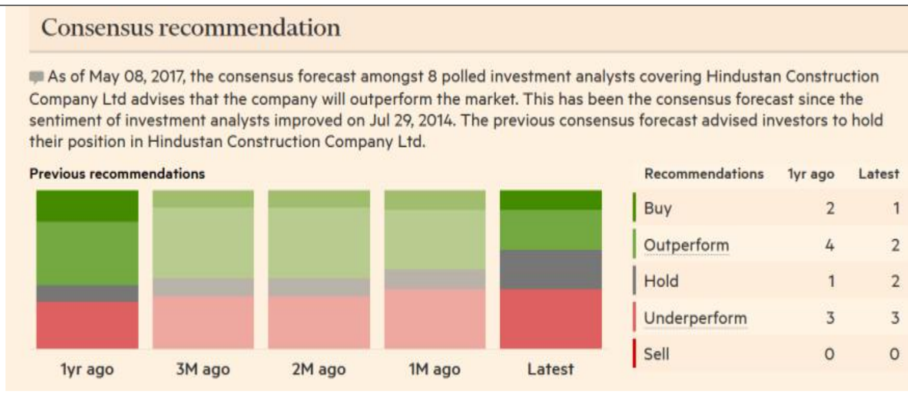
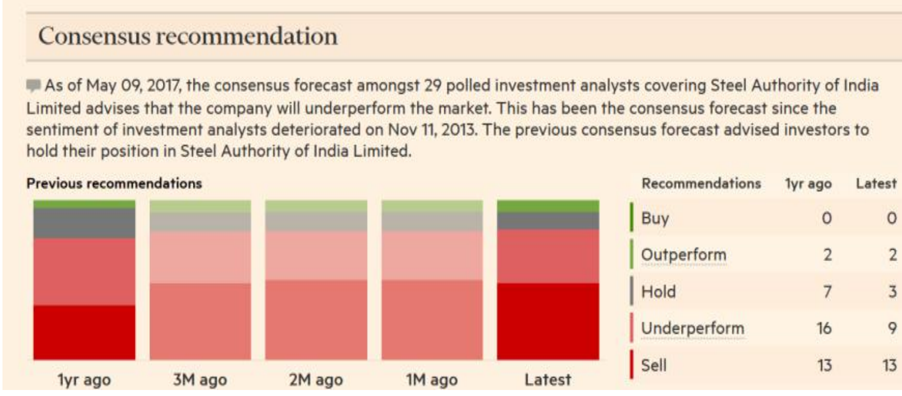
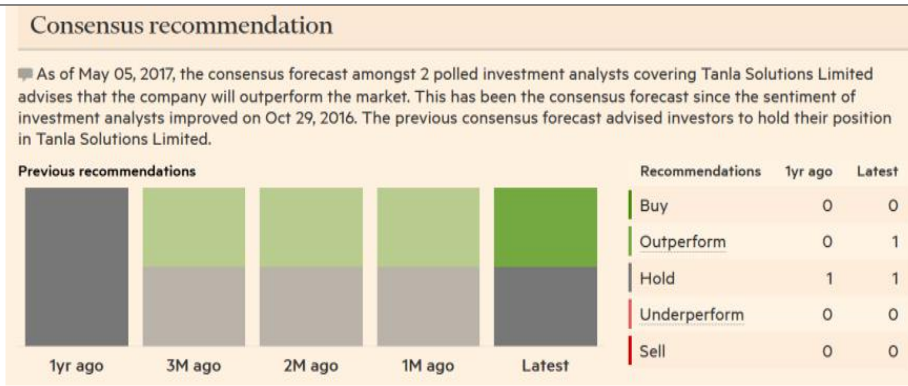
Table 4.6: Some companies with a very poor pass/fail score ratio

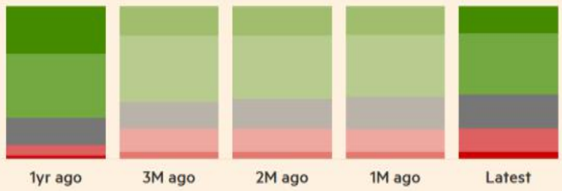
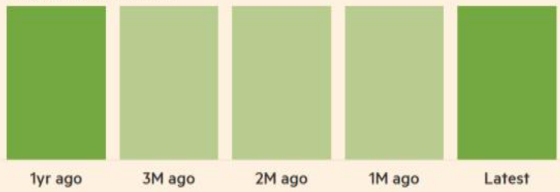
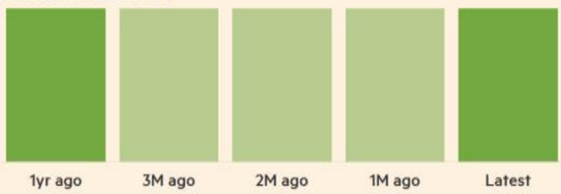
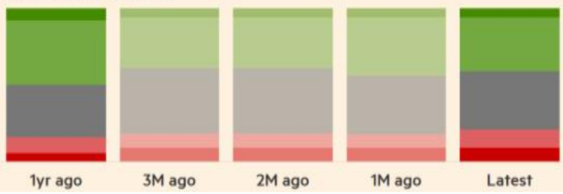
TICKER	Pass Score	Fail Score	Ratio
SAIL	3	10	0.3
HCC	3	11	0.272727

ULTRACEMCO	2	10	0.2
PBAINFRA	2	12	0.166667
SANGHVIFOR	2	12	0.166667
TI	2	13	0.153846
JITFINFRA	1	9	0.111111
IL&FSENGG	1	10	0.1
PIRPHYTO	1	10	0.1
MAXINDIA	1	11	0.090909

Now, to verify whether the results given by fundamental analysis are true or not we compare the recommendations of our algorithm with the recommendations provided by Financial Times [30] for the corresponding stock.

Table 4.7: Comparison between fundamental analysis and Financial Times

<table>
<tr><th>Stock Name</th><th>Recommendation by Financial Times</th><th>Fundamental Analysis Score (Pass , Fail)</th></tr>
<tr><td>Emmbi Industries</td><td>
</td><td>(15, 2)</td></tr>
<tr><td>Hindustan Constructio n Company</td><td>
</td><td>(3,11)</td></tr>
<tr><td>Steel Authority of India</td><td>
</td><td>(3,10)</td></tr>
<tr><td>Tanla Solutions</td><td>
</td><td>(15,1)</td></tr>
</table>

Stock Name	**Recommendation by Financial Times**	**Fundamental Analysis Score (Pass , Fail)**
UltraTech Cement	Consensus recommendation As of May 05, 2017, the consensus forecast amongst 45 polled investment analysts covering UltraTech Cement Ltd advises that the company will outperform the market. This has been the consensus forecast since the sentiment of investment analysts improved on Jul 22, 2014. The previous consensus forecast advised investors to hold their position in UltraTech Cement Ltd. Previous recommendations  Recommendations / 1yr ago / Latest Buy 14 8 Outperform 19 18 Hold 8 10 Underperform 3 7 Sell 1 2	(2,10)
Sandesh Ltd/	Consensus recommendation As of May 05, 2017, the consensus forecast amongst 2 polled investment analysts covering Sandesh Ltd advises that the company will outperform the market. This has been the consensus forecast since the sentiment of investment analysts deteriorated on Apr 06, 2016. The previous consensus forecast advised investors to purchase equity in Sandesh Ltd. Previous recommendations  Recommendations / 1yr ago / Latest Buy 0 0 Outperform 1 2 Hold 0 0 Underperform 0 0 Sell 0 0	(15,2)
Rane Brake Ltd.	Consensus recommendation As of May 05, 2017, the investment analyst covering Rane Brake Linings Ltd advises that the company will outperform the market. This has been the consensus forecast since the sentiment of investment analysts deteriorated on Apr 06, 2016. The previous consensus forecast advised investors to purchase equity in Rane Brake Linings Ltd. Previous recommendations  Recommendations / 1yr ago / Latest Buy 0 0 Outperform 2 1 Hold 0 0 Underperform 0 0 Sell 0 0	(14,2)
Asian Paints	Consensus recommendation As of May 05, 2017, the consensus forecast amongst 35 polled investment analysts covering Asian Paints Ltd advises investors to hold their position in the company. This has been the consensus forecast since the sentiment of investment analysts deteriorated on Apr 06, 2016. The previous consensus forecast advised that Asian Paints Ltd would outperform the market. Previous recommendations  Recommendations / 1yr ago / Latest Buy 3 2 Outperform 16 12 Hold 13 13 Underperform 4 4 Sell 2 3	(14,2)

Analyzing table 4.7, it can be seen that most of times fundamental analysis algorithm and the Financial Times recommendation match each other except for anomaly in some cases like Asian Paints where the Financial Times outlook has grown bleak over the past year while fundamental analysis shows a strong growth. This can explained as happening due to the inherent drawbacks of fundamental analysis as explained above.

Chapter 5

Portfolio Optimization

5.1 Introduction

Once we know the stocks we need to invest into and have an initial budget, the next task would be distributing the total amount into various stocks. A naïve thought would be equally divide the entire amount. Or maybe find the stocks with maximum returns and put all money into it or the other extreme which is find the stock with the lowest risk and put all money into it.

However, research shows that none of these give the best results. Portfolio optimization is the process of choosing the proportions of various assets to be held in a portfolio, in such a way as to make the portfolio better than any other according to some criterion. The criterion will combine, directly or indirectly, considerations of the expected value of the portfolio's rate of return as well as of the return's dispersion and possibly other measures of financial risk.

The efficient frontier is a concept in modern portfolio theory introduced by Harry Markowitz in 1952. It refers to investment portfolios which occupy the 'efficient' parts of the risk-return spectrum. Formally, it is the set of portfolios which satisfy the condition that no other portfolio exists with a higher expected return but with the same standard deviation of return. Thus, we need to obtain a portfolio which lies on the efficient frontier.

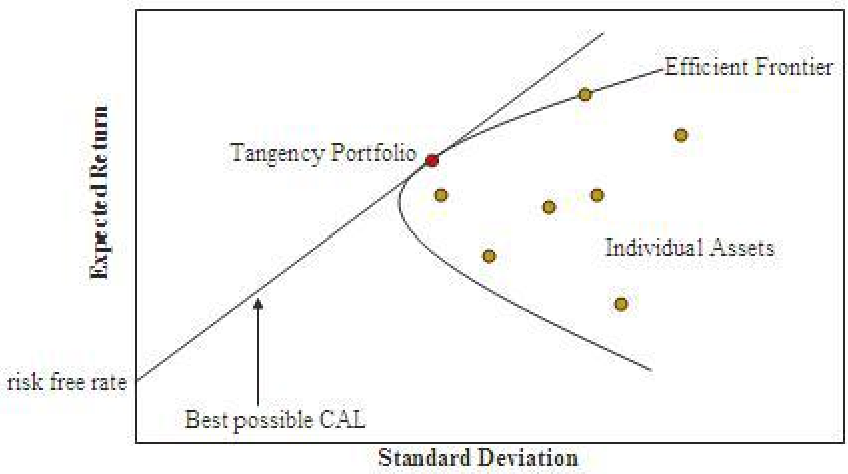


Figure 5.1: Efficient frontier

We made a comparative study of various portfolio optimization techniques and also propose to automate an existing model based on previously shown fundamental analysis

5.2 Mean variance optimization (Markowitz technique):

A mean-variance analysis is the process of weighing risk (variance) against expected return. By looking at the expected return and variance of an asset, investors attempt to make more efficient investment choices – seeking the lowest variance for a given expected return or seeking the highest expected return for a given variance level.

Different levels of diversification can be achieved in a portfolio by combining stocks with different variances and expected returns.

Let there be N stocks $x_1, x_2, x_3 \ldots, x_N$ and the weight of each stock is $w_1, w_2, w_3 \ldots, w_N$ such that stock x_i is allocated part of the total budget.
Also, the historical returns of all the stocks are known and are represented as $\mu_1, \mu_2, \mu_3 \ldots \mu_N$.
The risk associated with each of these stocks is characterised by the standard deviation and is given by $\sigma_1, \sigma_2, \sigma_3 \ldots, \sigma_N$.
The total mean and standard deviation of the portfolio considering allocation using weights is

In terms of covariance matrix the risk can be written as

Where, = $[w_1, w_2, w_3 \ldots w_N]$ and C_{NxN} is the Covariance matrix of the stocks returns.

To calculate C we first calculate the daily returns of all stocks. Considering we have previous k days data then

Where is the stock price of x_1 on i^{th} day.

Now, the overall cost of the optimisation is $cost = \sigma_{port} / \mu_{port}$ which needs to be minimised.

Thus, the problem is reduced to under the constraints that $w_1, w_2, w_N > 0$ and $w_1 + w_2 + w_3 \ldots + w_N = total\ budget$.

We solve this optimization using python's scipy optimization library. The SLSQP optimiser is used which is a sequential least squares programming algorithm.

This algorithm tends to converge with very high values for a few w_i while others are almost close to zero i.e. suggests to invest majority of the money in a very few stocks. Also, it assumes that all investors will want to have a similar portfolio and has no scope for including desired risk or return and investor views.
All returns used for mean variance optimization are annualised using the formula

The results are calculated considering 9 companies from different sectors, each having distinctly different risks and returns. It is seen that the overall portfolio has a risk significantly lesser than each individual stock. However, the returns are not high enough which can be explained by the fund allocation.

The algorithm almost ignores the extremely high returns stock due to their excessively high risk. The problem of convergence with very high values for a few w_i while others almost close to zero is evident.

Results:

Table 5.1: Results mean variance optimization

Stock Name	**Return %**	**Risk %**	**% Allocation**

ONGC	-4.57	1.73	15.4
ICICI	0.65	3.53	0
Colgate	19.55	1.08	73.7
BHEL	75.53	7.07	0
Tata Motors	13.20	5.53	0
Bajaj Finserv	89.45	7.28	0.6
Sun Pharma	29.48	2.88	10.2
JSW	1.61	5.43	0
Airtel	8.9	5.17	0
Total Portfolio	**17.29**	**0.90**	**1**

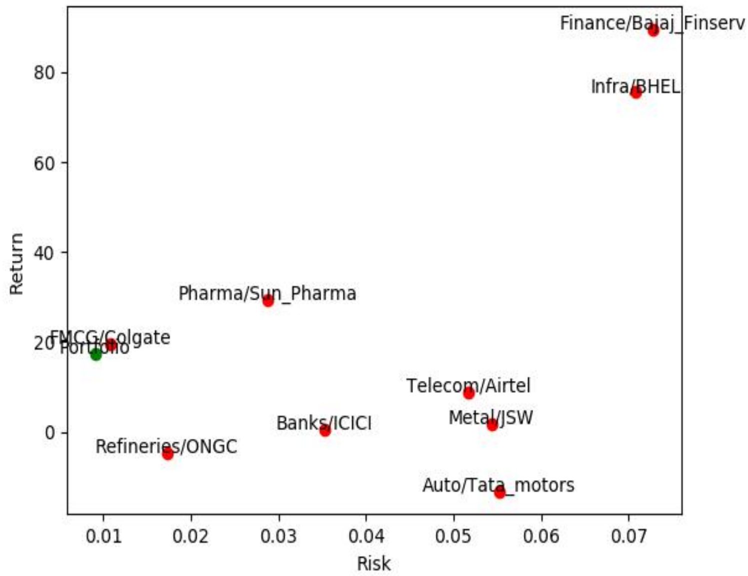


Figure 5.2: Risk vs. returns graph for = 0.1

5.3 Portfolio optimization via least squares on past returns:

In this method the objective is similar to the previous one, that is, to maximize returns and minimise the risk of the portfolio. However, the approach to obtain the optimization function varies.

We consider a returns matrix

Such that row gives returns of all assets at time *t* and j^{th} column gives the returns time series of the j^{th} asset.

Assume = $[w_1\ w_2, \ldots, w_N]$ be the weights matrix for budget allocation as in the mean variance optimization problem. Hence, the profit time series will be and total profit will be .

Now, is the returns to be maximized and) is thr risk to be minimized.

We have and additional factor that denotes the desired returns which gives flexibility to the user to change the optimization function. Also, B is the total budget.

Thus, the optimization is

Also another requirement is that , however, this is not strictly enforced as the optimization fails to converge in such a case.

The major advantage of this approach is that the 2 main drawbacks of mean variance optimization are addressed to some extent. However this still does not accommodate individual investor views.

Results:

Case 1: = 0.2

Table 5.2: Percentage allocation of total Budget for = 0.2

Stock Name	Return %	Risk %	% Allocation
TCS	35.4	4.36	0
ICICI	0.79	3.53	0
LIC	14.59	2.88	14.3

ABB	26.87	4.17	0
BPCL	-2.52	2.15	45.5
Sun Pharma	31.55	2.88	0
Infosys	33.7	3.59	40.1
Airtel	10.14	5.17	0
Total Portfolio	**17.29**	**0.90**	**1**

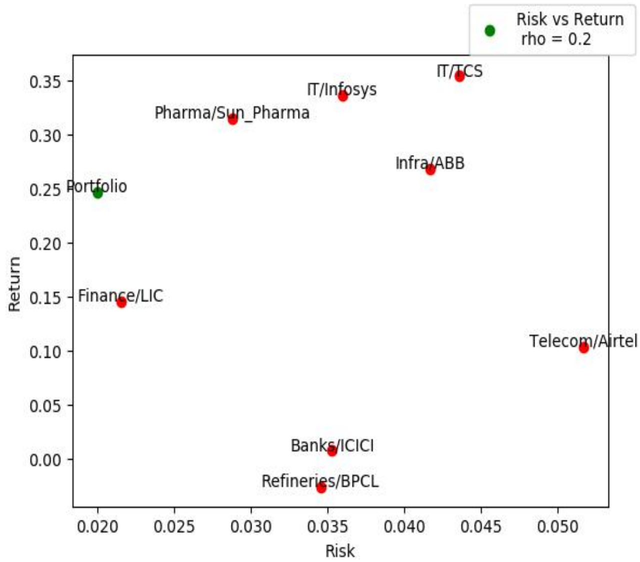


Figure 5.3: Risk vs. Returns for = 0.2

Case 2: = 0.3

Table 5.3: Percentage allocation of total Budget for = 0.3

Stock Name	**Return%**	**Risk %**	**% Allocation**
TCS	35.4	4.36	0
ICICI	0.79	3.53	0
LIC	14.59	2.88	33.5
ABB	26.87	4.17	0
BPCL	-2.52	2.15	28.7
Sun Pharma	31.55	2.88	0
Infosys	33.7	3.59	37.7
Airtel	10.14	5.17	0
Total Portfolio	**17.29**	**0.90**	**1**

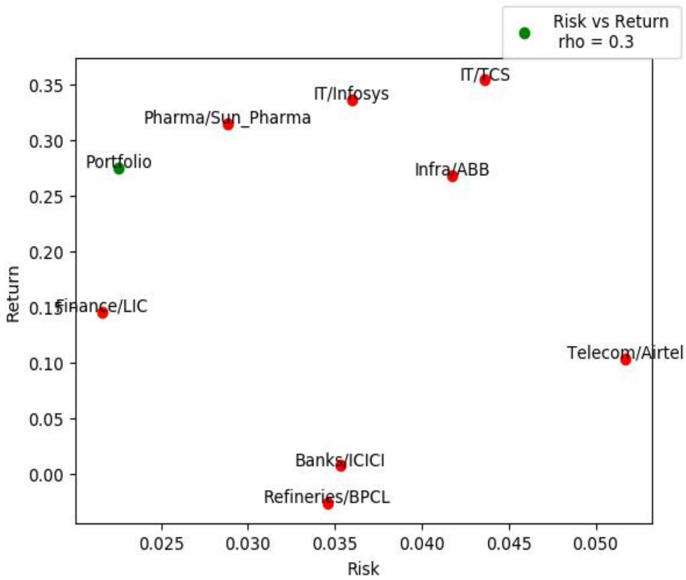


Figure 5.4: Risk vs. Returns graph for = 0.3

Case 3: = 0.4

Table 5.4: Percentage allocation of total Budget for = 0.4

Stock Name	Return %	Risk %	% Allocation
TCS	35.4	4.36	0
ICICI	0.79	3.53	0
LIC	14.59	2.88	10.8
ABB	26.87	4.17	0
BPCL	-2.52	2.15	0
Sun Pharma	31.55	2.88	55.7
Infosys	33.7	3.59	33.6
Airtel	10.14	5.17	0
Total Portfolio	**17.29**	**0.90**	**1**

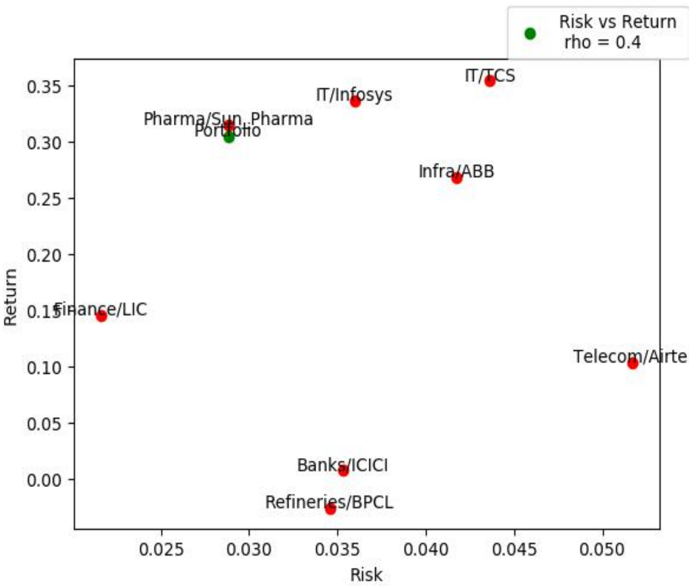


Figure 5.5: Risk vs. Returns graph for = 0.4

Case 4: = 0.5

Table 5.5: Percentage allocation of total Budget for = 0.5

Stock Name	Return %	Risk %	% Allocation
TCS	35.4	4.36	0
ICICI	0.79	3.53	0
LIC	14.59	2.88	0
ABB	26.87	4.17	0
BPCL	-2.52	2.15	0
Sun Pharma	31.55	2.88	67.2
Infosys	33.7	3.59	32.8
Airtel	10.14	5.17	0
Total Portfolio	**17.29**	**0.90**	**1**

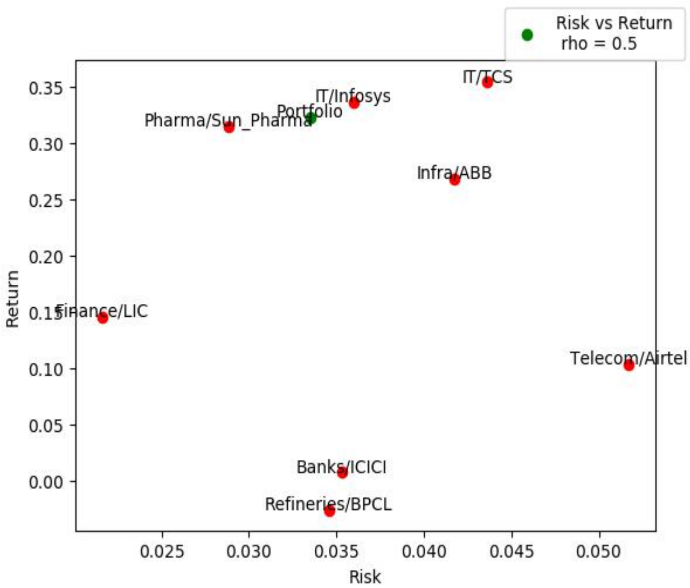


Figure 5.6: Risk vs. Returns graph for = 0.5

Plotting the portfolios with different desired returns show that all portfolios form a parabola which is the efficient frontier. Hence, we get the best possible portfolios for different risk return pairs

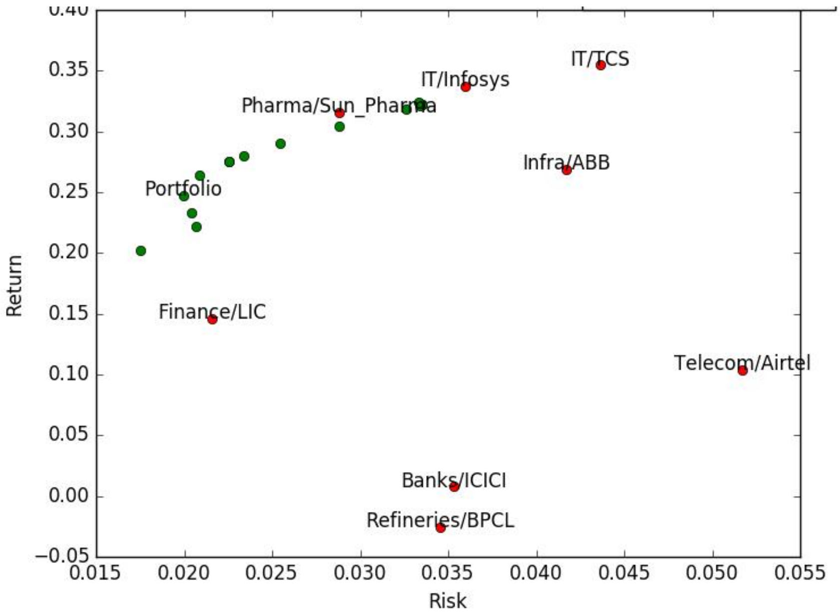


Figure 5.7: Portfolios lie on efficient frontier

5.4 Black-Litterman Portfolio optimization:

The Black-Litterman model [23] expresses the investors' views and market equilibrium in terms of probability distributions. It uses the Bayesian approach to develop a probability distribution for the expected return by using CAPM equilibrium distribution as a starting point and then combining investors' views into the distribution. Using the implied returns from CAPM as the prior and then adding the investors' views, a posterior distribution can be obtained.

First implied return is calculated using the following formula

Where,

δ = Risk aversion coefficient. It is generally an arbitrary assumption

Σ = A covariance matrix of the assets (NxN matrix)

ω = Weights of assets according to their market capitalization

After deriving the assets' implied returns, we can compute the expected return, E(R) which is an Nx1 vector, of the assets under the Black-Litterman model with the following equation.

$$E(R) = [(\tau \Sigma)^{-1} + P^T \Omega P]^{-1} [(\tau \Sigma)^{-1} \Pi + P^T \Omega Q] \tag{5.9}$$

τ = A scalar number indicating the uncertainty of the CAPM distribution (It is usually within the range of 0.025-0.05)

P = A matrix with investors views; each row a specific view of the market and each entry of the row represents the weights of each assets (*KxN* matrix)

Q = the expected returns of the portfolios from the views described in matrix P (*Kx1* vector)

Ω = A diagonal covariance matrix with entries of the uncertainty within each view (*KxK* matrix)

To automate portfolio optimization using Black Litterman model we propose to generate the investor view matrix using the fundamental analysis results discussed in the previous section.

Say we have two companies A and B with a fundamental pass/fail score tuple (P_A, F_A) and (P_B, F_B) respectively.

Let > so, we can conclude that A will perform better than B by a factor proportional to $P_A + F_B - P_B - F_A$.

If there are a total of 3 companies A. B and C to invest in then the investors' views matrix will contain an entry as shown

(5.10)

In another case if C is the top performing company we can say that is will perform better than everyone else by a factor proportional to $P_C - F_C - P_{\text{average of others}} + F_{\text{average of others}}$.

The entry in investor views matrix corresponding to this will be

$$P = [0 \;\; 0 \;\; 1], \qquad Q = [P_C - F_C - P_{\text{average of others}} + F_{\text{average of others}}]$$

Ω is the covariance matrix between the two views where the investors specify their confidence level on their views which for now we assume to be 1. We derive the following matrices

Once we compute E(R), then we can compute the posterior variance matrix, M, which will be used to compute the new covariance matrix. The new covariance matrix Σp takes into account of the additional variance resulting from the investor views.

$$M = [(\tau\Sigma)^{-1} + P^T \Omega^{-1} P]^{-1} \tag{5.11}$$

$$\Sigma p = \Sigma + M \tag{5.12}$$

With the new covariance matrix, we can calculate the new portfolio weights using thus getting an optimized value of ω.

Chapter 6
Technical Analysis

6.1 Introduction

Technical analysis [6][17] is a method of evaluating securities that involves a statistical analysis of market activity, such as price and volume. Technical analysis involves using charts or statistical indicators and oscillators to identify patterns that can be used as a basis for investment decisions. Technical analysis does not concern with a stock's valuation – the only thing that matters are past trading data and what information the data might provide about future price movements.

Technical analysis is based on three assumptions:

- **The market discounts everything**

  The Efficient Market Hypothesis states that a stock's price already reflects everything – that has or could affect a company – including fundamental factors. Everything from a company's fundamentals to broad market factors to market psychology are already priced into the stock. Hence, analysis of price movements is performed, which are the product of supply and demand for a particular stock in the market.

- **Price moves in trends**

  A stock price is more likely to continue a past trend than move erratically. Most technical trading strategies are based on this assumption.

- **History tends to repeat itself**

  The repetitive nature of the stock price is often used to understand trends and patterns in price movements.

Keeping these assumptions in mind, trend identification thus becomes the most important concept in technical analysis. A trend is basically the general direction in which a security or market is headed. Prices tend to move in a series of highs and lows over time which makes spotting trends a little difficult. The overall direction of these highs and lows constitute a trend.

There are three types of trends:

1. Uptrend

   An uptrend is classified as a series of higher highs and higher lows
2. Downtrend

   A downtrend consists of lower lows and lower highs
3. Sideways / Horizontal Trends

   Sideways or horizontal trends occur when there is little movement up or down in the peaks and troughs of a trend.

Trends can be identified using indicators such as Average Directional Index (ADX) or trend direction of prices. After identification of price movement to be a trending or sideways market; other indicators or oscillators can be used for trading.

In case of trending markets (uptrend or downtrend) the following indicators are used to identify appropriate buying and selling points:

1. Relative Strength Index (RSI)
2. Bollinger Bands
3. Moving Average Convergence Divergence (MACD)
4. Momentum / Rate of Change (ROC)
5. Accumulation Distribution Line (ADL)
6. Commodity Channel Index (CCI)
7. Average True Range (ATR)

In case of sideways market the following indicators are used to identify appropriate buying and selling points:

1. Support
2. Resistance

6.2 Technical indicators for trending markets

6.2.1 Average Directional Index (ADX)

The Average Directional Index (ADX), Minus Directional Indicator (-DI) and Plus Directional Indicator (+DI) represent a group of directional movement indicators that form a trading system. The Average Directional Index (ADX) measures trend strength without regard to trend direction. The other two indicators, Plus Directional Indicator (+DI) and

Minus Directional Indicator (-DI), complement ADX by defining trend direction. Used together, aids in determining both the direction and strength of the trend.

The calculation steps for the Average Directional Index (ADX) are detailed in each step:
Calculate the True Range (TR), Plus Directional Movement (+DM) and Minus Directional Movement (-DM) for each period.
Directional movement is positive when the current high minus the prior high is greater than the prior low minus the current low. The Plus Directional Movement (+DM) equals the current high minus the prior high or, provided it is positive. A negative value would simply be entered as zero.
Directional movement is negative when the prior low minus the current low is greater than the current high minus the prior high. The Minus Directional Movement (-DM) equals the prior low minus the current low, provided it is positive. A negative value would simply be entered as zero.

Smooth these periodic values over a 14-day window using the Wilder's smoothing techniques.

Divide the 14-day smoothed Plus Directional Movement (+DM) by the 14-day smoothed True Range to find the 14-day Plus Directional Indicator (+DI14). Also, divide the 14-day smoothed Minus Directional Movement (-DM) by the 14-day smoothed True Range to find the 14-day Minus Directional Indicator (-DI14). Multiply by 100 to move the decimal point two places. This +DI14 is the Plus Directional Indicator (green line) that is plotted along with ADX.

The Directional Movement Index (DX) equals the absolute value of +DI14 less - DI14 divided by the sum of +DI14 and - DI14. Multiply the result by 100 to move the decimal point over two places.

After all these steps, calculate the Average Directional Index (ADX). The first ADX value is simply a 14-day average of DX. Subsequent ADX values are smoothed by multiplying the previous 14-day ADX value by 13, adding the most recent DX value and dividing this total by 14.

Interpretation:

A strong trend (trending market) is present when ADX is above 25 and no trend (sideways market) is present when ADX is below 20. There appears to be a grey zone between 20 and 25. Plus Directional Index (+DI) signifies an uptrend whereas Minus Directional Index (–DI) signifies a downtrend.

Results:

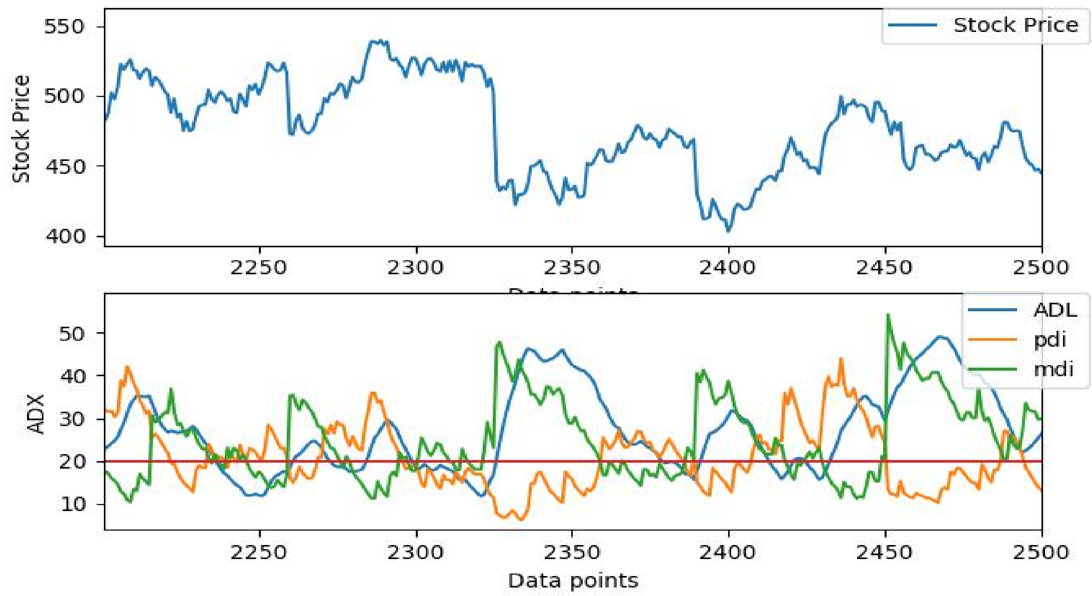


Figure 6.1: ADX results

6.2.2 Trend Direction

Trend direction of prices can yield information regarding the market condition i.e. whether it is moving in an uptrend/downtrend or sideways. Trading strategies depend on the direction of the trend of prices and hence it is important to consider this factor. Trend direction is equivalent to plotting a line over the smoothed data and obtaining its slope. The sign and magnitude of slope gives an idea about the direction and magnitude of the trend.

Calculations for obtaining trend direction have been given as follows:

First smooth the prices of the stock by obtaining a smoothed moving average over a period of w days

Calculate the slope(m) of the data by taking differences at every interval and find the average of all the slope values to finally yield the net slope (M) of the data

Interpretation:

If the slope of the trend direction is positive and has a high magnitude, it signifies strong trend. Similarly a negative slope with high magnitude denotes a downtrend.
For slope values in either direction with less magnitude are considered to be a sideways market.

6.2.3 Relative Strength Index (RSI)

The Relative Strength Index (RSI) is a momentum oscillator that measures the speed and change of price movements. RSI oscillates between zero and 100. Signals can also be generated by looking for divergences, failure swings and centreline crossovers. RSI can also be used to identify the general trend.

The calculation of Relative Strength Index is detailed in the following steps:
Calculate the daily change in stock price and classify it as gain (g) or loss (l). If the change in price is positive then it is a gain or else a loss. But, losses are also expressed as positive values

Obtain the average gain (G) and average loss (L) over a 14-day window using Wilder's smoothing techniques

Divide the 14-day smoothed average gain (G) by the 14-day smoothed average loss (L) to find the Relative Strength of the prices (RS)

After these steps, calculate the Relative Strength Index (RSI). Start by adding 1 to the Relative Strength (RS) and taking it's reciprocal after which it is multiplied by 100. This term is then subtracted from 100 to obtain the value of the Relative Strength Index (RSI)

Interpretation:

RSI is considered overbought when above 70 and oversold when below 30. An overbought condition signals a good selling point/bearish divergence whereas an oversold condition signals good buying points/bullish divergence.

Results:

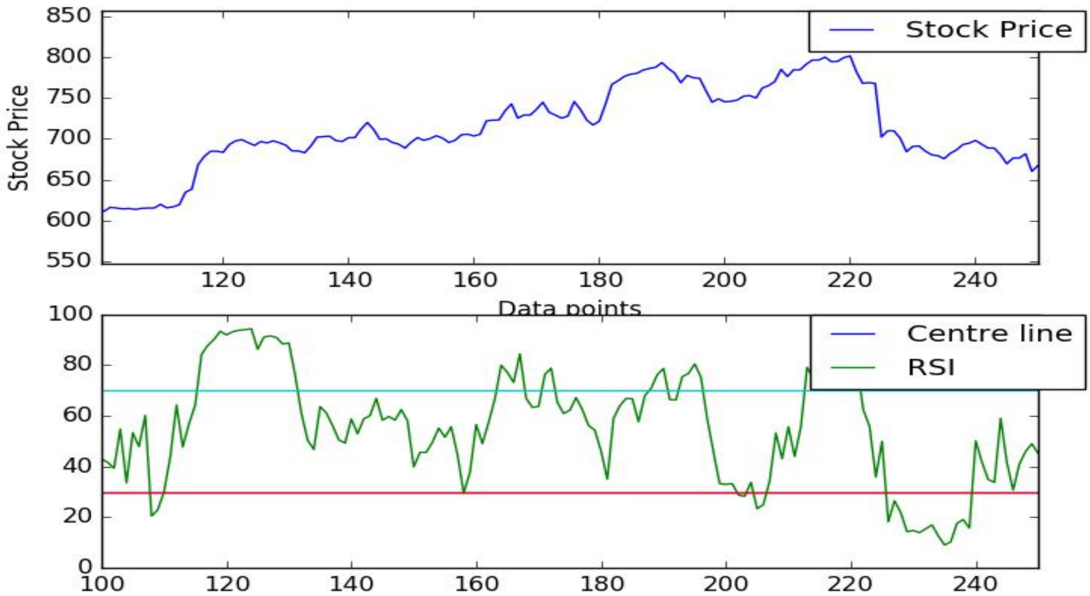


Figure 6.2: RSI results

6.2.4 Bollinger Bands

Bollinger Bands are volatility bands placed above and below the moving average of a stock price. Volatility is based on the standard deviation, which changes as volatility increases and decreases. The bands automatically widen when volatility increases and narrow when volatility decreases. Bollinger Bands can be used to signal buying or selling points or to determine the strength of the trend.

The middle band is a simple moving average that is usually set at 20 periods. A simple moving average is used because the standard deviation formula also uses a simple moving average. The look-back period for the standard deviation is the same as for the simple moving average. The outer bands are usually set 2 standard deviations above and below the middle band.

Calculations for finding the Bollinger bands are described in the following steps:
Obtain the rolling mean (RM) of stock prices over a period of 14 days

Calculate the rolling standard (RStd) deviation of stock prices over the same period of 14 days

The upper band (UB) is acquired by adding 2 times standard deviation of stock prices with the rolling mean and the lower band (LB) is acquired by subtracting 2 times standard deviation of stock prices

Interpretation:

At indices where the price of the stocks rises above the upper band, it is bound to come down. Thus, at these indices potential sell signals arise. Similarly, at points where the price of the stock falls below the lower band, it is bound to rise up again. Thus, at these indices potential buy signals arise.

Results:

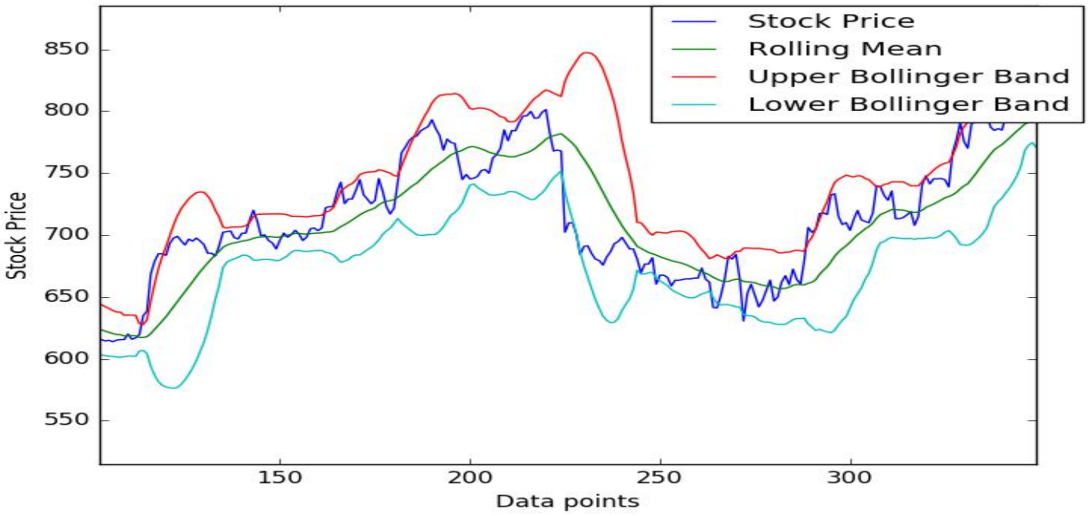


Figure 6.3: Bollinger bands result

6.2.5 Moving Average Convergence/Divergence (MACD)

The Moving Average Convergence/Divergence oscillator (MACD) is one of the simplest and most effective momentum indicators available. The MACD turns two trend-following indicators, moving averages, into a momentum oscillator by subtracting the longer moving average from the shorter moving average. As a result, the MACD offers the best of both: trend following and momentum. The MACD fluctuates above and below the zero line as the moving averages converge, cross and diverge. Signal line crossovers, centreline crossovers and divergences are to be looked for to generate buy or sell signals. Because the MACD is unbounded, it is not particularly useful for identifying overbought and oversold levels.

Convergence occurs when the moving averages move towards each other. Divergence occurs when the moving averages move away from each other. The shorter moving average (12-day) is faster and responsible for most MACD movements. The longer moving average (26-day) is slower and less reactive to price changes in the underlying security.

The MACD Line oscillates above and below the zero line, which is also known as the centreline. The direction depends on the direction of the moving average cross. Positive MACD indicates that the 12-day EMA is above the 26-day EMA. Positive values increase as the shorter EMA diverges further from the longer EMA. This means upside momentum is increasing. Negative MACD values indicate that the 12-day EMA is below the 26-day EMA. Negative values increase as the shorter EMA diverges further below the longer EMA. This means downside momentum is increasing.

Calculations for MACD are described in the following steps:
First calculate Exponential Moving Average (EMA) over the stock price. First value of the Exponential Moving Average is same as the simple average of stock prices. Subsequent values are obtained by multiplying the new prices by a factor (m) and then adding to the previous average. Thus new points are given more weight as compared to previous points.

Obtain 2 moving averages with different window sizes of 12-days and 26-days respectively.
Calculate Moving Average Convergence/Divergence (MACD) curve by subtracting the 26-day EMA from the 12-day EMA.

Also acquire a 9-day EMA over the MACD curve which is known as the signal line
Calculate the difference between the MACD line and the signal line which is also known as the MACD Histogram.

Interpretation:

Signal line crossovers are the most common MACD signals. The signal line is a 9-day EMA of the MACD Line. As a moving average of the indicator, it trails the MACD and makes it easier to spot MACD turns. A bullish crossover occurs when the MACD turns up and crosses above the signal line. A bearish crossover occurs when the MACD turns down and crosses below the signal line.

Results:

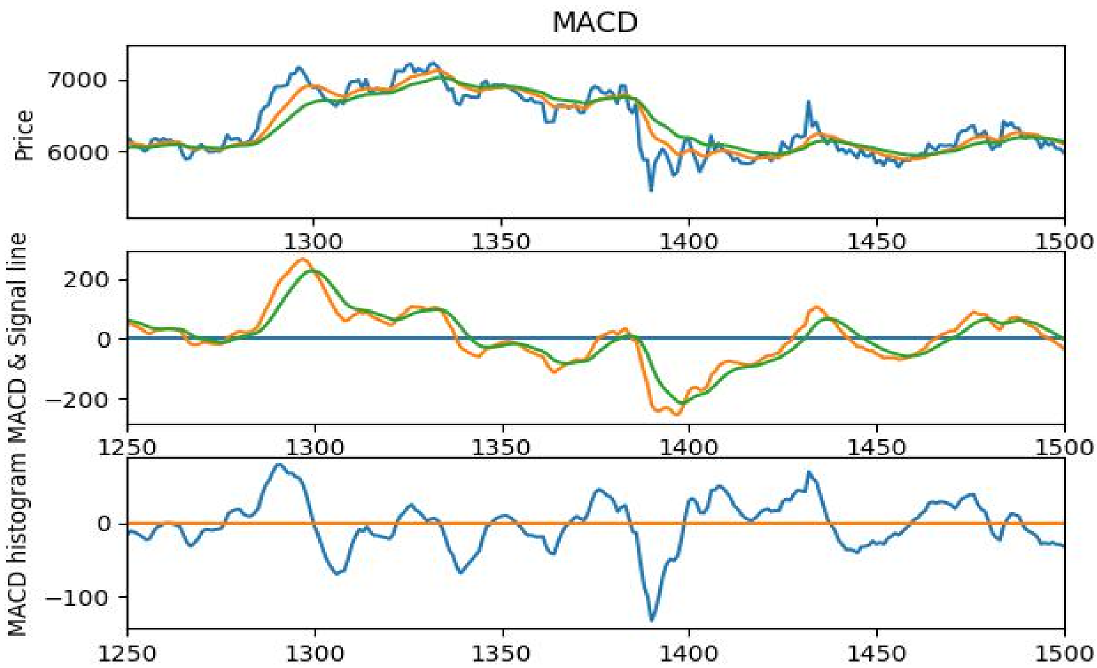


Figure 6.4: MACD results

6.2.6 Momentum/Rate of Change (ROC)

Momentum measures the rate-of-change of a security's price. As the price of a security rises, price momentum increases. The faster the security rises (the greater the period-over-period price change), the larger the increase in momentum. Once this rise begins to slow, momentum will also slow. As a security begins to trade flat, momentum starts to actually decline from previous high levels. However, declining momentum in the face of sideways trading is not always a bearish signal. It simply means that momentum is returning to a more median level.

Calculation of Momentum is done as follows:

Obtain the rate of change of the price value at a particular index with respect to an index lesser by the given window size

Interpretation:

Higher value of momentum indicates that the stock price is rising whereas lower values show a fall in stock price.

Results:

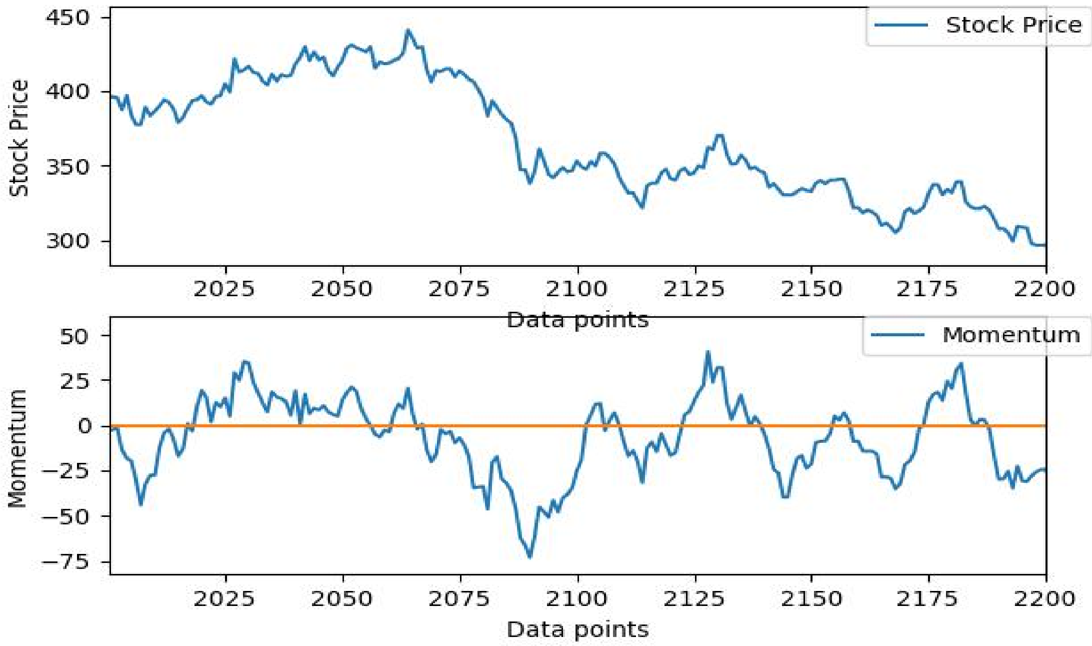


Figure 6.5: Momentum/ROC results

6.2.7 Accumulation Distribution Line (ADL)

The Accumulation Distribution Line is a volume-based indicator designed to measure the cumulative flow of money into and out of a security. As with cumulative indicators, the Accumulation Distribution Line is a running total of each period's Money Flow Volume. First, a multiplier is calculated based on the relationship of the close to the high-low range. Second, the Money Flow Multiplier is multiplied by the period's volume to come up with a Money

Flow Volume. A running total of the Money Flow Volume forms the Accumulation Distribution Line. This indicator can be used to affirm a security's underlying trend or anticipate reversals when the indicator diverges from the security price.

Calculations involved in obtaining Accumulation Distribution line is as follows:

Initially calculate the Money Flow Multiplier (mf) which is given by the ratio of differences between Close and low and High and Close to the difference between High and low at the particular index

Next step is to calculate the Money Flow Volume (mv) which is given as the money flow multiplier multiplied with the Volume traded for the stock at the index

Initialize previous ADL as zero. ADL at every index is given by the summation of the previous ADL with the Current Period's Money Flow Volume

Interpretation:

If a security is in a strong downtrend or uptrend, the accumulation/distribution likely follows the direction of the price movements, and therefore, confirms the downtrend or uptrend. If the accumulation/distribution line and a security's price are diverging, it may be a bullish or bearish signal.

If a security's price is in a downtrend while the accumulation/distribution line is in an uptrend, the indicator shows there may be buying pressure and the security's price may reverse. Consequently, the security may reverse and trend up. Conversely, if a security's price is in an uptrend while the accumulation/distribution line is in a downtrend, the indicator shows there may be selling pressure, or high distribution. This may cause the security's price to reverse and turn into a downtrend.

Results:

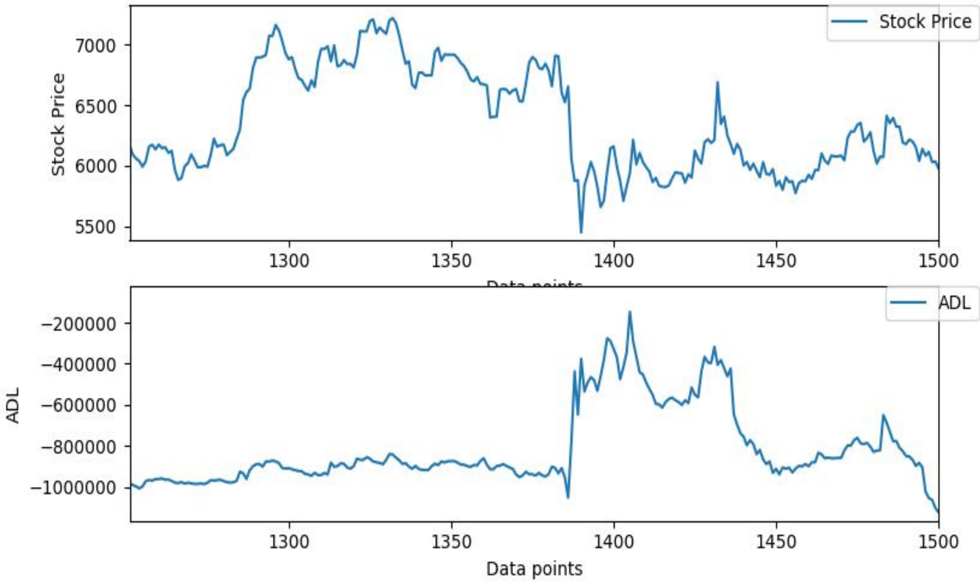


Figure 6.6: ADL results

6.2.8 Commodity Channel Index (CCI)

The Commodity Channel Index (CCI) is a versatile indicator that can be used to identify a new trend or warn of extreme conditions. In general, CCI measures the current price level relative to an average price level over a given period of time. CCI is relatively high when prices are far above their average. CCI is relatively low when prices are far below their average. In this manner, CCI can be used to identify overbought and oversold levels.

Calculations for the Commodity Channel Index (CCI) have been described as follows:
Start off by calculating the typical price (TP) of a security which is given by the average of the High, Low and Close

Obtain a 14-day simple moving average over the typical price

Finally, Commodity Channel Index (CCI) is given by the current typical price less by the moving average of typical price previously calculated divided by a constant times mean deviation (MD) of typical price, where the constant = 0.015

Interpretation:

CCI measures the difference between a security's price change and its average price change. High positive readings indicate that prices are well above their average, which is a show of strength. Low negative readings indicate that prices are well below their average, which is a show of weakness.

The Commodity Channel Index (CCI) can be used as either a coincident or leading indicator. As a coincident indicator, surges above +100 reflect strong price action that can signal the start of an uptrend. Plunges below -100 reflect weak price action that can signal the start of a downtrend.

Results:

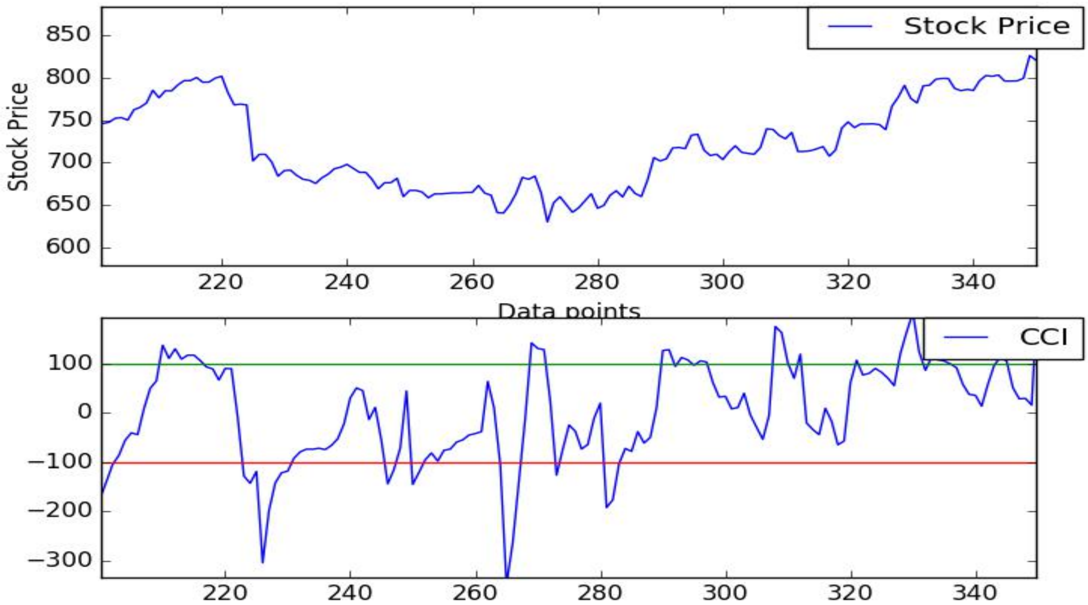


Figure 6.7: CCI results

6.2.9 Average True Range (ATR)

The Average True Range (ATR) is an indicator that measures volatility. To define this indicator, we need to define the ideology of True Range. True Range (TR) is defined as the greatest of the following:

Current High less the current Low

Current High less the previous Close (absolute value)

Current Low less the previous Close (absolute value)

If the current periods high is above the prior periods high and the low is below the prior periods low, then the current periods high-low range will be used as the True Range. This is an outside day that would use Method 1 to calculate the TR. Methods 2 and 3 are used when there is a gap or an inside day. A gap occurs when the previous close is greater than the current high (signalling a potential gap down or limit move) or the previous close is lower than the current low (signalling a potential gap up or limit move).

Calculations for the Average True Range (ATR) have been delineated as follows:
The first TR value is simply the current High minus the current Low. For later indices also calculate the absolute values of Current High minus the previous Close and Current Low minus the previous Close

Typically, the Average True Range (ATR) is based on 14 periods on daily data. The first 14-day ATR is the average of the daily TR values for the last 14 days. After that, we smooth the data by incorporating the previous periods ATR value.

Interpretation:

ATR is a unique volatility indicator that reflects the degree of interest or disinterest in a move. Strong moves, in either direction, are often accompanied by large ranges, or large True Ranges. This is especially true at the beginning of a move. Uninspiring moves can be accompanied by relatively narrow ranges. As such, ATR can be used to validate the enthusiasm behind a move or breakout. A bullish reversal with an increase in ATR would show strong buying pressure and reinforce the reversal. A bearish support break with an increase in ATR would show strong selling pressure and reinforce the support break.

Results:

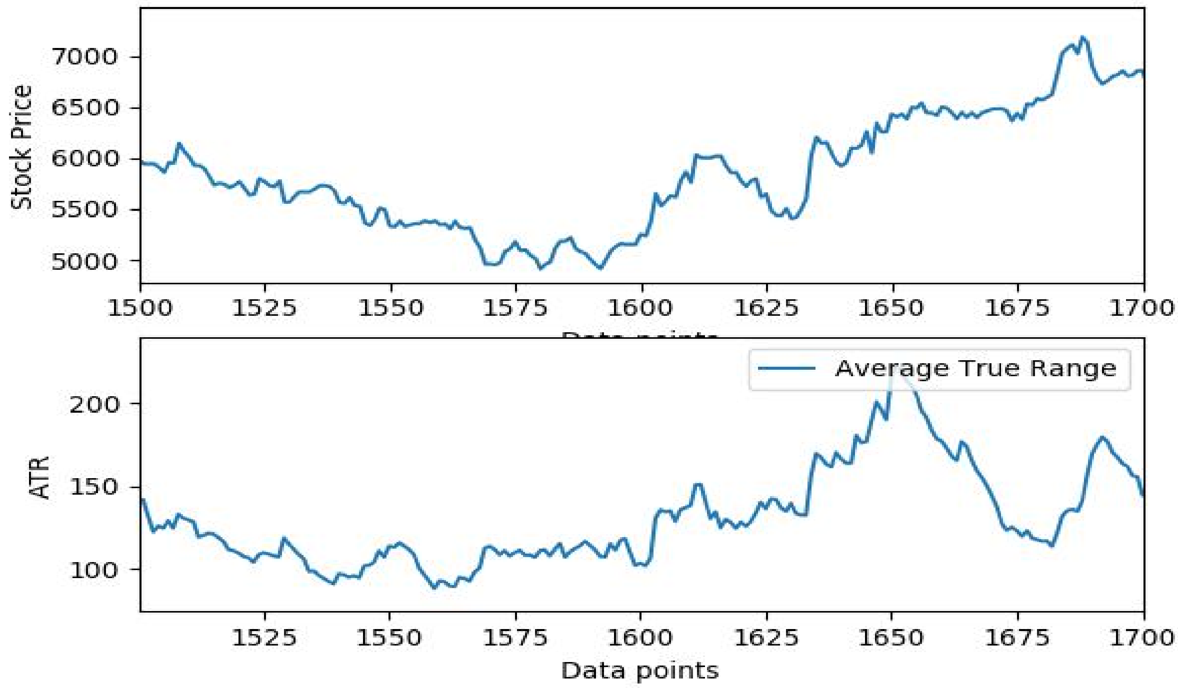


Figure 6.8: Average True range results

6.3 Support and Resistance

Support and resistance represent key junctures where the forces of supply and demand meet. In the financial markets, prices are driven by excessive supply (down) and demand (up). Supply is synonymous with bearish, bears and selling. Demand is synonymous with bullish, bulls and buying. These factors give us buying and selling points when the current stock is not in trend.

Support is the price level at which demand is thought to be strong enough to prevent the price from declining further. The logic dictates that as the price declines towards support and gets cheaper, buyers become more inclined to buy and sellers become less inclined to sell. By the time the price reaches the support level, it is believed that demand will overcome supply and prevent the price from falling below support. In our evaluations, the value of support is the minima of the past 14 days.

Resistance is the price level at which selling is thought to be strong enough to prevent the price from rising further. The logic dictates that as the price advances towards resistance, sellers become more inclined to sell and buyers become less inclined to buy. By the time the price reaches the resistance level, it is believed that supply will overcome demand and prevent the price from rising above resistance. In our evaluations, the value of resistance is the maxima over the past 14 days.

If a support or resistance level is broken, it signals that the relationship between supply and demand has changed. A resistance breakout signals that demand (bulls) has gained the upper hand and a support break signals that supply (bears) has won the battle.

Calculations for finding the Support and Resistance lines have been given as follows:
The Support line is given by the minimum of a moving window of size 14

The Resistance line is given by the maximum of a moving window of size 14

Interpretation:

The buying points are characterized by areas in which the stock price goes below the support value whereas the selling points are characterized by areas in which the stock price goes above the resistance value.

Results:

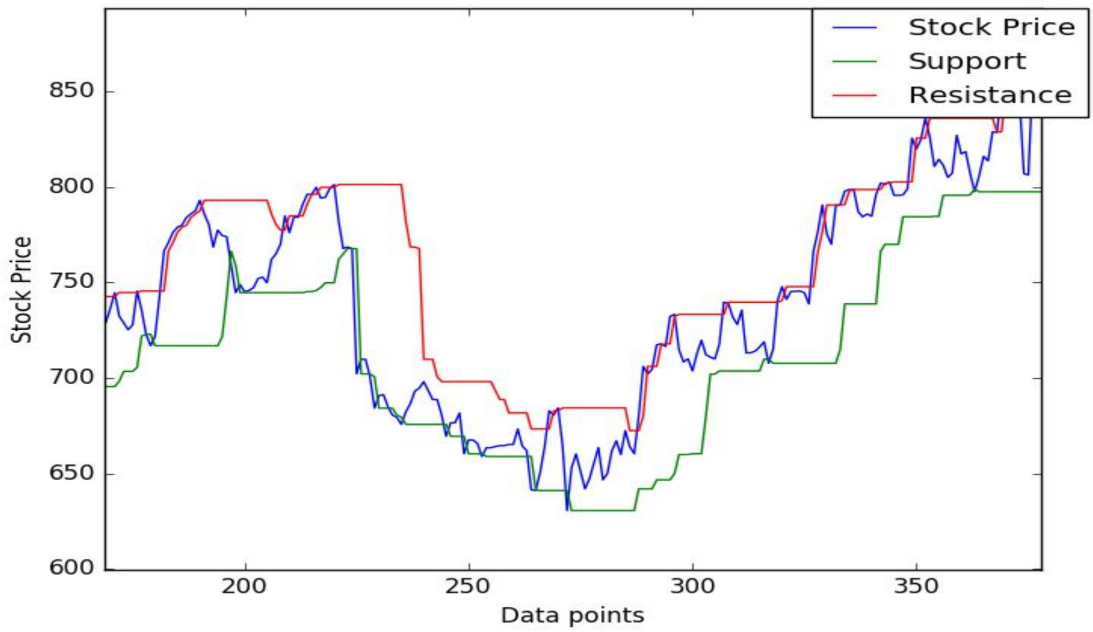


Figure 6.9: Support resistance results

6.4 Branching Model

All the technical factors seen above are not effective independently. To have a positive impact on the portfolio, they should be used in unison. This ideology gives rise to the first model we implemented to increase profits, i.e. the branching model. The script for the model is available in Appendix A.

Each technical factor, as explained, signifies when to buy, sell or hold shares on a particular day. Hence, we can classify strong buying/selling points when many factors tell us to buy/sell at the same time. We buy or sell more shares on these particular days. Similarly, we buy or sell lesser amount of shares when few factors tell us to buy/sell data. In some cases, there are conflicting opinions due to various factors, and we need a method to resolve these conflicts.

We thus assigned a variable β for each day, given by

Hence, we buy shares when β is positive and sell shares when β is negative. The amount we trade increases with the increase in absolute value of β.

On simulating these results, we obtained decent amount of profit for positive trend data. However, the amount of profit significantly reduces when the data is not trending. As shown in Figure, a net worth of Rs. 50,000 was obtained once Rs. 10,000 is invested in the Airtel stock.

Realizing the drawbacks of the above approach, we decided to split the data for in-trend and no-trend analysis.

The final model is tested on stocks from companies from various sectors. The results are shown in the Figure 6.10. Initially, Rs. 10,000 was allotted and the net worth of cash and shares is plotted with time.

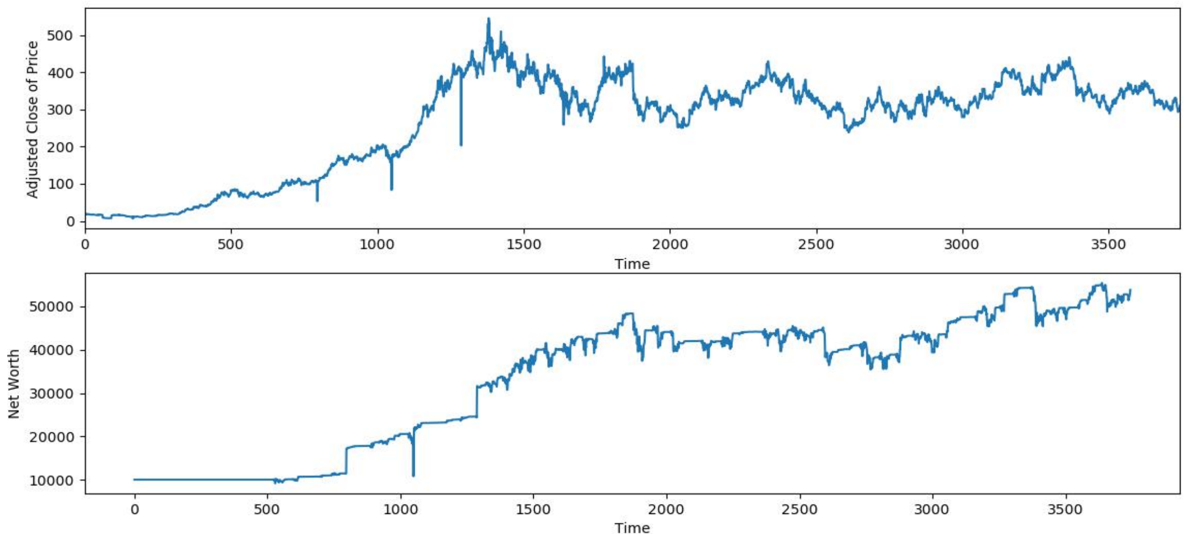


Figure 6.10: Branching Model applied for Airtel stock

As explained before, the technical factors signifying buy/sell points for in-trend data and the technical factors signifying buy/sell points for no-trend data are different. Hence, we modified the algorithm in such a way that the first step was classifying chunks of data as in-trend and no-trend. This is done by calculating the value of ADX. If the ADX is greater than 25, the data is classified as in-trend. Otherwise, the data is classified as no-trend.

Once the data is classified, we use support and resistance to analyse the no-trend data and we use RSI, CCI, ADL, Bollinger Bounce and MACD to analyse the in-trend data. Once this is done, we use the previous formula to calculate the number of stocks we should buy or sell.

On simulating the results, we observed that the profits obtained were significantly large in both positive trend and no-trend stock. However, our model did not do well when it came to perpetually bearish stock. These results are shown on Airtel stock. As seen from Figure 6.11, the profit obtained is much more than the previous case. Also, as seen in Figure 6.12, the algorithm was simulated on bearish trend (The Airtel data inverted). Losses were incurred in this process.

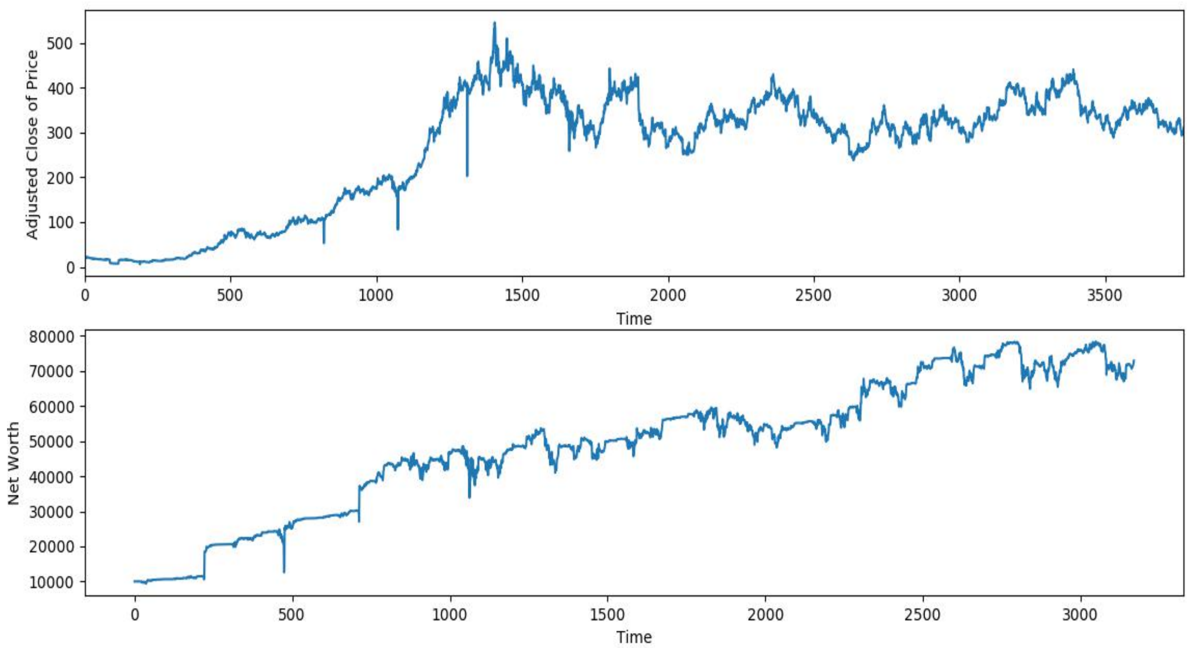


Figure 6.11: In trend and No trend analysis applied on Airtel stock

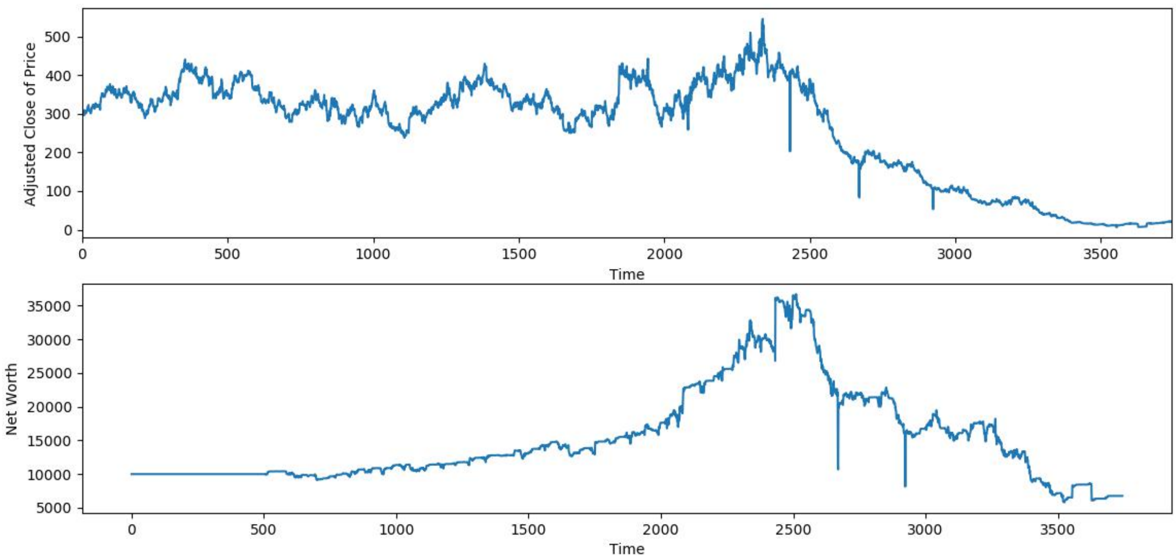


Figure 6.12: In trend and No trend analysis applied on for bearish trend (Inverted Airtel)

To overcome this drawback, we introduced the market leaving condition. When this condition is satisfied, it means that the stock has entered a perpetually bearish trend and it would be best to quit the market till a point when the stock starts trending positive again.

To signify a perpetually bearish stock, we look back to a window of the past 100 days. If the 100 day Maxima co-insides with the maxima of a window running from 80^{th} to 100^{th} day, and the 100 day minima co-insides with the minima of the past 20 days, then we can consider the stock to be trending negative. Hence, we quit the market at this point.
We define a re-entry point when our indicators show a positive trend. These indicators are the RSI and Momentum Histogram.

On simulating these results, we find that the performance of our algorithm improves because of the market leaving condition. As the losses at bearish trends reduce, it gives rise to a cascade effect, effectively increasing the earnings towards the end. Figure 6.13 shows Market exit strategy for a bearish stock, and as seen, profits are achieved.

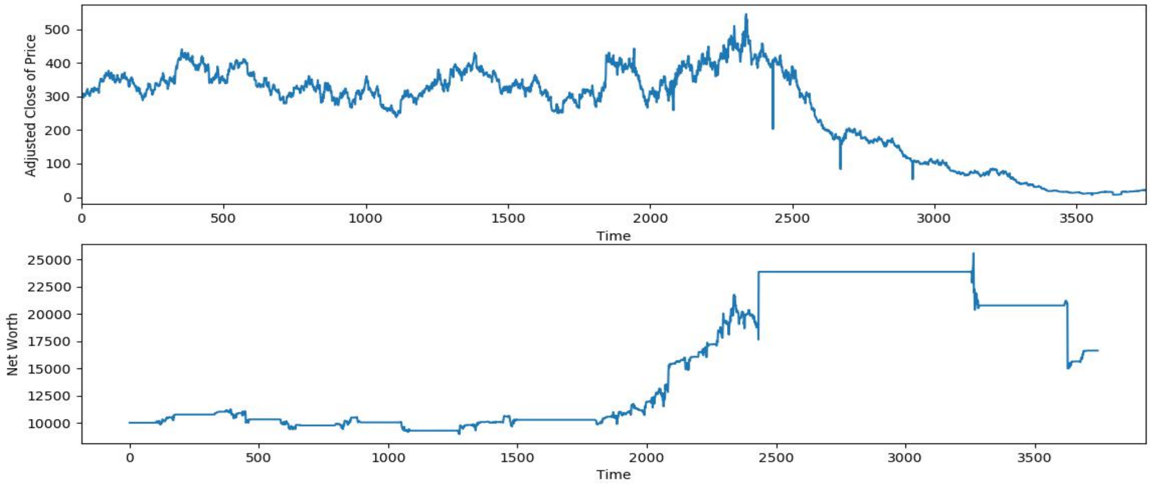


Figure 6.13: Market exit strategy applied to bearish stock (Inverted Airtel)

6.5 Options Trading

The exit strategy definitely reduces the losses, but the earnings remain stagnant for long periods of time. However, there are some strategists who manage to earn big during bearish stocks. Taking inspiration from them and the beautiful strategies they explore, we came across the market strategy of options trading. Options are contracts that grant the right, but not the obligation to buy or sell an underlying asset at a set price on or before a certain date.

Short selling is the sale of a security that is not owned by the seller, or that the seller has borrowed. Short selling is motivated by the belief that a security's price will decline, enabling it to be bought back at a lower price to make a profit [2]. Effectively, some shares are borrowed from a shareholder and returned after a fixed period of days. In this time, if the price drops, then the short-seller makes profit. If not, the shareholder makes profits.

Implementing this feature into our algorithm maximized the profits we could achieve from the branching model. Short selling, however, has its drawbacks. The risk involved is simply too high, as the shares which are being sold don't actually belong to the seller. If the price of shares actually increases, the seller will have to compensate for this after the fixed period. Figure 6.14 shows the simulation of the algorithm including short selling for bearish trends. It is simulated on the Inverted Airtel data. As visible clearly, the profits obtained are much more than the profits obtained by applying a market exit strategy only.

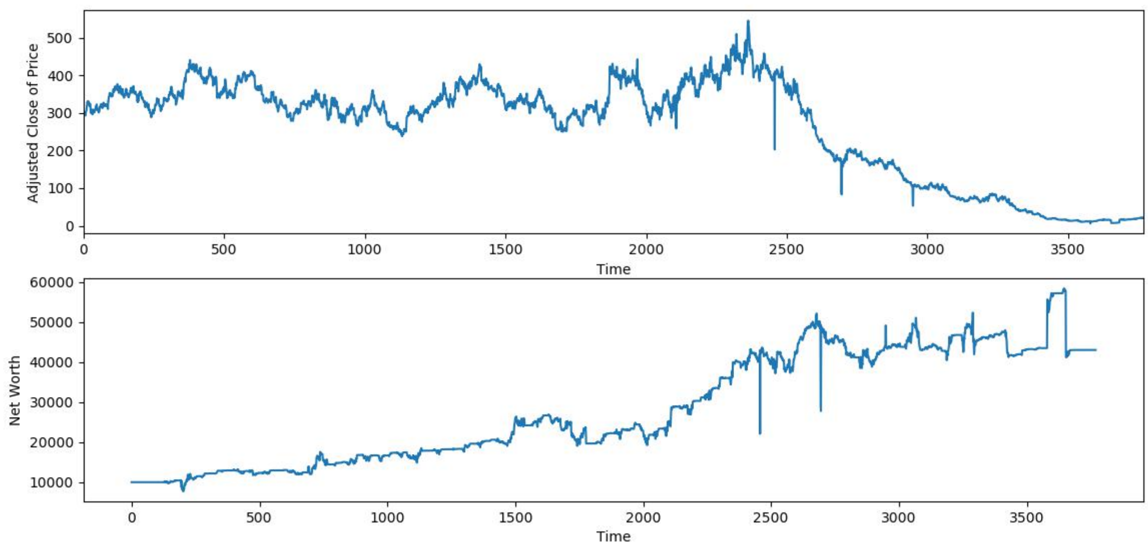


Figure 6.14: Short Selling strategy applied to bearish stock (Inverted Airtel)

The final model is tested on stocks from companies from various sectors. The results are shown in the Figures 6.15-6.17 Initially, Rs. 10,000 was allotted and the net worth of cash and shares is plotted with
time.

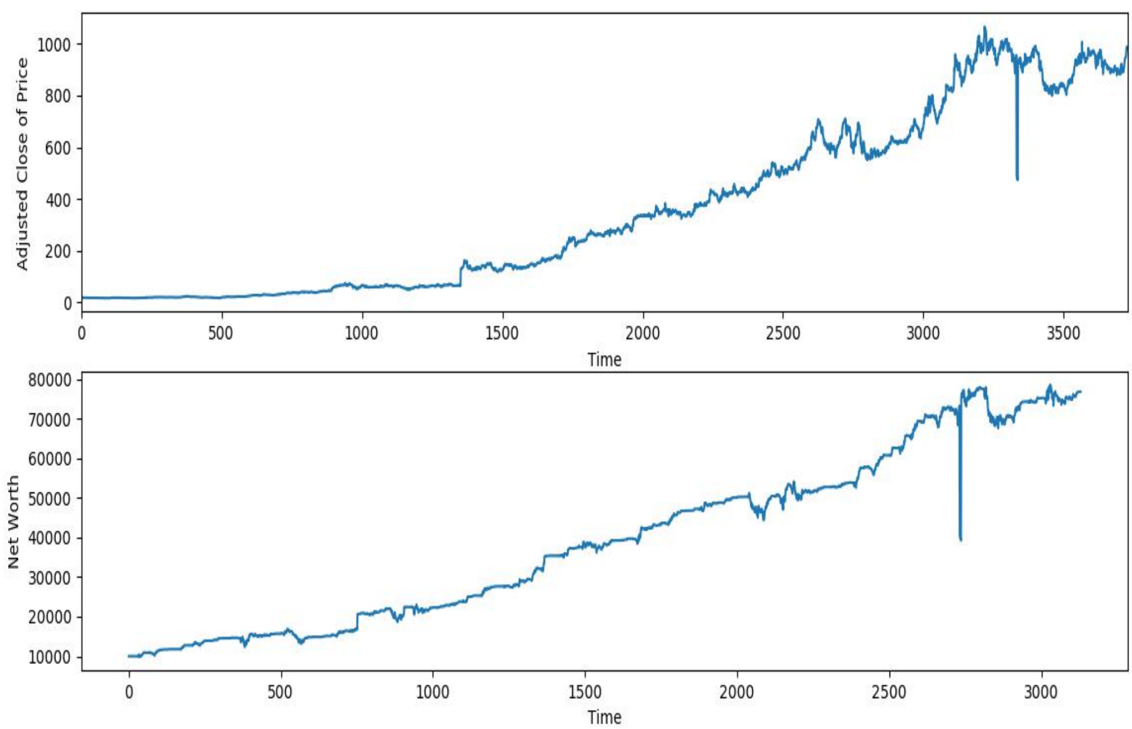


Figure 6.15: Branching Model simulated on Colgate stock (Food sector)

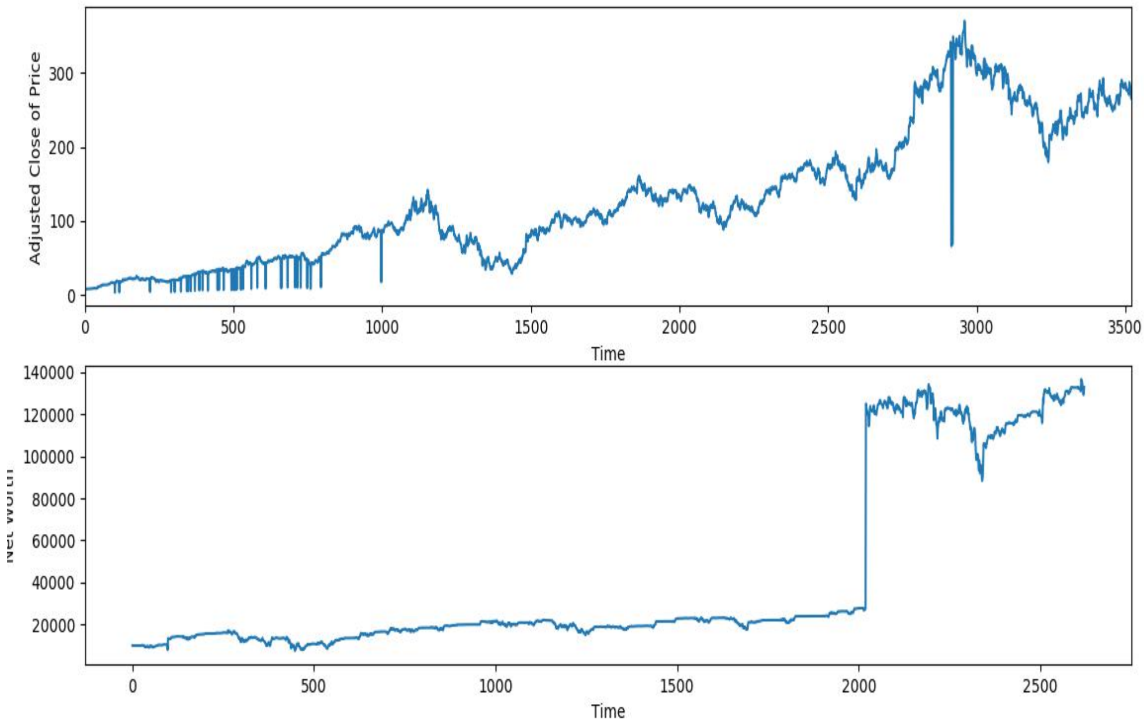


Figure 6.16: Branching Model simulated on ICICI bank

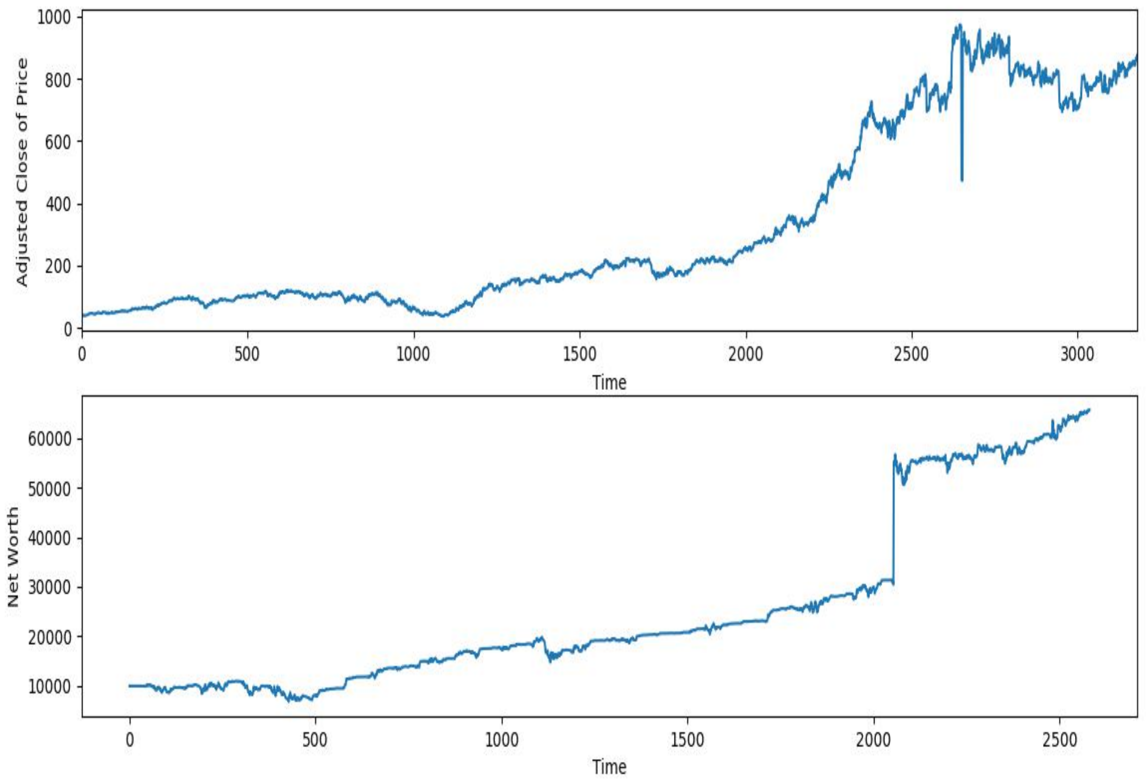


Figure 6.17: Branching model applied on HCL stock (IT sector)

6.6 Branching Model flow of events

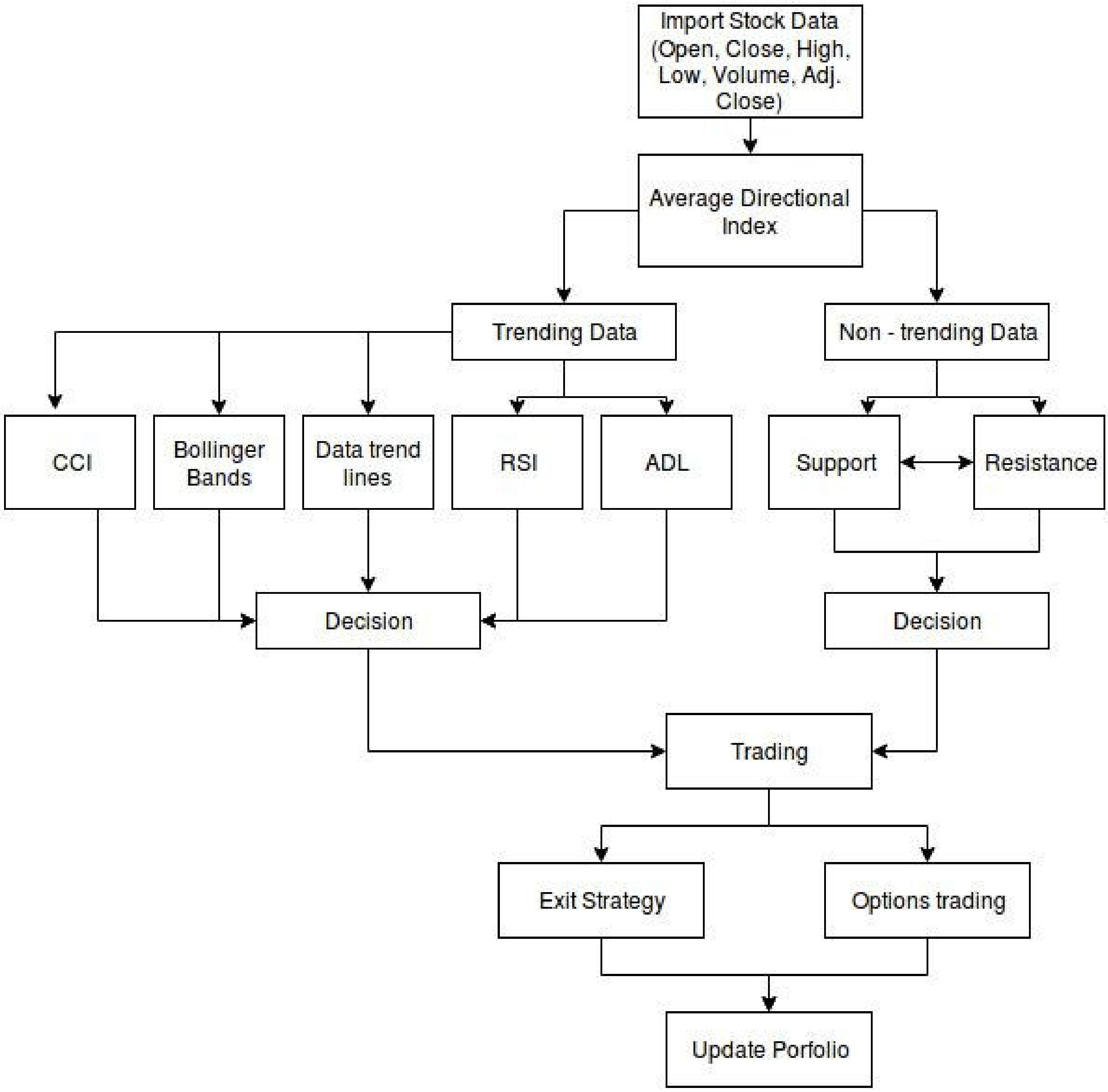


Figure 6.18: Branching Model flow of events

6.15 Need for Machine Learning

Drawbacks of the branching model:

1. The technical indicators lag behind the fluctuations in stock price and hence unison of different indicators giving same decision rarely occurs.
2. The branching model exhaustively trades by buying and selling at a lot of points since trading occurs even when not all indicators are in tandem. It may lead to reduced profits.

Hence, we need to classify the decisions properly and trade at good indices which lead to increased profits. Thus, machine learning is used to solve this problem. Also, by using Machine learning the trading decisions can be automated which otherwise require human effort.[18]

Chapter 7

Reinforcement Learning Model for Trading

7.1 Introduction

Reinforcement Learning [11][1] is a type of Machine Learning algorithm, which maps a particular action to each input state for a given set of data. A reward is obtained for every action, and actions are taken in such a way that rewards are maximized. The code implemented is provided in appendix A.

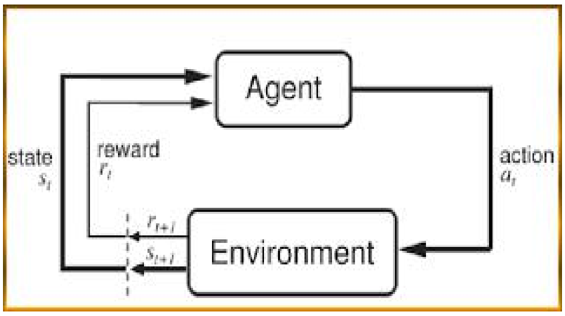


Figure 7.1: Basic Reinforcement Learning Model

The first step to reinforcement learning, ideally, is characterizing the stock data into a finite number of 'states'. To do this, we use the various technical factors derived, and they characterize the stock data from the past 'n' days. The number of possible states is thus dependant on the number of factors used, and the number of steps each factor is quantized into. If we use too many factors and/or too many quantization steps, the number of states shoots up drastically. This case is unwanted, as the amount of historical data is limited, and each state should occur a significant number of times throughout the history. On the other hand, if the number of states is too less then we don't have a significant basis to characterize the idiosyncrasies of the stock at any point of time. The optimal number of states is generally the number of training samples divided by the order of 10^2.

Now that we defined the state 's', we define 'π', the policy function which represents taking an action. Hence π(s) is an action taken on state 's'. Generally π(s) as a function just evaluates the value of all possible actions given the state s and returns the highest value action. We call the function that accepts a state *s* and returns the value of that state $v\pi(s)$. This is the value function. Similarly, there is an action-value function $Q(s, a)$ that accepts a state ‘s’ and an action ‘a’ and returns the value of taking that action given that state. The number of actions we can take at any point of time are 3, i.e. buy, sell and hold.

Q-learning[26], like virtually all RL methods, is one type of algorithm used to calculate state-action values. It falls under the class of temporal difference (TD) algorithms, which suggests that time differences between actions taken and rewards received are involved. With TD algorithms, we make updates after every action taken. In most cases, that makes more sense. We make a prediction (based on previous experience), take an action based on that prediction, receive a reward and then update our prediction.

Now, there’s a need to define a method to calculate rewards. To provide a simple idea to how our algorithm calculates rewards for a particular action taken at a given state, we shall consider the benefits of taking that particular action over the remaining actions. Hence, if our algorithm decides to buy shares at a particular time, the reward is calculated as a scaled version of the difference between our net worth when we buy and our net worth if we would have held, after a fixed number of days called the reward extent. If our algorithm decides to sell shares at any given point, the reward is a scaled version of the difference between our net worth when we sell and our net worth if we would have held shares until a fixed number of days. If our algorithm decides to hold shares, we subtract the net worth after a few days from the net worth after the more profitable of the two other actions.

Here's the tabular Q-learning update rule:

γ is a parameter 0→1 that is called the *discount factor*. Basically it determines how much each future reward is taken into consideration for updating our Q-value. If γ is close to 0, we heavily discount future rewards and thus mostly care about immediate rewards. α is the learning rate, which basically determines the weight of the past Q value in the current Q value. A higher learning rate signifies that the Q table will not be dependent on the past values, and only on the current Q-value.

We can perceive the Q-value as a weighted average of the reward for a particular state action pair through the history of the data. Hence, our Q-learning algorithm gets more refined with time. This means that it improves as the number of training samples available increases.

7.2 Testing and results

Now, we move on to the testing period. As the Q-table contains the weighted average of rewards, a higher maximum Q value for a particular action should mean that the action taken should be more rigorous. Hence, we should buy more if the max Q value for buy is relatively higher for one state than another. Using this property to the best of our interest, we basically normalize the maximum Q-value amongst that of the 3 actions, and convert it to an integer between 0 and 1. Once this is done, we multiply this normalized value to a particular amount of cash we have set aside for transactions, and buy/sell this multiplied value. Once this is done, the transaction is complete for the particular day.

In the same way, the algorithm runs for each day in the training period and updates the Q-table. According to this table, our algorithm takes actions for each day in the testing period. Our results plot the stock price change throughout time (both testing and training periods) and the net worth change in the testing period. These results are plotted for stock data of different companies.

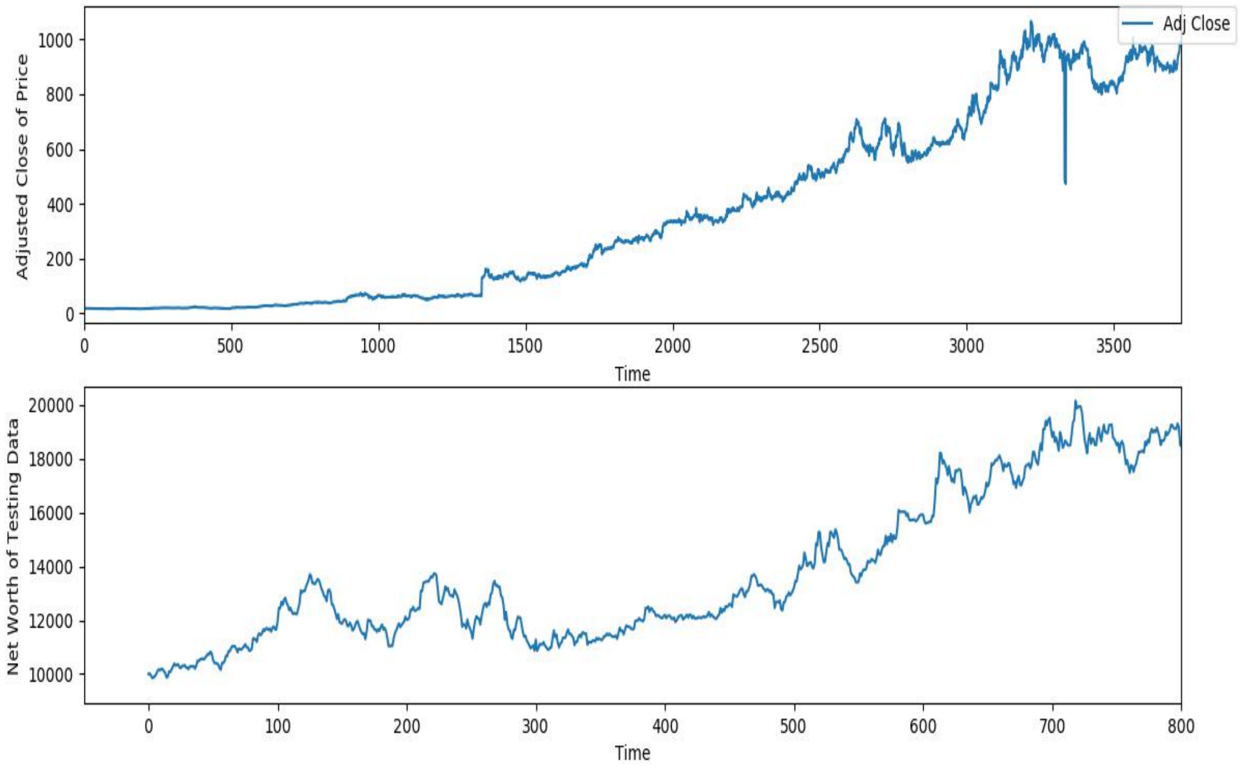


Figure 7.2: Reinforcement Learning applied on Colgate stock (FMCG)

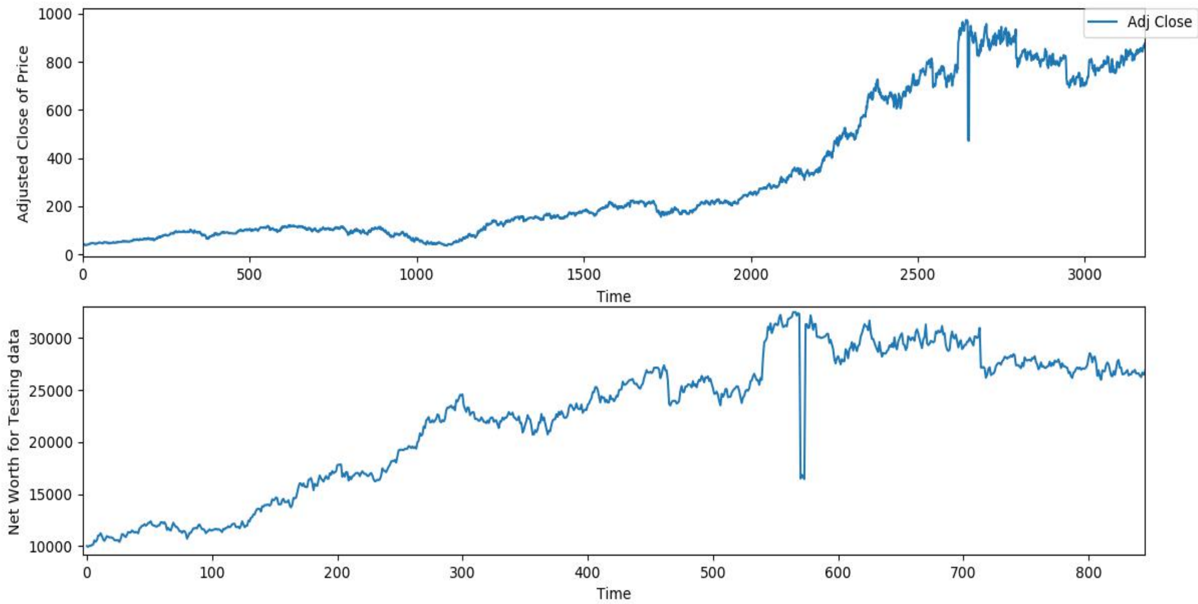


Figure 7.3: Reinforcement learning for HCL stock (IT industry)

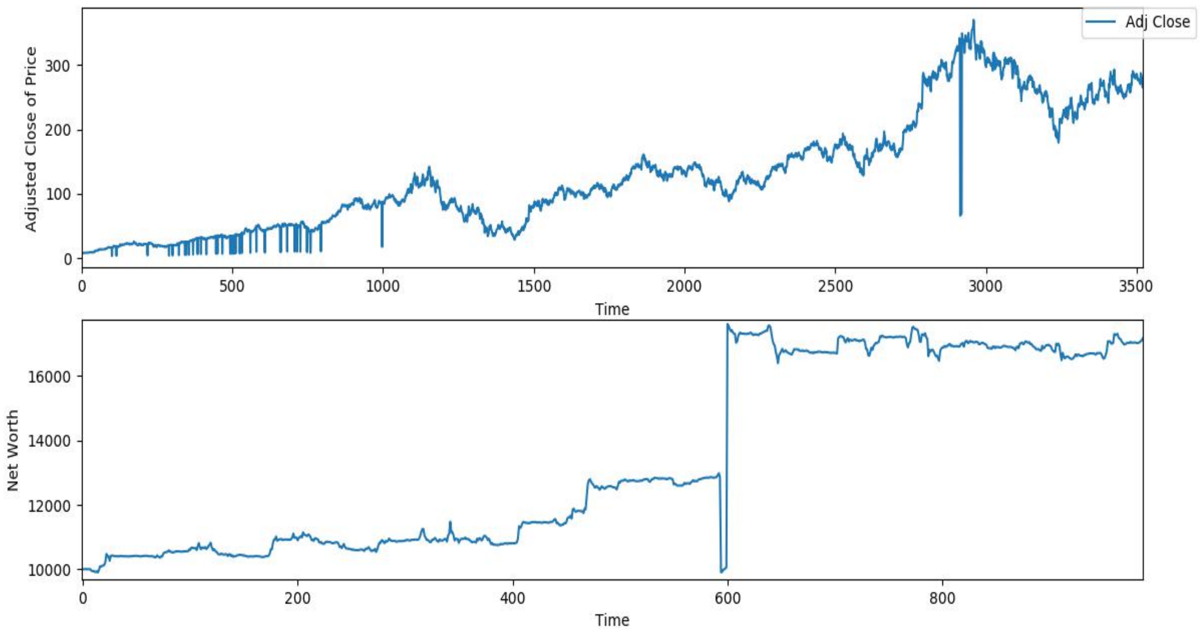


Figure 7.4: Reinforcement learning on ICICI Bank stock

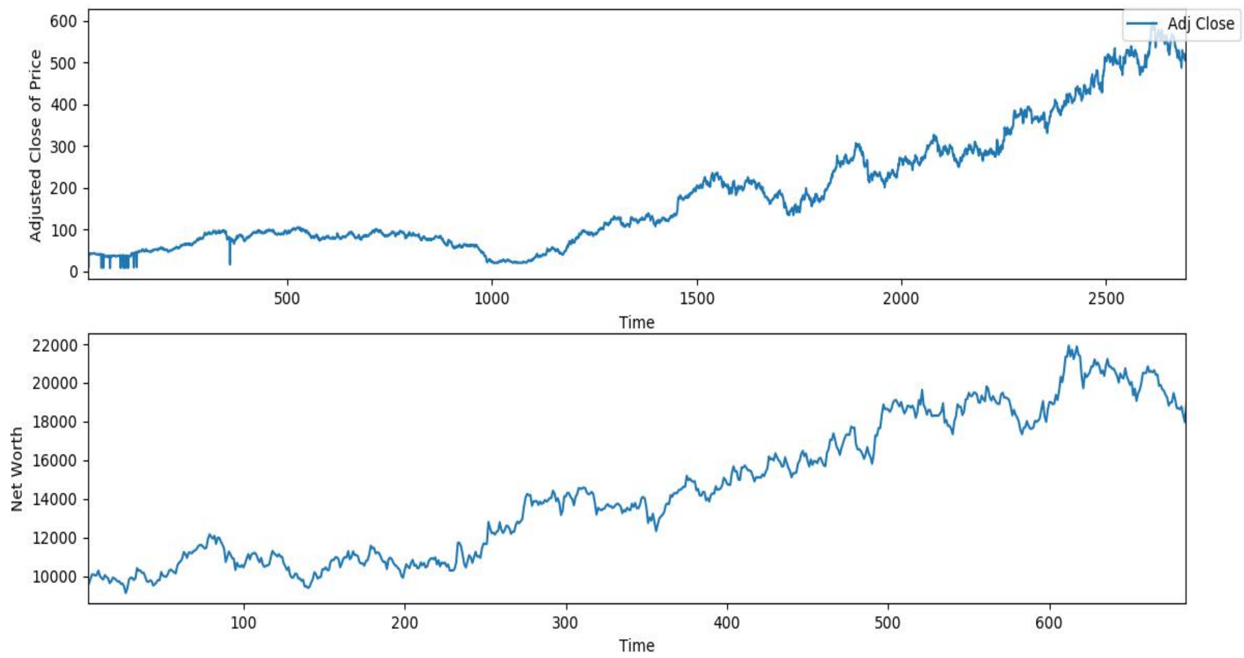


Figure 7.5: Reinforcement learning on Tata Motors stock (Auto)

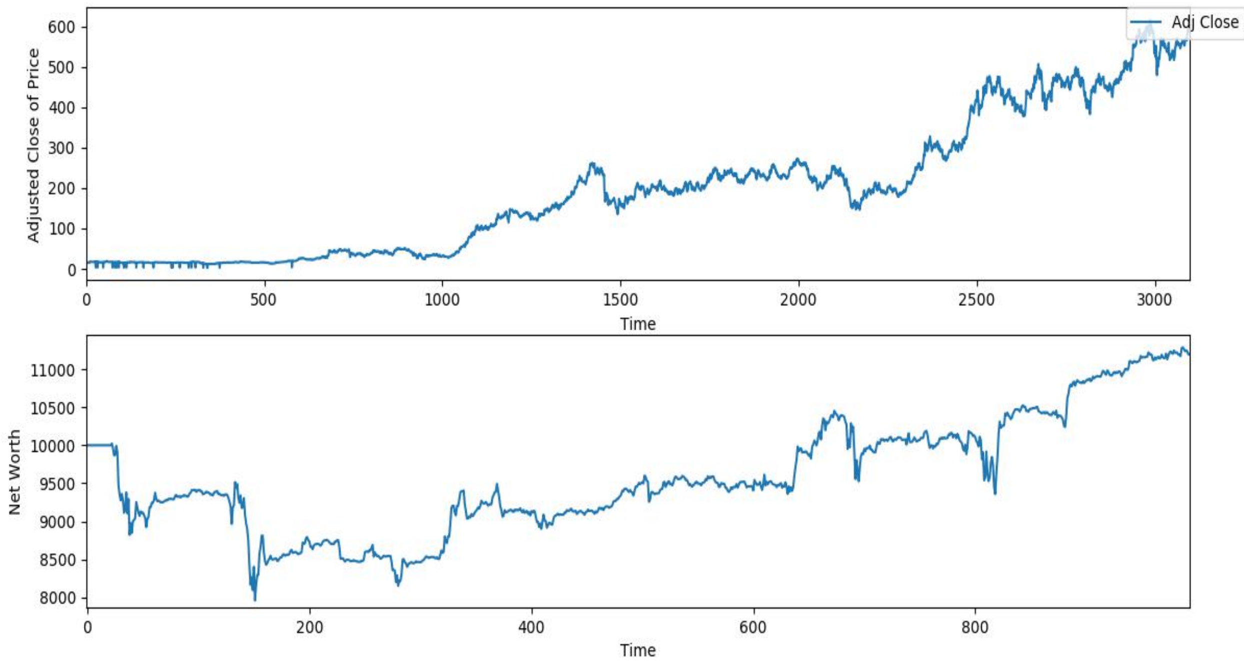


Figure 7.6: Reinforcement learning on LIC stock (Finance)

As seen from the figures, Reinforcement learning is beneficial in most cases, as net worth is trending positive most of the time. However, a major issue faced on simulating the algorithm over a large range of companies was that the net worth tends to follow the stock data in quite a few cases. Hence, the parameters we feed for every stock are different and relative to the properties of each stock. This leaves a scope for improvement in the future, as the parameters fed to the RL algorithm can be made adaptive, and can change with respect to the fundamental factors of each stock.

Reinforcement learning is ideally a case of unsupervised learning and hence requires an ample amount of data to ensure proper training. In case data seems to be less we propose a method of combining a supervised learning algorithm to be used to obtain a model for the reward to develop a relationship with the state. In the case of trading, majority of the points occur as beneficial holding points as compared to buying and selling points since the technical indicators or statistical oscillators (states for Reinforcement Learning model) that are used in finance lag behind the price fluctuations. Since the occurrence of buying and selling points is very less as compared to the length of the data a model for calculating the reward can be derived based on a linear relationship between technical factors and profit over the portfolio. Thus Multivariate Gradient Descent Algorithm [3] can be used to train on a data that we can log from the branching model [6.12] to establish a relationship between rewards and states.

Where, θ_i for *i=1, 2…, number of factors* are the weights that will be assigned by the Gradient Descent Algorithm. [24]

Chapter 8

Neural Network based trading model

8.1 Motivation for using neural networks

There are several distinguished features [27] that propound the use of neural network as a preferred tool over other traditional models of forecasting decisions in stock market trading. Neural networks are nonlinear in nature which is analogous to most of the natural real world systems which are also non-linear. Neural networks are preferred over the traditional linear models, because the linear models generally fail to understand the data pattern and analyze the underlying non-linear nature of the system. Model must be specified before the estimation of the parameters is done and generally it happens that pre-specified nonlinear models may fail to observe the critical features of the complex system under study.

Neural networks are data driven models. The novelty of the neural network lies in their ability to discover nonlinear relationship [28] in the input data set without a priori assumption of the knowledge of relation between the input and the output. The input variables are mapped to the output variables by squashing or transforming by a special function known as activation function. They independently learn the relationship inherent in the variables from a set of labelled training example and therefore involves in modification of the network parameters. Neural Networks have a built in capability to adapt the network parameters to the changes in the studied system. A neural network trained to a particular input data set corresponding to a particular environment; can be easily retrained to a new environment to predict at the same level of environment. Moreover, when the system under study is non-stationary and dynamic in nature, the neural network can change its network parameters (synaptic weights) in real time. So, neural network suits better than other models in predicting the stock market returns.

ANNs are very good at pattern recognition problems and with enough elements (called neurons) can classify any data with arbitrary accuracy. Unlike the branching model which exhaustively trades by buying and selling at a lot of points, the Neural Network model trades at relatively selected few points but does manage to earn greater profits compared to the branching model.

8.2 Neural Network Architecture and Design:

Neural networks are composed of a number of interconnected simple processing elements called neurons or nodes. They operate in parallel and actually resemble the biological neurons.

The neuron acts as a processing unit to transform the input to get an output. The neuron, like other linear or polynomial approximation, relates a set of input variables

{Xi} for i=1,2,3……k to set of one or more output variables {Yi} for i=1,2,3,……k. But in case of the neural network the only difference is that it does not require any prior equation as in case of other approximation methods, rather the input variables are mapped to the output set by squashing or transforming by a special function known as activation function. Each neuron has a weight and a bias assigned to it. Each neuron receives an input signal, which transmits through a connection that multiplies its strength by the scalar weight w, to form the product w*X. A bias is added to the weighted input and is then passed through a transfer function to get the desired output. The weight w and the bias b are the adjustable parameters of the neuron and are adjusted so that the neuron exhibits a desired behaviour.

The network has k inputs, m neurons in the first hidden layer, n neurons in the second layer and p neurons in the output layer. The layers are fully connected, such that every neuron in each layer is connected to every neuron in the next layer. The output of one hidden layer is the input of the following layer. Each neuron in the first hidden layer has k inputs. So there are kxm no of weighted input connections to the layer. Similarly, the second hidden layer has mxn inputs. The output layer has n inputs and p outputs. Selection of the hidden layers in the network and the no of the neurons in each of the layers are fundamental to the structure of the neural network. The input and the output neurons can easily be determined from the no of the input and the output variables used in the model as they are equal to the input and the output variables. The relationship between the input and the output of a neuron is established by the transfer function of the layer. The transfer function is a step function or a sigmoid function which takes the weighted input n and produces the output Y. Based on the performance of the network model transfer function are finalized for the network model.

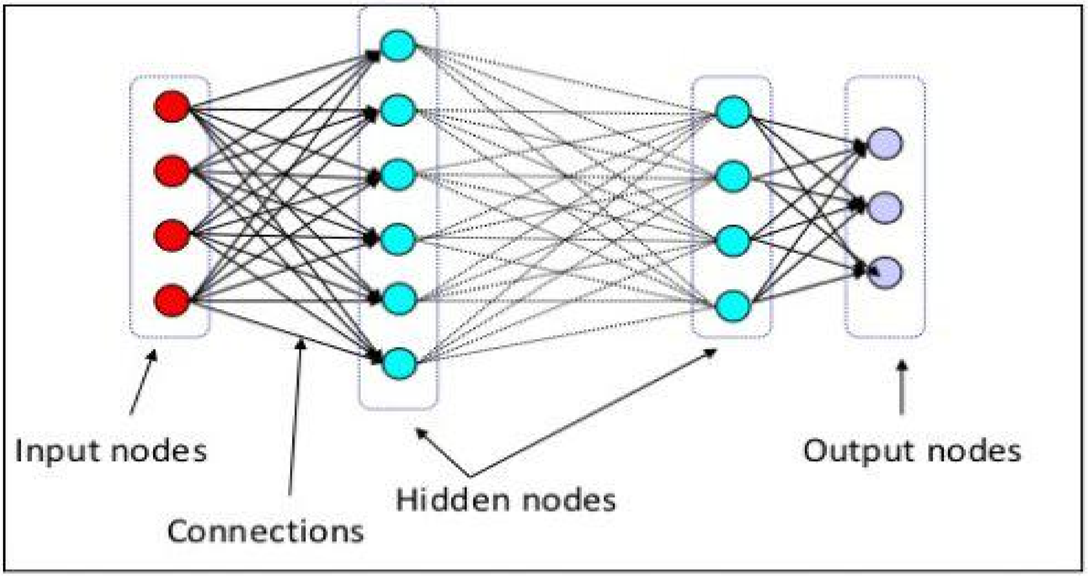


Figure 8.1: NN Model

Choosing the right activation function also greatly affects the working of the network. The conventional sigmoid activation function suffers from the problem of vanishing gradients at high enough input values. This is resolved by using “Relu” activation which rightly blows up the activation without any constraint.

Table 8.1: Specification of Neural Networks

Specification	Neural Network 1	Neural Network 2
Input Neuron size (m)	10	4
Size of 1st layer (n)	100	100
Size of 2nd layer (p)	50	50
Output Layer	7	3
Activation	Relu	Relu

8.3 Methodology

The data employed in the study consists of daily closing prices of various stocks. The data is collected from the historical data available on the website of Yahoo Finance. The study makes an attempt to design a simple neural network model where in most of the critical issues pertaining to performance of the neural network will be addressed. The performance of the neural network largely depends on the model of the Neural Network. Issues critical to the neural network modelling like selection of input variables, data pre-processing techniques, network architecture design and performance measuring statistics, are considered carefully.

Artificial neural network have found profound success in the area of pattern recognition, it can be trained to discern the criteria used to classify, and can do so in a generalized manner by repeatedly showing a neural network inputs classified into groups.

The conventional methodology of applying Neural Network for stock market prediction is predicting the stock value [29] for a particular day. Our approach is to predict actions for the end user (Buy, Sell and Hold). The output values of the network are used as probabilities which inform the user the number of stocks to be sold or the amount of money to be invested to in a particular market. So, instead of the common approach of predicting the stock price like a regression does, we treat the task as a classification problem.

To incorporate portfolio data in the model, we also provide the percent profit the user had made since the last buying point. Also the effective buy price (i.e. the mean of all buying points) is also fed to the network. These 2 parameters attempt to provide the portfolio information to the model.

By repeatedly showing a neural network inputs classified into groups, the network can be trained to discern the criteria used to classify, and it can do so in a generalized manner allowing successful classification of new inputs not used during training.

The model has various technical factors as the input and 3 classes as the output (Buy, Sell and Hold).

There are two neural networks which are designed for two different strategies. First is designed for trending market and the other one is designed for sideways market. The two neural networks help to predict actions to be taken in different trading scenarios.

8.4 Selection of Input variables:

Selection of input variable for the neural network model is a critical factor for the performance of the neural network because it contains important information about the complex non-linear structures of the data. The training input is generated using algorithm mentioned in …. .

The input vector is a set of technical factors which are calculated on a window of 14 working days.

First neural network is designed for trending market. The input variables for this network includes Upper- Bollinger band, Lower- Bollinger band, MACD, CCI, RSI, ADL.

Since the Bollinger bands operate along with the daily stock price, they must be fed in such a way that the model understands to correlate the two. So the difference between the daily stock price and the 2 Bollinger-Bands is fed to the network both during training and testing.

Form the interpretation of MACD [reference], whenever MACD falls from the previous value, it indicates a good 'buying point' and when MACD rises up, and it indicates a good 'selling point'. To incorporate this in our network, we passed both the current MACD value and the previous MACD value. This enables the network to detect any rise or fall in the MACD value.

Second neural network is designed for sideways market. The input variables for this network include Support, Resistance and Adjusted Close index.

Form the interpretation of support and resistance, stock price above resistance indicates a good selling point and values below support indicate good buying points. So we pass the difference between stock price and the support and resistance respectively. Since, when both the difference values become positive or negative, the model learns to understand that an action needs to be taken.

Apart from the above steps, a bias in the learning is introduced by pre-multiplying the factors before feeding it as input to the network. The RSI[reference] gives meaningful information when it is above 80 (good buying point) or below 20 (good selling point). When the RSI value is in between 20 and 80 the factor is simply multiplies by 0 so as to prevent the network from assigning more weight to that input.

8.5 Data Pre-processing:

The inputs to the Neural Network must be normalized so that the model doesn't become biased to a particular input feature.

For normalization, we used the Mean-Variance normalization. This approach scales the data to have mean 0 and variance 1.

This normalization is applied to each set of factors individually. One problem with this normalization is that with the addition of each new data point to the set, the overall mean and the variance changes. So, initially we take a large data set of several companies from various sectors and calculate the overall mean and variance for each factor. We assume that this value of mean and variance will not change with addition of new data points. This value of mean and variance is then used for all further iterations and remains constant.

For other factors which rely on sign changes like MACD, Support and Resistance, this normalization is not applied as it would lead to loss of sign and hence loss of crossing information to the network. For such data sets, the data points are simply divided a random arbitrary constant which was decided manually by observing the data

8.6 Network Training

After the neural network model is constructed, training of the neural network is the next essential step of the forecasting model. Training of neural network is an iterative process of non-linear optimization of the parameters like weights and bias of the network. The result of the training process of the network depends on the algorithm used for the purpose. The back propagation algorithm is used for training. A back propagation network uses a supervised learning method for training. In one complete cycle of the training process, a set of input data {X1, X2, X3…} is presented to the input node. The corresponding target output {Y1, Y2, Y3}, is presented to the output node in order to show the network what type of behaviour is expected. The output signal is compared with the desired response or target output and consequently an error signal is produced. This desired response is obtained from the output of the branching model. The training and testing datasets consists of different stocks.

In each step of iterative process, the error signal activates a control mechanism which applies a sequence of corrective adjustments of the weights and biases of the neuron. The corrective

adjustments continue until the training data attains the desired mapping to obtain the target output as closely as possible. After a number of iterations the neural network is trained and the weights are saved in the local directory. The test set of data is presented to the trained neural network to test the performance of the neural network. The result is recorded to see how well the net is able to make decisions for optimal portfolio using the adjusted weights of the network.
RMSprop algorithm was used to train the neural network.

RmsProp [28] is an optimizer that utilizes the magnitude of recent gradients to normalize the gradients. We always keep a moving average over the root mean squared (hence Rms) gradients, by which we divide the current gradient. Let $f'(\theta t)$ be the derivative of the loss with respect to the parameters at time step t. In its basic form, given a step rate α and a decay term γ we perform the following updates:

$$r_t = (1-\gamma)\, f'(\theta_t)^2 + \gamma_{r_{t-1}} \tag{8.4}$$

$$v_{t+1}\, f'(\theta_t) \tag{8.5}$$

$$\theta_{t+1} = \theta_t - v_{t+1} \tag{8.6}$$

8.7 Network output

The output of the network gives the confidence of taking an action. The 3 outputs are first normalized using min-max normalization and the confidence of the action is calculated by taking the percentage.

Now, consider the ideal outputs for the no trending neural network to be [0,0,1], [0,1,0], [1,0,0] corresponding to sell, old and buy actions respectively. We, first normalize the obtained outputs between 0 and 1 under the constraints that the sum of all three parts should equal unity. This enables us to treat the outputs as probability values. To select appropriate action we select the output with probability greater than 0.5. After selecting the action the confidence with which it is proposed by the neural network is inversely proportional to its difference with 1. The confidence estimates thus obtained help decide the amount of money or stocks to invest in that decision. This approach greatly helped improve the profit obtained in simulated trading.

8.8 Performance of the Neural Network

The Neural Network for trending market and sideways market is trained over labeled dataset and the performance of the neural network is compared with the branching model. Two neural networks are used simultaneously to make trading decisions

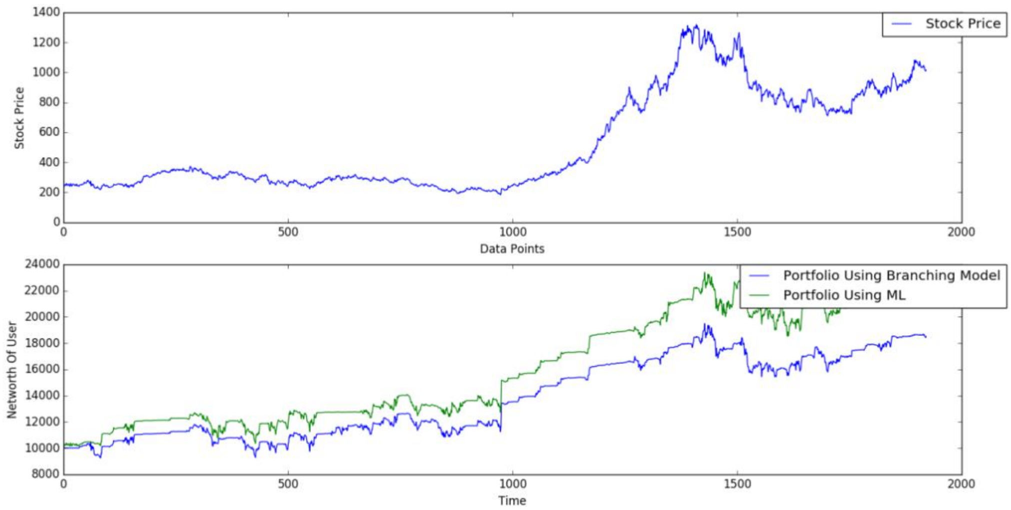


Figure 8.2: Results for Infosys

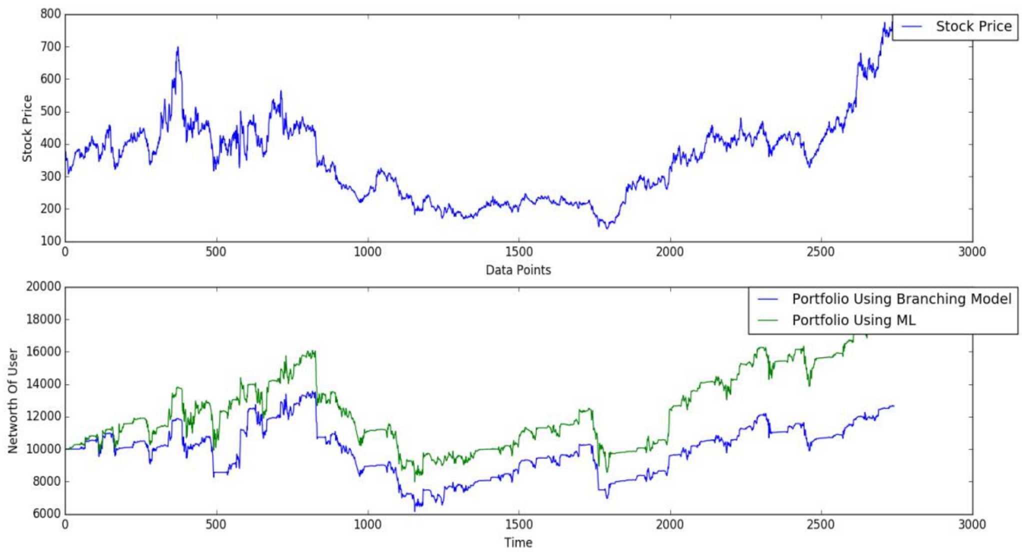


Figure 8.3: Results for Tata Comm.

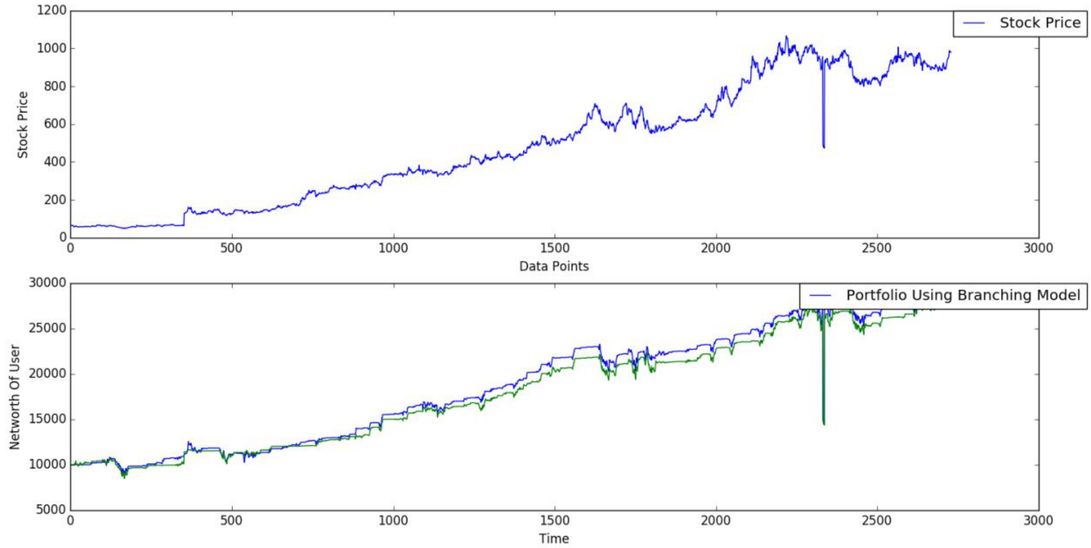


Figure 8.3: Results for Colgate

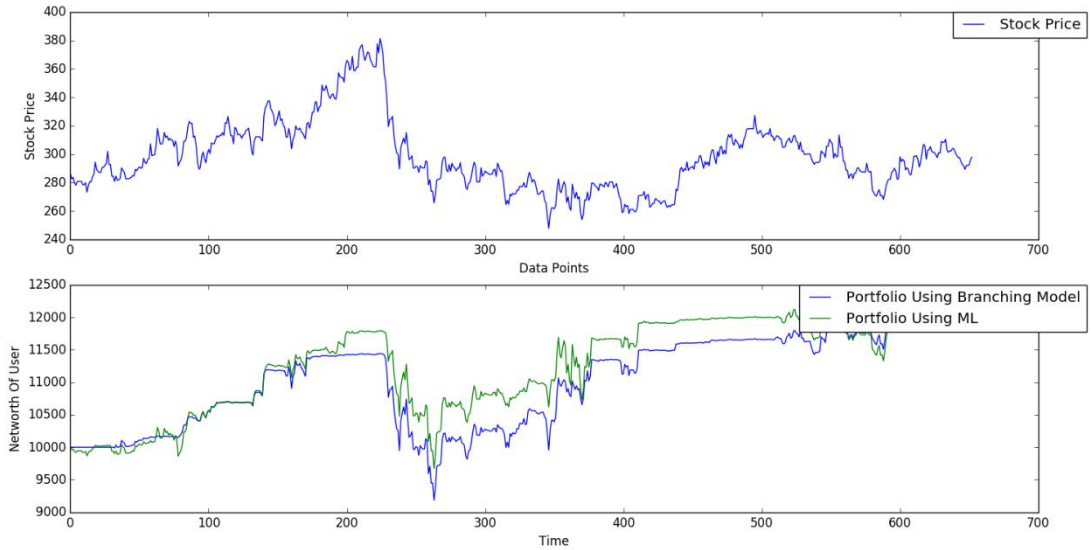


Figure 8.5: Results for Coal India

From the above graphs, it is clear that the trained model performs very well and even returns greater profits than the branching model. However, the neural network model sometimes fails to negotiate sharp drop in prices which leads to degraded profits for certain stocks.

Chapter 9

Conclusion

The models proposed to solve the problem of efficient trading have proved to yield good results. Thus, a machine is now capable of making intelligent investments or trading on its own and also providing suggestions to humans investing in the stock market. The machine does not suggest actions to be taken by just viewing the market condition (which what most websites do today) but also recommends actions specific to a portfolio by verifying the profitability before investment.

To improve trading strategies three models i.e. one model without Machine learning, Algorithmic Trading using Branching, and two models using Machine learning, Reinforcement learning and Neural Networks, have been put forward and a comparative study has been conducted between all three models. Neural Networks which was trained using data collected from branching model outperformed the branching model and it could successfully filter many false buy or sell signals provided by the indicators. Reinforcement Learning Model did give good results for a few companies but could not always outperform the branching model due to lack of training data. Thus we proposed a solution to develop a model which could relate financial statistical parameters to the rewards.

By incorporating techniques of portfolio optimization a machine is now capable of distributing money amongst various suggested and/or previously invested securities in a manner that would yield maximum returns while minimizing risk. Two techniques i.e. Markowitz mean-variance optimization and Least squares method have been implemented and a comparative study has been carried out. Also modern techniques which take into account individual investor views and also perform much better than the traditional portfolio optimization approaches are difficult to automate and we have proposed a solution to automate it using fundamental analysis.

Fundamental analysis was performed using ‘pass’ and ‘fail’ score strategy over the data from Cash Flow, Income Statement and Balance Sheet of various securities. Companies with higher pass score to fail score ratio are fundamentally strong and good to invest in. The top companies are provided as suggestions to invest in along with top traded securities in the market to optimize a portfolio.

Future Scope

There are many tracks over which the scope of this project could be extended. The following

1. The scope of this project can be extended by including sentiment analysis of investors or brokers that can help make decisions either for intraday trading and/or value investing.
2. A Portfolio management web application can be developed using the algorithm described in this project which can provide trading strategies and suggestions to users to maximize their profits.
3. The results of the proposed algorithms can also be improved by incorporating many other factors like sentimental analysis, qualitative analysis, news which affect the supply and demand and hence stock prices.

References

[1] J. Moody, L. Wu, Y. Liao and M. Saffell, "Performance functions and reinforcement learning for trading systems and portfolios", Journal of Forecasting, vol. 17, no. 56, pp. 441-470, 1998.

[2] Mittal, A. & Goel, A. (2012). Stock prediction using twitter sentiment analysis. Stanford University Working Paper.

[3] LeCun, Y., Bottou, L., Orr, G. B., & Muller, K.-R. (1998b). Efficient backprop. In Neural networks, tricks of the trade, Lecture Notes in Computer Science LNCS 1524. Springer Verlag.

[4] Joseph D. Piotroski, "Value investing: The use of Historical Financial Statement Information to Separate Winners from Losers"

[5] Avinash Balachandran, Durgesh Saraph and Erjie Ang, "Learning to Identify Winning Stocks"

[6] "StockCharts.com | Simply The Web's Best Financial Charts", Stockcharts.com, 2017. [Online]. Available: https://stockcharts.com/. [Accessed: 15- Feb- 2017].

[7] Pawar, Prashant. Machine Learning applications in financial markets. Diss. Indian Institute of Technology, Bombay Mumbai.

[8]"UK Home | Investopedia", Investopedia, 2017. [Online]. Available: http://www.investopedia.com/. [Accessed: 15- May- 2017].

[9] Balakrishnan, Anusha and Kalpit Dixit. "Predicting Market Volatility Using Semantic Vectors and Google Trends." (2015).

[10] Gold, Carl, FX Trading via Recurrent Reinforcement Learning, Computational Intelligences for Financial Engineering, 2003. Proceedings. 2003 IEEE International Conference on. p. 363-370. March 2003.

[11] 2017. [Online]. Available: http://outlace.com/rlpart3.html. [Accessed: 15- Jan- 2017].

[12] Kar, A.: Stock prediction using artificial neural networks. Department of Computer Science and Engineering, IIT, Kanpur

[13] Huang, W. "Forecasting Stock Market Movement Direction With Support Vector Machine". Computers & Operations Research (2004): n. pag. Web.

[15] "The Nasdaq Dozen", NASDAQ.com, 2016. [Online]. Available: http://www.nasdaq.com/investing/dozen/. [Accessed: 27- Nov- 2016].

[16] Markowitz, Harry, Portfolio Selection, Journal of Finance, pages 77-91, March 1952.

[17] Chan, Raymond Hon Fu, Spike Tsz Ho Lee, and Wing-Keung Wong. Technical Analysis And Financial Asset Forecasting. 1st ed. Print.

[18] Aydin, Alev Dilek, and Seyma Caliskan Cavdar. "Prediction Of Financial Crisis With Artificial Neural Network: An Empirical Analysis On Turkey". International Journal of Financial Research 6.4 (2015): n. pag. Web.

[19] F. Mayambala, Mean-Variance Portfolio Optimization, 1st ed. Linköping: Department of Mathematics, Linköping University, 2015.

[20] E. Allaj, "Black-Litterman Model, Active Portfolio Management, and Portfolio Optimization", SSRN Electronic Journal.

[21] J. Park and S. Boyd, "Portfolio Optimization", Stanford, 2016

[22] "Yahoo Finance - Business finance, stock market, quotes, news", In.finance.yahoo.com, 2016. [Online]. Available: https://in.finance.yahoo.com/. [Accessed: 19- Dec- 2016].

[23] Black, Fischer and Robert Litterman, Global Portfolio Optimization, Financial Analysts Journal, pages 28-43, September-October 1992

[24] Tieleman, T. and Hinton, G. (2012) Lecture 6.5-rmsprop: Divide the Gradient by a Running Average of Its Recent Magnitude. COURSERA: Neural Networks for Machine Learning, 4, 26-31.

[25] Hamilton JD (1989) A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica 57(2): 357–384

[26] Dempster M, Leemans V (2006) An automated FX trading system using adaptive reinforcement learning. Expert Syst Appl 30(3): 543–552

[27] H. Mizuno, M. Kosaka, H. Yajima, N. Komoda. "Application of Neural Network to Technical Analysis of Stock Market Prediction". Studies in Informatic and Control, Vol.7, No.3, 1998, pages.111–120.

[28] J.E. Dayhoff, J.M. DeLeo, "Artificial neural networks: Opening the black box". Cancer, 91 (8 Suppl.) (2001), pp. 1615–1635.

[29] Majumdar, M. and Hussian, M.D.A (2010) Forecasting of Indian stock market index using artificial neural network. Available online at: www.nseindia.com/content/research/FinalPaper206.pdf

[30] "Financial Times", Ft.com, 2017. [Online]. Available: http://www.ft.com. [Accessed: 5-May- 2017].