

A Project Report on

**Directional Analytics for Day Trading in Stock Market**

Submitted in partial fulfilment for the award of the degree of

Master of Business Administration

In **Business Analytics**

Submitted by

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Under the Guidance of

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# Candidate’s Declaration

I, **Anand Mohan** hereby declare that I have completed the project work towards the first year

of Master of Business Administration in Business Analytics at, REVA University on the topic

entitled **Directional Analytics for Day Trading in Stock Market** under the supervision of

Dr. **JB Simha, Chief Mentor-RACE**. This report embodies the original work done by me in

partial fulfilment of the requirements for the award of the degree for the academic year **2022**.

Place: Bengaluru Name of the Student: Anand Mohan



Date: 10 October. 22 Signature of Student



# Certificate

This is to Certify that the Project work entitled **Directional Analytics for Day Trading in Stock Market** carried out by **Anand Mohan** with **SRN R19MBA53**, a bonafide student of REVA University, is submitting the first-year project report in fulfilment of the award of **Master of Business Administration in Business Analytics** during the academic year **2022**. The Project report has been tested for plagiarism and has passed the plagiarism test with a similarity score of less than 15%. The project report has been approved as it satisfies the academic requirements in respect of the project work prescribed for the said Degree.

Signature of the Guide Signature of the Director

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Guide Director

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Names of the Examiners

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2. <Name><Designation><Signature>

Place: Bengaluru

Date:



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Their encouragement also helped me in the completion of this project.

Place: Bengaluru

Date: 10 October. 22



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# List of Abbreviations

|  |  |  |
| --- | --- | --- |
| **Sl. No** | **Abbreviation** | **Long Form** |
| 1 | **LR** | **Logistic Regression** |
| 2 | **DT** | **Decision Tree** |
| 3 | **RF** | **Random Forest** |
| 4 | KNN | k-Nearest Neighbours |
| 5 | **XG Boost** | Extreme Gradient Boosting |
| 6 | CRISP-DM | Cross-Industry Standard Process for Data Mining |
| 7 | VWAP | volume-weighted average price |
| 8 | NSE | National Stock Exchange |
| 9 | HDFC | Housing Development Finance Corporation Limited |
| 10 | SBI | State Bank of India |
| 11 | RSI | Relative Strength Index |
| 12 | MACD | Moving Average Convergence Divergence |
| 13 | ADX | Average Directional Index |

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# Abstract

The application of machine learning for stock prediction is attracting a great deal of attention in recent years. An enormous quantity of analysis has been conducted in this area and multiple existing results have shown that machine learning ways may well be with success used toward stock predicting using stocks’ historical knowledge. Most of those existing approaches have targeted short-term prediction of stocks’ historical value and technical indicators. During this thesis, twenty-two years' price of stock daily Returns is being utilized and investigated for accuracy of the predictions.

The objective of the project is to get the right stock and collect all relevant data to make correct forecasting. Build the right models by using multiple Modelling techniques and explore some of the state-of-the-art solutions to minimize the prediction errors.

A rule-based model is being developed to try and do hypothesis testing to see whether or not the chosen stock's value is crossing any of the subsequent moving averages: the 7-day, 13-day, 20-day, 100-day, and 200-day moving averages. It will be a purchase decision if the projection indicates that the value will be higher than various Moving Averages. Exponential statistic Models are then utilized to produce identical 5 hypothesis testing models. After that, any five ARIMA-based statistic models are created to support the buy or sell recommendation for the underlying stock.

Then various numerous Classification Models have been applied particularly K neighbors Classifier, Logistic Regression Modelling, and Auto Keras Classification Model using Structured knowledge classifier. The results show that AutoKeras Classification Model achieves the most effective prediction Accuracy followed by the Logistic Regression Classification Model and Then KNN Classification Model. SMA-7 samples and EMA-7 samples using T-test applied mathematics Hypothesis testing Models conjointly provided fairly smart accuracy.

Then various used regression Modelling Algorithms are used for predicting the close value and compared the Metrics, particularly MAE and MAPE.

The OLS-Linear Regression Model, Lasso Regression Model, Lasso regression Model using Cross Validation, The KNN rule, Decision Tree rule, GridSearchCV rule with Hyper-parameter standardization, Random Forest Regression Model, XGBoost Model, Using PCA with LSTM, Using PCA with LSTM with Moving Average variables (Feature Engineering), LSTM Neural Network Model, Regression Model using AutoKeras are the Regression Models used for predicting the close value.

The OLS-Linear Regression Model and Regression Model using AutoKeras offer the most effective results. Random Forest Regression Model and using PCA with LSTM conjointly provided smart results.

The project findings demonstrate that machine learning models may well be utilized to aid basic analysts with decisions relating to stock investment.

Keywords: Stock prediction, Hypothesis testing, ARIMA, Classification Models, Regression Model, LSTM, PCA, AutoKeras

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# Chapter 1: Introduction

Trading in the stock market has gone through tremendous advancements through the use of certain programming rules or predefined algorithms. Whereas the use of algorithms gives edges like decreased expenses, decreased latency, and bereft of emotions, it brings up challenging situations for retail traders because of the inaccessibility of required technologies to shape such systems. As more innovativeness has resulted in the generation of newer Trading algorithms, comparing the effectiveness and accuracy of these algorithms seems to be a daunting task. Trading algorithms might go fine occasionally on back testing in controlled environments; however, live validations are still becoming grim prospect, because of several things like value variations, quiet news, and existing noise. Hence, a feasible solution could be to identify and implement more than a few popular stock evaluation strategies and enforce the best practices in simulated environments (Shah et al., 2019).

The Stock market, as a result of its high volatility, is a new field for researchers, scholars, traders, investors, and companies. The number of Machine-Learning associated techniques that are developed have created the potential to predict the market to an extent (Sonkiya et al., 2021).

An outsized inventory of stock prediction strategies has evolved over the years, though the consistency of the precise prediction overall performance of maximum of these strategies stays debatable. For buying and selling shares via a dealer, there is mostly a fee paid to the dealer for each buy and sale. The rate of commission varies from dealer to dealer; however, it'll almost devour up the income due to the fact the Trading frequency will increase, in spite of brokers being discount brokers (Huang et al., 2021).

The requirement is to overcome the ambiguities of Fundamental and technical evaluation, and additionally the glaring development in the modelling strategies has pushed several researchers to check new strategies for stock value forecasting. An alternative form of collective intelligence has emerged, and new innovative strategies square measure being used for stock price predictions. The mechanisms contain the work of machine learning algorithms for exchange shares analysis and forecast (Rouf et al., 2021).

The previous Chapter discusses the importance of Machine-Learning associated techniques that are developed for investments in the stock market. The chapter discusses that an outsized inventory of stock prediction strategies has evolved over the years and also informs additionally that the glaring development in the modelling strategies has pushed several researchers to check new strategies for stock value forecasting. In the next chapter, some of the available literature will be scanned which would throw light on various related aspects of Machine-Learning methods and other methodologies, and also study and research other related issues which would help assist better in Day trading in Stock Market.

# Chapter 2: Literature Review

The stock market is highly variable and indeterministic due to various parameters impacting price movements in numerous sizes and layers. According to efficient market theory, the market corrects itself, meaning that the current share price represents the appropriate total combined price, which is neither excessively low nor excessively high (Rajkar et al., 2021).

Even though much trading is conducted by algorithms at speeds and a scope that exceed human cognition, humans are not marginalised by but remain a crucial cog in contemporary algorithmic trading .Whereas ultrafast HFT algorithms enhances traders’ ability to seize arbitrage opportunities long before any human would have been able to identify them, machine learning expands the scope of data mining and data processing and thus, enhances the capacity to trawl markets in search of patterns and correlations to exploit (Hansen, 2020).

In its actual work in the practical world, algorithmic trading has made rapid progress in technology, and this has led to an arms-race among participants for acquiring the fastest and most efficient algorithms and machines. As a side effect, increased competition has eroded profits. Regulators have also clamped down on algorithmic trading, following accusations of market manipulation. Market manipulation, once thought of as a predominantly developing market issue has now featured quite prominently in developed countries via AT. One of the outcomes of this scenario is that AT is resorting to high risk strategies in hopes of making profits (Mukerji et al., 2019).

use of fundamental analysis leads to achieving a rate of return above the average market return which affects the effectiveness of investment decisions for traders. in the same direction it concluded that traders Using the fundamental analysis to identify the expected return for companies and to open short positions by selling the shares of companies whose return is expected to decrease in the future and then cover these positions by buying back the shares of these companies (Elbialy, 2019).

Companies must pay attention to the right funding sources to run their business. Both in terms of capital and risk costs so as to minimize the possibility of risks that can hinder the process of investment growth and optimize corporate profits. Companies must be careful in increasing funding sources from debt, although this can be profitable, but on the other hand it can be a big risk if the company fails to pay its obligations, which can cause losses to the company (Anjani & Syarif, 2019).

The efficient market hypothesis confirms that advantages gained by an investor are vulnerable to be neutralized by others when they have access to the same kind of market information. Investors then try to find extra information to help in trading and consider that historical data may provide indications of future price movements (Faijareon & Sornil, 2019).

Technical Analysis might be a trading discipline utilized to check ventures and distinguish trading openings by examining measurable patterns assembled from exchanging action, similar to value moment and volume (Thanekar & Shaikh, 2021).

Fundamental analysis involves economy analysis, industry analysis and company analysis of the stock intended for purchase. Technical analysis involves the employment of several technical indicators like MACD, OBV, Moving average, etc on the past stock market prices. The merits and demerits of each of the tools are also discussed (Kimbonguila et al., 2019).

The expectation of different cryptocurrency like Bitcoin, Ethereum, Litecoin and Ripple digital currency price in examination with the anticipated cost by the volatility regression model effectively and trend indicators before, a great many instatements and gave the forecast in value climb for entire month (Dahham & Ibrahim, 2020).

an increase in the implicit market volatility is the forerunner of a future increment in the synchronization of the returns of the stock markets, which would imply a greater level in the systemic risk and a decrease in the benefits of portfolio diversification as a risk minimization tool. In this sense, from an investor’s point of view, our research helps them monitor one of the factors associated with the synchronization of equity market returns (Magner et al., 2021).

Momentum trading primarily targets early recognition of trading opportunities resulting due to very strong market movement in one or the other direction. The object is to persist with the trend and hold the position as long as the trend continues. Momentum trading is amongst proven investment strategies across major markets(Mohapatra & Misra, 2020).

Some literature has used both supervised and unsupervised machine learning techniques for securities market predictive modelling and located that both kinds of models will create predictions with some accuracy. The assumption is being shared that even machine learning techniques haven't been ready to predict monthly securities market returns with high accuracy and this belief is being reiterated in this paper (Alhomadi, 2021).

There has been an increase in the use of machine learning and artificial intelligence (AI) for the analysis of image-based cellular screens. The accuracy of these analyses, however, is greatly dependent on the quality of the training sets used for building the machine learning models. We propose that unsupervised exploratory methods should first be applied to the data set to gain a better insight into the quality of the data (Omta et al., 2020).

The central idea of PCA is to identify correlations and patterns in a dataset of higher dimensions and reduce it to a significantly lower dimension without loss of any vital information. The need for the PCA technique is because the high dimensionality data is highly complex due to inconsistencies in the features that increase the computation time (Dar, 2021).

The reason for using logistic regression instead of linear regression is due to two reasons : The first reason: The dependent variable is, in linear regression, a continuous variable, while the logistic regression is a discrete variable (Al-Bairmani & Ismael, 2021).

In the decision tree, the hidden rules along with the constraints can be extracted from the data and can be mapped with the nodes and branches of the tree, which makes it more convenient for understanding. However, the complexity of the model increases with the increase in the size of the datasets. To handle the complexity, a wide number of advanced algorithms have been adopted in the field of DT for classification and regression (Jena & Dehuri, 2020).

structure of the DT algorithm consists of several nodes, i.e., root, decision and leaf. The root node initiates the tree while the decision nodes are responsible for decision-making, i.e., switching from one node to another. The leaf nodes act as an output from decision nodes (Hafeez et al., 2021).

Random decision forests easily adapt to nonlinearities found in the data and therefore tend to predict better than linear regression. More specifically, ensemble learning algorithms like random forests are well suited for medium to large datasets (Schonlau & Zou, 2020).

KNN stands for k nearest neighbour classifications, identifying new records by a combination of K's most recent historical records. KNN is a well-known statistical method that has been studied intensively in pattern recognition over the past 40 years (Wang, 2019).

The extreme gradient boosting algorithm XGBoost8 is an ensemble learning algorithm with the advantages of high flexibility, strong predictability, strong generalization ability, high scalability, high model training efficiency, and great robustness. XGBoost has been widely applied for its multitudinous advantages, but its classification effect in the case of data imbalance is often not ideal (Zhang et al., 2022).

several classification metrics can be derived from the confusion matrix in order to evaluate and compare the performance of several machine-learning models. Accuracy is the most used metric in machine-learning problems to determine the precision of a model according to its correctly classified examples and the total size of the dataset. Another useful metric that considers the dataset class distribution is the F1-score. This metric is helpful as it takes false positives and false negatives to determine the performance of a model. In addition, the AUC is used to determine whether a model is capable of differentiating among classes by comparing the rates of false-positive and true-positive instances (Silva & Naranjo, 2020).

At the core of the performance evaluation of different classification algorithms we find the so-called confusion matrix. The confusion matrix is defined as the matrix providing the mix of predicted vs. actual class instances. It allows for the definition of a wide range of performance metrics namely accuracy, precision and recall (Markoulidakis et al., 2021).

The previous chapter discusses all current techniques used to build better Forecasting or Trading Strategies. With all options discussed in the Literature review, still, the volatility of the market is a concern which is being discussed in the next chapter.

# Chapter 3: Problem Statement

Investors are looking at algorithmic trading as an option to reduce volatility. Fundamental analysis is being used for evaluating a share's intrinsic value for long-term investment opportunities. Technical analysis on the other hand assists the traders to evaluate trends in the stock's price, momentum, and volume from a statistical perspective. However, the consistency of the prediction performance of most of these techniques remains debatable and the volatility of the market is still unpredictable. Therefore, it is the constant endeavor of investors to find better, easy, and simple Modelling techniques for forecasting any share’s price for day trading in the stock market. Such a process should also evaluate the degree of risks concerned and minimize the chances of loss with the highest possible accuracy.

# Chapter 4: Objectives of the Study

Based on the problem statement mentioned in the previous chapter, the objectives of the project are as follows.

* Firstly, the objective of this project is to get the right stock and collect all relevant data to make correct forecasting. Understand the data pattern using Exploratory Data Analysis and Hypothesis testing and perform data preparation which enables the production of clean and well-curated info with extra Features addition that results in more sensible and correct model outcomes.
* Secondly, the objective of the project is to start with simple models whose iteration speed would be higher and can be understood easily namely linear regression and decision tree. Then move to something more complex by using multiple other Machine Learning and Deep Learning Techniques.
* Thirdly the objective of the project is to explore some state-of-the-art solutions to minimize prediction errors. For every forecasting Technique, there will be errors, and since the stock market has high volatility, hence the chances of errors are more. Therefore, some standard Error Metrics are being used in this project to measure the error of the forecasting models and quantitatively compare their performances.

# Chapter 5: Project Methodology

The current Chapter will introspect more on the project Methodology that would be implemented and endeavours for continuous improvement that will be taken up while working on the project.

The CRISP-DM framework has been used for the project. The process of CRISP-DM is split into Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment.

Business understanding provides Fundamental and Technical analysis of HDFC stock to demonstrate why the HDFC stock dataset has been used for this project. Data understanding explains the different columns used in the HDFC dataset. Data preparation explains that Handling Missing values, Features Addition and Data Scaling using MinMax Scaler were the steps used for processing the dataset before being used for Modelling. Hypothesis testing, Classification Models, ARIMA Models, and different Regression Models were used in the Data Modelling phase. The data evaluation phase examines the results of different Modelling techniques which were used in the Data Modelling phase. Deployment speaks about developing a front-end API for the deployment Dashboard.

The CRISP-DM may execute in a very not-strict manner (could travel and forth between completely different phases). The arrows indicating the requirement between phases also are vital to one another phase. CRISP-DM itself is not a one-time method. Each method may be a new learning expertise, that new things are being learned throughout the method, and it may trigger alternative business queries (Cornellius Yudha Wijaya, 2021).



Figure 5.1 CRISP-DM Process Diagram

The previous Chapter explains the CRISP-DM framework. The framework comprises 6 different phases. Threads from Business understanding are gathered to more or less get a complete overview and blue wire print of the different consecutive phases of the data mining process.

# Chapter 6: Business Understanding

This chapter helps to determine whether HDFC Bank stock is the right stock which is one of the datasets under consideration for this capstone project. All relevant data is collected and inferences are made using Fundamental and Technical Analysis of HDFC stock. Similar analysis is made for SBI and KOTAK bank stock which are the other two dataset under consideration for this capstone project. The analysis made for SBI and KOTAK bank stock

Has been done in implementation document which can be accessed in the GitHub link as provided in the Appendix section of the report.

## Fundamental Analysis of HDFC stock:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **PARTICULARS** | **JUN 2021** | **SEP 2021** | **DEC 2021** | **MAR 2022** | **JUN 2022** |
| **Quarterly Result (All Figures in Cr.)** | | | | | |
| Net Profit | 7,729.64 | 8,834.31 | 10,342.20 | 10,055.18 | 9,195.99 |
| **Promoters Details** | | | | | |
| Promoters | 25.89 | 25.83 | 25.80 | 25.78 | 25.73 |
| **Investors Details** | | | | | |
| Investors | 74.11 | 74.17 | 74.20 | 74.22 | 74.27 |
| **PARTICULARS** | **MAR 2018** | **MAR 2019** | **MAR 2020** | **MAR 2021** | **MAR 2022** |
| **Profit & Loss (All Figures in Cr. Adjusted EPS in Rs.)** | | | | | |
| Net Profit | 17,486.73 | 21,078.17 | 26,257.32 | 31,116.53 | 36,961.36 |
| Adjusted  EPS (Rs.) | 33.69 | 38.70 | 47.89 | 56.44 | 66.65 |
| **Balance Sheet (All Figures are in Crores.)** | | | | | |
| Total Liabilities | 10,63,934.32 | 12,44,540.69 | 15,30,511.26 | 17,46,870.52 | 20,68,535.05 |
| Total Assets | 10,63,934.32 | 12,44,540.69 | 15,30,511.26 | 17,46,870.52 | 20,68,535.05 |
| **Cashflow (All Figures are in Crores.)** | | | | | |
| Closing Cash | 123,062 | 81,818 | 87,940 | 121,273 | 155,386 |

Table 6.1– Fundamental Analysis of HDFC stock

HDFC Bank’s 52 week high is 1,725 and 52 weeks low is 1,271.60. It is located in India, Bahrain, Hong Kong, and Dubai. It has 6,378 branches,18,620 ATMs and 21,683 banking outlets. It was founded in 1994 and is headquartered in Mumbai, India.

## Technical Analysis of HDFC stock:

For 14 days, if RSI is in the range 25-45 it would mean that HDFC stock is trending downwards, RSI between 45-55 will mean that the HDFC stock indicates sideways movement. it will be trending upwards if RSI is in the range of 55-75. if RSI is below 25, HDFC stock is oversold and RSI more than 75 indicates HDFC stock is overbought. Presently RSI is 58.72 meaning that HDFC stock is moving in an upward trend.

MACD is calculated by subtracting 26 days EMA from 12 days EMA. if the MACD is more than 0 and also greater than 9 days EMA, HDFC stock will be trending upwards. if the MACD is less than 0 and also lesser than 9 days EMA, HDFC stock will trend downwards. Currently, MACD is 18.97 indicating that HDFC stock is showing an upward trend.

For 20 days, the position of the close price for the High-low range will define the Stochastic indicator which determines the momentum in HDFC stock. Stochastic in the range 55-80 will indicate that the stock is trending upwards. Between 45 and 55, it will be in a sideways trend, and in the range 20-45, the HDFC stock will indicate trending downwards. Stochastic above 80 would mean that HDFC stock is overbought and less than 80 will tell that HDFC stock is oversold. Currently Stochastic is 89.62 which means that HDFC stock is overbought and hence the investor should wait for some time so that the Stochastic indicator gives a lesser value.

We can decide how strongly HDFC stock is trending upwards or downwards using ADX. for 14 days, an increasing ADX will indicate HDFC stock trending upwards or downwards very strongly. A decreasing ADX means that no strong trend will exist either upwards or downwards. Currently, HDFC stock ADX is 11.43 meaning it will show a weak upward or downward trend.

Bollinger band is positive and negative standard deviations from SMA. For 20 days, if the close price of HDFC stock moves quite away from a positive standard deviation will mean that HDFC stock is overbought and if the close price of HDFC stock moves away from a negative standard deviation then the HDFC stock will be considered oversold. Currently, the upper band is 1514.69 and the lower band is 1,261.46. The close price of HDFC stock is 1493.05 which means HDFC stock is overbought (moneycontrol, n.d.)**.**

The previous Chapter performed the fundamental and technical analysis of HDFC,KOTAK and SBI stock. The next chapter explains the Data Understanding section of the CRISP-DM framework. The data Understanding section will get a clear understanding of the dataset before data preparation, process, and analysis.

# Chapter 7: Data Understanding

Daily Trading Data of HDFC,KOTAK and SBI Bank from the year 2000 to 2022 is being used for this study. This study uses NSE Data. Following are the details for every column used in the HDFC,KOTAK and SBI dataset:

Name and symbol: This column tell us the corporate name (usually abbreviated) and also the symbol mentioned thereto. Share tables list stocks in alphabetical order symbol-wise, and anybody would like to use them all together in all stock communications.

There are completely different series columns utilized by NSE and BSE Stock exchanges. The dataset under consideration for the project is EQ. It stands for Equity. For this series, intraday commerce is feasible additionally to Delivery Trades.

The previous close nearly always refers to the previous day's final worth of security once the market formally closes for the day. It will apply to a stock, bond, commodity, futures or options contract, market index, or other security.

The opening price is the first trade worth that was recorded throughout the day’s commerce. The high is the highest worth at that a stock is listed during a period. The low is the lowest worth of the period. The previous closing is going to be a consecutive session's opening price.

The last price is the one at which the foremost recent transaction happens. The close is the last commerce worth recording once the market is closed on the day

VWAP may be a technical analysis indicator used on intraday charts that resets at the beginning of each new commerce session. it is a commerce benchmark that represents the typical worth which the security listed throughout the day, based on both volume and worth. Trading Volume shows the number of shares listed for the day, listed in lots of 100 quantities of shares. Share turnover may be an estimation of stock liquidity, calculated by dividing the whole number of shares traded throughout some period by the average number of shares outstanding for the same duration of time.

The previous Chapter explains the HDFC stock-related feature variables that may be used as the independent variables. The close price of the HDFC stock represents the Target or dependent variable utilized in the Modelling algorithms. Different Modelling algorithms are utilized one by one for the target variable which is the close price of the HDFC stock and the findings are being compared in Leader Boards for the Target variable. The next chapter explains the Data Preparation section of our CRISP-DM framework. Within the data preparation section, the data will be cleaned and remodeled before process and analysis.

# Chapter 8: Data Preparation

The HDFC data which is taken from NSE comes with a lot of limitations and that has to be processed which includes the following steps:

**Handling Missing values**: Three of the features’ trades, ‘Deliverable Volume’, and’% Deliverable had quite one hundred periods of missing values therefore those columns need to be dropped as they are having several missing values. Implementing the mean, median, and mode imputation methodology needs to have refrained commonly because those might render values that may introduce bias into the dataset. Second, the strategy solely looks at the variable itself and therefore might come up with values that don't seem to be representative of trends within the dataset.

**Features Addition:** Additionally, computed variables were added to the dataset that for sure would influence stock returns. These are moving averages for rolling periods of seven days,13 days,20 days,100 days, and two hundred days. conjointly enclosed were EMA for seven days,13 days,20 days,100 days, and two hundred days. That's going to be useful in evaluating the securities market returns. one day's previous lag values of volume are also added in the concert of the input feature. The prediction has its uncertainty; however, these indicators have helped monetary economists in the past perceive the longer-term movement of the stock costs. Analysis of the connection between extra added features and securities market returns are explored and therefore the analysis findings indicate that there are key options just like the ones that are embraced in the analysis, which demonstrated the existence of a correlation between those options and stock markets’ returns.

**Data Scaling using MinMax Scaler:** Many machine learning algorithms work higher when features are on a relatively similar scale and close to normally distributed. MinMaxScaler, RobustScaler, StandardScaler, and normalizer are scikit-learn ways to preprocess info for machine learning. The methodology which is needed to be deployed depends on the model kind and feature values.

Data Scaling is a data preprocessing step for numerical variables. several machine learning algorithms like the Gradient descent process, KNN algorithmic rule, linear and logistical regression, etc. need data scaling to supply sensible results. varied scalers are defined for this purpose. The fit(data) methodology is employed to work out the mean and std dev for a given feature so that it will be used further for scaling. The transform(data) methodology is employed to perform scaling using mean and std dev calculated using the fit () methodology. The fit transform () method does both fit and transform.

MinMax Scaler is one of the approaches to data scaling that is being used. Here, the minimum of features is created up to zero, and the most of features are up to one. MinMax Scaler shrinks the data inside the given range, sometimes from zero to one. It transforms data by scaling variables to a given range. It scales the worth to a selected value range while not varying the form of the initial distribution. The previous Chapter is intended on making ready the data to be future-ready for the Model Building processes. the next chapter explains the Data Modelling section of the CRISP-DM framework.

# Chapter 9: Data Modeling

## Classification Modelling on close price:

6-day consecutive closing price for the stock under consideration is being taken. These 6 days consecutive closing prices will be tabulated week on week for the entire dataset and will be utilized as 6 different feature variables for building the classification Model.

The difference between 7th and 8th day Closing price is determined. If the 8th day closing price is seen an increase from the 7th day by 0.7% or more, the direction of the closing price can be made as positive.

If the 8th day closing price is seen a decrease from the 7th day by -0.7% or less, the direction of the closing price can be made as negative. Between -0.7% and 0.7%, the direction of the closing price for the stock under consideration can be treated as sideways.

For data within the 0.7% and -0.7% band, usually the advice to the investor will be to hold on to existing portfolios and wait for the direction of the closing price to show as either negative or positive change. If there is a negative change, usually the advice to the investor will be to not to invest in such a circumstance. If there is a positive change the investor will be suggested to invest.

It is to be determined how many times the positive changes are identified by predicting and how many times positive changes are there in the actual data. This will be utilized to evaluate how many times true positives were detected and how many times the false positives were predicted in the prediction. Similar process to be followed for detecting true negatives and false negatives. Similar process to be followed for detecting true neutrals and false neutrals. Based on prediction accuracy, it can be suggested whether to invest or not to invest to the prospective investor.

Computation is being done to evaluate whether it is positive change, negative change or no change between 7th and 8th day closing price. The rule is being set to determine as to what has to be seen as direction change.0.7% change,1% change and 1.5% change -these are different classes of direction for which rule is being set which is to be followed for computing the direction change as either positive change, negative change or no change.

once it is determined say for example 0.7% change has the best prediction accuracy among all different classes of direction namely 0.7% change,1% change and 1.5% change then the range of consecutive days to be utilized as feature variable is increased to 10 days. Therefore,10-day consecutive closing price for the stock under consideration is being taken. These 10 days consecutive closing prices will be tabulated week on week for the entire dataset and will be utilized as different feature variables for building the classification Model.

Similar process is again repeated for range of consecutive days to be utilized as feature variable increased to 14 days. The prediction accuracy is determined to confirm that say 0.7% change has the best prediction accuracy among all different classes of direction even when range of consecutive days to be utilized as feature variable is increased to 14 days.

## Classification Modelling on Technical Indicators:

Similarly, all technical indicators can be utilized in Technical Analysis to build another sets of classification Models. All different types of technical indicators namely momentum indicators, trend indicators, volatility indicators, volume indicators can be utilized as feature variables based on the input dataset and different classification models can be built to determine their prediction accuracy.

Generally Open price, High price, low price, close price and volume for the stock under consideration will be utilized to derive feature variables from technical indicators. These derived feature variables will then be used as the feature variables to predict the direction of the close price. The Actual direction of the close price is estimated as percentage change of the close price between upper-band +0.5% and lower band -0.5% for all technical indicators-based classification Models. Eight different Classification models based on four different types of technical indicators are being built.

For momentum indicators, Awesome Oscillator Indicator, KAMA Indicator, Percentage Price Oscillator, Percentage Volume Oscillator, ROC Indicator, RSI Indicator, Stochastic Oscillator, TSI Indicator, Ultimate Oscillator, WilliamsR Indicator are being utilized as the feature variables to predict the direction of the closing price and determine the prediction accuracy.

For trend indicators, ADX Indicator, Aroon Indicator, CCI Indicator, Ichimoku Indicator, KST Indicator, MACD, PSAR Indicator, EMA Indicator, WMA Indicator, Vortex Indicator are being utilized as the feature variables to predict the direction of the closing price and determine the prediction accuracy.

For volatility indicators, Average True Range, Bollinger Bands, Donchian Channel, Keltner Channel, Ulcer Index are being used as feature variables. Lower and upper band of these volatility indicators are also utilized as feature variables and the direction of the closing price is predicted to determine what is the prediction accuracy.

For volume indicators, AccDistIndex Indicator, ChaikinMoneyFlow Indicator, EaseOfMovement Indicator, ForceIndex Indicator, MFI Indicator, OnBalanceVolume Indicator, VolumePriceTrend Indicator, VolumeWeightedAveragePrice, NegativeVolumeIndex Indicator, DailyLogReturn Indicator are used as feature variables and the direction of the closing price is predicted as to whether it is positive change, Negative change or Neutral to determine what is the prediction accuracy.

Various Classification models namely Logistic Regression Classifier, Decision Tree Classifier, Random Forest Classifier, K Nearest Neighbours Classifier and XG Boost Classifier is deployed and their prediction accuracy is being compared.

When the majority of the 15 various models or all of them move in the same direction, a choice on whether to invest or not to invest on the stock under consideration must be made. if for example say 10000 is invested in HDFC stock, and say it is predicted as positive change for the next day. The same prediction process is repeated for say 100 times and evaluated how much is the net gain and loss based on that.

The entire process is tried and tested for a different dataset altogether to ensure that Any stock on the stock market can utilise the same procedure to forecast whether to invest or not to invest, which is helpful. Daily Trading Data of SBI and Kotak Mahindra company from the year 2000 to 2022 is being used to repeat the entire process which had been implemented for the HDFC dataset.

The previous chapter focuses on employing various Modelling algorithms to determine the accuracy of the trend prediction. The next chapter speaks about the Data Evaluation phase of the CRISP-DM framework. The Data Evaluation phase is the results of the Data Modelling phase and discusses the Metrics utilized to determine the extent of successes achieved from the different Modelling Algorithms employed on the Target Variable.

# Chapter 10: Data Evaluation

The previous chapter discusses the accuracy of stock prediction using classification models. various Classification Models predict the direction of the close value of HDFC stock and estimate using different error metrics. The Analysis and Results chapter will examine all the results derived from the various models and figure out the best model which has been most successful in minimizing the prediction errors.

## Data Evaluation for HDFC Stock

Direction Detection by 6,10,14 days consecutive closing prices split week on week:

**(0-Negative,1-Neutral,2-Positive)**

#### **RF Classifier**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** |
| percentage change between upper-band +0.7% and lower band -.07% (6 days consecutive closing prices split week on week) | | | | | |
| **0** | **0.91** | **0.81** | **0.86** | **544** | **0.87** |
| **1** | **0.85** | **0.90** | **0.88** | **580** |
| **2** | **0.85** | **0.89** | **0.87** | **547** |
| percentage change between upper-band +0.7% and lower band -.07%  (10 days consecutive closing prices split week on week) | | | | | |
| **0** | **0.87** | **0.86** | **0.87** | **559** | **0.87** |
| **1** | **0.87** | **0.87** | **0.87** | **550** |
| **2** | **0.87** | **0.88** | **0.87** | **561** |
| percentage change between upper-band +0.7% and lower band -.07%  (14 days consecutive closing prices split week on week) | | | | | |
| **0** | **0.80** | **0.77** | **0.79** | **536** | **0.80** |
| **1** | **0.79** | **0.81** | **0.80** | **543** |
| **2** | **0.80** | **0.81** | **0.80** | **590** |
| percentage change between upper-band +1.0% and lower band -.1.0% | | | | | |
| 0 | 0.90 | 0.09 | 0.16 | 425 | 0.53 |
| 1 | 0.50 | 0.97 | 0.66 | 759 |
| 2 | 0.63 | 0.22 | 0.32 | 487 |
| percentage change between upper-band +1.5% and lower band -.1.5% | | | | | |
| 0 | 1.00 | 0.02 | 0.03 | 234 | 0.70 |
| 1 | 0.70 | 1.00 | 0.82 | 1103 |
| 2 | 0.90 | 0.04 | 0.07 | 253 |

Table 10.1– Accuracy Predictions on Direction Detection by 6,10,14 days consecutive closing prices split week on week using RF Classifier Model

From Table 10.1, it can be observed that random forest modelling done for percentage change in close price between upper-band +0.7% and lower band -.0.7% has given considerable efficiency in prediction.

#### **XG Boost Classifier**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** |
| percentage change between upper-band +0.7% and lower band -.07% | | | | | |
| 0 | 0.39 | 0.16 | 0.23 | 384 | 0.40 |
| 1 | 0.43 | 0.61 | 0.51 | 386 |
| 2 | 0.35 | 0.42 | 0.38 | 344 |
| percentage change between upper-band +1.0% and lower band -.1.0% | | | | | |
| 0 | 0.40 | 0.08 | 0.13 | 313 | 0.48 |
| 1 | 0.49 | 0.90 | 0.64 | 521 |
| 2 | 0.37 | 0.14 | 0.20 | 280 |
| percentage change between upper-band +1.5% and lower band -.1.5% | | | | | |
| 0 | 0.42 | 0.05 | 0.08 | 213 | 0.64 |
| 1 | 0.65 | 0.98 | 0.78 | 704 |
| 2 | 0.56 | 0.08 | 0.13 | 197 |

Table 10.2– Accuracy Predictions on Direction Detection by 6,10,14 days consecutive closing prices split week on week using XG Boost Classifier Model

From Table 10.2, it can be observed that logistic regression modelling done for percentage change in close price between upper-band +1.5% and lower band -.1.5% has given the highest efficiency in prediction. However, it predicts only neutral direction with 0.65 precision but its precision for predicting upward or downward trend should have been still better. Hence, **XG Boost** Modelling results can be considered but with caution.

### Go Long Direction Prediction using Technical Indicators

**(0-Non positive,1-Positive):** The direction of the close price is estimated as percentage change of the close price between upper-band +0.5% and lower band -0.5%-if the percentage change of the closing price is more than 0.5%, the direction of the closing price is treated as positive and suitable for long Trading in stock market. Otherwise, the direction of the close price is treated as non-positive and not suitable for long Trading in stock market.

#### **LR Classifier**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** | **Roc AUC score** |
| Volume Indicators as Feature Variables | | | | | |  |
| **0** | **0.90** | **0.99** | **0.94** | **658** | **0.92** | **0.91** |
| **1** | **0.98** | **0.83** | **0.90** | **452** |
| Momentum Indicators as Feature Variables | | | | | |  |
| **0** | **0.79** | **0.84** | **0.81** | **685** | **0.76** | **0.74** |
| **1** | **0.71** | **0.63** | **0.67** | **423** |
| Trend Indicators as Feature Variables | | | | | |  |
| 0 | 0.78 | 0.92 | 0.85 | 679 | 0.80 | 0.76 |
| 1 | 0.83 | 0.59 | 0.69 | 431 |
| volatility Indicators as Feature Variables | | | | | |  |
| 0 | 0.73 | 0.98 | 0.84 | 658 | 0.77 | 0.73 |
| 1 | 0.93 | 0.47 | 0.63 | 452 |

Table 10.3– Go Long Direction Prediction with Technical Indicators as Feature Variables using LR Classifier Model

From Table 10.3, it can be observed that logistic regression modelling done for percentage change in close price between upper-band +0.5% and lower band -.0.5% has given considerably good accuracy score for all technical categories of indicators namely Volume, momentum, trend and volatility. Precision and f1-score are also satisfactory. Recall can be improved further for trend indicators. ROC AUC score has been considerably satisfactory for all technical indicators.

#### **DT Classifier**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** | **Roc AUC score** |
| Volume Indicators as Feature Variables | | | | | |  |
| 0 | 0.75 | 0.87 | 0.81 | 658 | 0.75 | 0.73 |
| 1 | 0.75 | 0.59 | 0.66 | 452 |
| Momentum Indicators as Feature Variables | | | | | |  |
| 0 | 0.75 | 0.82 | 0.78 | 685 | 0.72 | 0.69 |
| 1 | 0.66 | 0.55 | 0.60 | 423 |
| Trend Indicators as Feature Variables | | | | | |  |
| 0 | 0.72 | 0.75 | 0.73 | 679 | 0.66 | 0.64 |
| 1 | 0.57 | 0.53 | 0.55 | 431 |
| volatility Indicators as Feature Variables | | | | | |  |
| 0 | 0.70 | 0.80 | 0.75 | 658 | 0.68 | 0.65 |
| 1 | 0.63 | 0.51 | 0.56 | 452 |

Table 10.4– Go Long Direction Prediction with Technical Indicators as Feature Variables using DT Classifier Model

From Table 10.4, it can be observed that DT modelling done for percentage change in close price between upper-band +0.5% and lower band -.0.5% has given considerably good accuracy score Volume indicators. Recall and accuracy can be improved further for trend and volatility indicators. ROC AUC score has been more than 50% for all technical indicators.

#### **RF Classifier**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** | **Roc AUC score** |
| Volume Indicators as Feature Variables | | | | | |  |
| 0 | 0.82 | 0.96 | 0.89 | 658 | 0.85 | 0.83 |
| 1 | 0.93 | 0.69 | 0.79 | 452 |
| Momentum Indicators as Feature Variables | | | | | |  |
| 0 | 0.75 | 0.90 | 0.82 | 685 | 0.75 | 0.70 |
| 1 | 0.76 | 0.51 | 0.61 | 423 |
| Trend Indicators as Feature Variables | | | | | |  |
| 0 | 0.77 | 0.95 | 0.85 | 679 | 0.80 | 0.75 |
| 1 | 0.87 | 0.56 | 0.68 | 431 |
| volatility Indicators as Feature Variables | | | | | |  |
| 0 | 0.75 | 0.97 | 0.84 | 658 | 0.79 | 0.75 |
| 1 | 0.92 | 0.53 | 0.67 | 452 |

Table 10.5– Go Long Direction Prediction with Technical Indicators as Feature Variables using RF Classifier Model

From Table 10.5, it can be observed that Random Forest modelling done for percentage change in close price between upper-band +0.5% and lower band -.0.5% has given considerably good accuracy score for all technical indicators. Recall and accuracy can be improved further for all especially for predicting upward direction trend. ROC AUC score has been considerably satisfactory for all technical indicators.

#### **KNN Classifier**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** | **Roc AUC score** |
| Volume Indicators as Feature Variables | | | | | |  |
| 0 | 0.61 | 0.89 | 0.72 | 658 | 0.60 | 0.83 |
| 1 | 0.51 | 0.17 | 0.26 | 452 |
| Momentum Indicators as Feature Variables | | | | | |  |
| 0 | 0.68 | 0.87 | 0.76 | 685 | 0.67 | 0.70 |
| 1 | 0.62 | 0.34 | 0.43 | 423 |
| Trend Indicators as Feature Variables | | | | | |  |
| 0 | 0.62 | 0.87 | 0.73 | 679 | 0.60 | 0.75 |
| 1 | 0.45 | 0.16 | 0.24 | 431 |
| volatility Indicators as Feature Variables | | | | | |  |
| 0 | 0.60 | 0.88 | 0.71 | 658 | 0.59 | 0.75 |
| 1 | 0.47 | 0.16 | 0.24 | 452 |

Table 10.6– Go Long Direction Prediction with Technical Indicators as Feature Variables using KNN Classifier Model

From Table 10.6, it can be observed that KNN Classifier modelling done for percentage change in close price between upper-band +0.5% and lower band -.0.5% can be improved further for accuracy score for all technical indicators. ROC AUC score has been considerably satisfactory for all technical indicators.

#### **XG Boost Classifier**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** | **Roc AUC score** |
| Volume Indicators as Feature Variables | | | | | |  |
| 0 | 0.84 | 0.95 | 0.89 | 658 | 0.86 | 0.83 |
| 1 | 0.90 | 0.73 | 0.81 | 452 |
| Momentum Indicators as Feature Variables | | | | | |  |
| 0 | 0.78 | 0.83 | 0.80 | 685 | 0.75 | 0.70 |
| 1 | 0.70 | 0.61 | 0.65 | 423 |
| Trend Indicators as Feature Variables | | | | | |  |
| **0** | **0.81** | **0.92** | **0.86** | **679** | **0.82** | **0.75** |
| **1** | **0.85** | **0.65** | **0.74** | **431** |
| volatility Indicators as Feature Variables | | | | | |  |
| **0** | **0.81** | **0.91** | **0.86** | **658** | **0.82** | **0.75** |
| **1** | **0.84** | **0.69** | **0.76** | **452** |

Table 10.7– Go Long Direction Prediction with Technical Indicators as Feature Variables using XG Boost Classifier Model

From Table 10.7, it can be observed that XG Boost modelling done for percentage change in close price between upper-band +0.5% and lower band -.0.5% has given considerably good accuracy score for all technical categories of indicators namely Volume, momentum, trend and volatility. Precision and f1-score are also satisfactory. Recall can be improved further for trend indicators. ROC AUC score has been considerably satisfactory for all technical indicators.

### Go Short Direction Prediction using Technical Indicators

**(0-Negative,1-non-Negative):** The direction of the close price is estimated as percentage change of the close price between upper-band +0.5% and lower band -0.5%-if the percentage change of the closing price is less than -0.5%, the direction of the closing price is treated as Negative and suitable for Short Trading in stock market. Otherwise, the direction of the close price is treated as non-negative and not suitable for Short Trading in stock market.

#### **LR Classifier**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** | **Roc AUC score** |
| Volume Indicators as Feature Variables | | | | | |  |
| **0** | **0.97** | **0.83** | **0.90** | **399** | **0.93** | **0.91** |
| **1** | **0.91** | **0.99** | **0.95** | **711** |
| Momentum Indicators as Feature Variables | | | | | |  |
| 0 | 0.70 | 0.59 | 0.64 | 394 | 0.76 | 0.73 |
| 1 | 0.79 | 0.86 | 0.82 | 714 |
| Trend Indicators as Feature Variables | | | | | |  |
| **0** | **0.91** | **0.56** | **0.69** | **414** | **0.81** | **0.76** |
| **1** | **0.79** | **0.97** | **0.87** | **696** |
| volatility Indicators as Feature Variables | | | | | |  |
| 0 | 0.89 | 0.44 | 0.59 | 399 | 0.78 | 0.70 |
| 1 | 0.75 | 0.97 | 0.85 | 711 |

Table 10.8– Go Short Direction Prediction with Technical Indicators as Feature Variables using LR Classifier Model

From Table 10.8, it can be observed that LR modelling done for percentage change in close price between upper-band +0.5% and lower band -.0.5% has given considerably good accuracy score for all technical categories of indicators namely Volume, momentum, trend and volatility. Precision and f1-score are also satisfactory. Recall can be improved further for trend indicators. ROC AUC score has been considerably satisfactory for all technical indicators.

#### **DT Classifier**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** | **Roc AUC score** |
| Volume Indicators as Feature Variables | | | | | |  |
| 0 | 0.66 | 0.67 | 0.67 | 399 | 0.76 | 0.74 |
| 1 | 0.81 | 0.81 | 0.81 | 711 |
| Momentum Indicators as Feature Variables | | | | | |  |
| 0 | 0.58 | 0.55 | 0.56 | 394 | 0.70 | 0.66 |
| 1 | 0.76 | 0.78 | 0.77 | 714 |
| Trend Indicators as Feature Variables | | | | | |  |
| 0 | 0.55 | 0.44 | 0.49 | 414 | 0.66 | 0.61 |
| 1 | 0.70 | 0.79 | 0.74 | 696 |
| volatility Indicators as Feature Variables | | | | | |  |
| 0 | 0.56 | 0.43 | 0.49 | 399 | 0.67 | 0.62 |
| 1 | 0.72 | 0.81 | 0.76 | 711 |

Table 10.9– Go Short Direction Prediction with Technical Indicators as Feature Variables using DT Classifier Model

From Table 10.9, it can be observed that DT modelling done for percentage change in close price between upper-band +0.5% and lower band -.0.5% has given considerably good accuracy score for volume and momentum indicators. Precision for predicting downward trend can be further improved. ROC AUC score has been more than 50% for all technical indicators.

#### **RF Classifier**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** | **Roc AUC score** |
| Volume Indicators as Feature Variables | | | | | |  |
| 0 | 0.87 | 0.71 | 0.78 | 399 | 0.85 | 0.82 |
| 1 | 0.85 | 0.94 | 0.89 | 711 |
| Momentum Indicators as Feature Variables | | | | | |  |
| 0 | 0.72 | 0.50 | 0.59 | 394 | 0.75 | 0.70 |
| 1 | 0.76 | 0.89 | 0.82 | 714 |
| Trend Indicators as Feature Variables | | | | | |  |
| 0 | 0.87 | 0.46 | 0.60 | 414 | 0.77 | 0.71 |
| 1 | 0.75 | 0.96 | 0.84 | 696 |
| volatility Indicators as Feature Variables | | | | | |  |
| **0** | **0.88** | **0.55** | **0.68** | **399** | **0.81** | **0.76** |
| **1** | **0.79** | **0.96** | **0.87** | **711** |

Table 10.10– Go Short Direction Prediction with Technical Indicators as Feature Variables using RF Classifier Model

From Table 10.10, it can be observed that RF modelling done for percentage change in close price between upper-band +0.5% and lower band -.0.5% has given considerably good accuracy score for all technical indicators. Recall and accuracy can be improved further for all especially for recalling downward direction trend. ROC AUC score has been considerably satisfactory for all technical indicators.

#### **KNN Classifier**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** | **Roc AUC score** |
| Volume Indicators as Feature Variables | | | | | |  |
| 0 | 0.45 | 0.42 | 0.44 | 399 | 0.61 | 0.82 |
| 1 | 0.69 | 0.71 | 0.70 | 711 |
| Momentum Indicators as Feature Variables | | | | | |  |
| 0 | 0.53 | 0.54 | 0.53 | 394 | 0.66 | 0.70 |
| 1 | 0.74 | 0.73 | 0.74 | 714 |
| Trend Indicators as Feature Variables | | | | | |  |
| 0 | 0.44 | 0.37 | 0.40 | 414 | 0.59 | 0.71 |
| 1 | 0.66 | 0.72 | 0.69 | 696 |
| volatility Indicators as Feature Variables | | | | | |  |
| 0 | 0.44 | 0.43 | 0.43 | 399 | 0.60 | 0.76 |
| 1 | 0.68 | 0.69 | 0.69 | 711 |

Table 10.11– Go Short Direction Prediction with Technical Indicators as Feature Variables using KNN Classifier Model

From Table 10.11, it can be observed that KNN modelling done for percentage change in close price between upper-band +0.5% and lower band -.0.5% can be improved further for accuracy score for all technical indicators. ROC AUC score has been considerably satisfactory for all technical indicators.

#### **XG Boost Classifier**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** | **Roc AUC score** |
| Volume Indicators as Feature Variables | | | | | |  |
| 0 | 0.86 | 0.79 | 0.82 | 399 | 0.88 | 0.82 |
| 1 | 0.89 | 0.93 | 0.91 | 711 |
| Momentum Indicators as Feature Variables | | | | | |  |
| **0** | **0.72** | **0.59** | **0.64** | **394** | **0.77** | **0.70** |
| **1** | **0.79** | **0.87** | **0.83** | **714** |
| Trend Indicators as Feature Variables | | | | | |  |
| 0 | 0.84 | 0.60 | 0.70 | 414 | 0.81 | 0.71 |
| 1 | 0.80 | 0.93 | 0.86 | 696 |
| volatility Indicators as Feature Variables | | | | | |  |
| 0 | 0.79 | 0.64 | 0.71 | 399 | 0.81 | 0.76 |
| 1 | 0.82 | 0.91 | 0.86 | 711 |

Table 10.12– Go Short Direction Prediction with Technical Indicators as Feature Variables using XG Boost Classifier Model

From Table 10.12, it can be observed that XG Boost modelling done for percentage change in close price between upper-band +0.5% and lower band -.0.5% has given considerably good accuracy score for all technical categories of indicators namely Volume, momentum, trend and volatility. Precision and f1-score are also satisfactory. Recall can be improved further for recalling downward trend direction. ROC AUC score has been considerably satisfactory for all technical indicators.

# Chapter 11: Deployment

In the Future, there is a deployment Dashboard proposed. The data pipeline shown below explains the deployment plan to be taken up where the business requirement would be to develop a front-end API as an executable application.



Figure 11.1 Deployment Proposal

As per the proposal for future assignments, the dashboard takes API as an input

Derived from the machine/deep learning algorithms for multi-label features with an end-to-end UI Interface.



Figure 11.2 Illustration of Dashboard

# Chapter 12: Analysis and Results

All the models are now combined and below is the description for the final results.

Analysis for HDFC Stock is given below.

## **Direction Detection by 6,10,14 days consecutive closing prices split week on week**:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** |
| percentage change between upper-band +0.7% and lower band -.07% (6 days consecutive closing prices split week on week) | | | | | |
| **0** | **0.91** | **0.81** | **0.86** | **544** | **0.87** |
| **1** | **0.85** | **0.90** | **0.88** | **580** |
| **2** | **0.85** | **0.89** | **0.87** | **547** |
| percentage change between upper-band +0.7% and lower band -.07%(10 days consecutive closing prices split week on week) | | | | | |
| **0** | **0.87** | **0.86** | **0.87** | **559** | **0.87** |
| **1** | **0.87** | **0.87** | **0.87** | **550** |
| **2** | **0.87** | **0.88** | **0.87** | **561** |
| percentage change between upper-band +0.7% and lower band -.07%(14 days consecutive closing prices split week on week) | | | | | |
| **0** | **0.80** | **0.77** | **0.79** | **536** | **0.80** |
| **1** | **0.79** | **0.81** | **0.80** | **543** |
| **2** | **0.80** | **0.81** | **0.80** | **590** |

Table 12.1– Leader Board-comparison of Metrics for Direction Detection by 6,10,14 days consecutive closing prices split week on week using RF Classifier Model

From Table 12.1, it can be observed that RF modelling done for percentage change in close price between upper-band +0.7% and lower band -.0.7% has given the highest efficiency in prediction among all Modelling techniques namely logistic regression, decision tree, random forest, k nearest neighbours and XG Boost Modelling. It predicts upward, neutral and downward trend direction with reasonably good precision. F1-score combining the precision and recall of a classifier into a single metric is also reasonably good. This has been tested and proven with 6,10- and 14-days consecutive closing prices split week on week as 6,10 and 14 feature variables. Hence, Random Forest Modelling provides a reasonably good modelling technique to be able to provide optimal prediction performance.

### Go Long Direction Prediction using Technical Indicators

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** | **Roc AUC score** |
| Volume Indicators as Feature Variables for Logistic Regression Classifier | | | | | |  |
| **0** | **0.90** | **0.99** | **0.94** | **658** | **0.92** | **0.91** |
| **1** | **0.98** | **0.83** | **0.90** | **452** |
| Momentum Indicators as Feature Variables for  Logistic Regression Classifier | | | | | |  |
| **0** | **0.79** | **0.84** | **0.81** | **685** | **0.76** | **0.74** |
| **1** | **0.71** | **0.63** | **0.67** | **423** |
| Trend Indicators as Feature Variables for  XG Boost Classifier | | | | | |  |
| **0** | **0.81** | **0.92** | **0.86** | **679** | **0.82** | **0.75** |
| **1** | **0.85** | **0.65** | **0.74** | **431** |
| volatility Indicators as Feature Variables for  XG Boost Classifier | | | | | |  |
| **0** | **0.81** | **0.91** | **0.86** | **658** | **0.82** | **0.75** |
| **1** | **0.84** | **0.69** | **0.76** | **452** |

Table 12.2– Leader Board-comparison of Metrics for Go Long Direction Prediction with Technical Indicators as features using Classification Models

From Table 12.2, it can be observed that logistic regression modelling done for percentage change in close price between upper-band +0.5% and lower band -.0.5% has given highest precision, recall, f1-score and accuracy score for volume and momentum indicators whereas XG Boost Classifier provided best prediction performance for trend and volatility indicators.

### Go Short Direction Prediction using Technical Indicators

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Target Variable** | **precision** | **recall** | **f1-score** | **support** | **accuracy score** | **Roc AUC score** |
| Volume Indicators as Feature Variables for  Logistic Regression Classifier | | | | | |  |
| **0** | **0.97** | **0.83** | **0.90** | **399** | **0.93** | **0.91** |
| **1** | **0.91** | **0.99** | **0.95** | **711** |
| Momentum Indicators as Feature Variables for  XG Boost Classifier | | | | | |  |
| **0** | **0.72** | **0.59** | **0.64** | **394** | **0.77** | **0.70** |
| **1** | **0.79** | **0.87** | **0.83** | **714** |
| Trend Indicators as Feature Variables for  Logistic Regression Classifier | | | | | |  |
| **0** | **0.91** | **0.56** | **0.69** | **414** | **0.81** | **0.76** |
| **1** | **0.79** | **0.97** | **0.87** | **696** |
| volatility Indicators as Feature Variables for  Random Forest Classifier | | | | | |  |
| **0** | **0.88** | **0.55** | **0.68** | **399** | **0.81** | **0.76** |
| **1** | **0.79** | **0.96** | **0.87** | **711** |

Table 12.3– Leader Board-comparison of Metrics for Go Short Direction Prediction with Technical Indicators as features using Classification Models

From Table 12.3, it can be observed that logistic regression modelling done for percentage change in close price between upper-band +0.5% and lower band -.0.5% has given highest precision, recall, f1-score and accuracy score for volume and trend indicators whereas XG Boost Classifier provided best prediction performance for momentum indicators. Similarly Random Forest Classifier provided best predictions for volatility indicators.

# Chapter 13: Conclusions and Recommendations for future work

The hypothesis testing rule's percentage accuracy was repeatedly verified using five SMA Models. EMA was used to recreate the five other different models created using SMA. T-test was used to perform hypothesis testing if the sample size for testing was lesser than 30 samples. Z-Test was used to validate null and alternate hypothesis testing for samples larger than 30.

ARIMA Time series modelling was used to create an additional five different models. The construction of all 15 models, was used to forecast day trading in the stock market.

Prediction accuracy was then compared with Classification Model Algorithms. When the majority of the various models or all of them move in the same direction, a choice on whether to purchase or sell the stock must be made.

This project then solely focuses on predicting the close price of the HDFC stock using Regression algorithms deploying both Machine Learning and Deep Learning Techniques.

What works in the Indian stock market must be proven with evidence. Any stock on the stock market can utilize the same procedure to forecast buy or sell choices, which is helpful.

Recommendations for Future Work: it is assumed that returns are more or less constant over time. However, the assumption that the returns are constant over time is restrictive, and not true. Returns are highly dependent on time. This project has not discussed how to address one major drawback of stock prediction, namely that over different periods the stock returns can change drastically to either extremely low returns during stock market crashes or extremely high returns during stock market booming periods. In future projects, it can be shown how to define Bullish and Bearish regimes using modern machine learning techniques. The techniques already discussed in this project will then be used to estimate the direction of close price for each of the Normal and Crash regimes. The Sentiment Analysis Approach may also need to be explored using Text Analytics for predicting stock market returns.

# Bibliography

Al-Bairmani, Z. A. A., & Ismael, A. A. (2021). Using Logistic Regression Model to Study the Most Important Factors Which Affects Diabetes for the Elderly in the City of Hilla / 2019. *Journal of Physics: Conference Series*, *1818*(1). https://doi.org/10.1088/1742-6596/1818/1/012016

Alhomadi, A. (2021). Forecasting stock market prices : A machine learning approach. *Digital Commons*, *11*(2), 16–36.

Anjani, T., & Syarif, A. D. (2019). The Effect of Fundamental Analysis on Stock Returns using Data Panels ; Evidence Pharmaceutical Companies listed on IDX. *International Journal of Innovate Science and Research Technology*, *4*(7), 500–505.

Cornellius Yudha Wijaya. (2021). *CRISP-DM Methodology For Your First Data Science Project*. https://towardsdatascience.com/crisp-dm-methodology-for-your-first-data-science-project-769f35e0346c

Dahham, A. Z. D., & Ibrahim, A. A. (2020). Effects of Volatility and Trend Indicator for Improving Price Prediction of Cryptocurrency. *IOP Conference Series: Materials Science and Engineering*, *928*(3). https://doi.org/10.1088/1757-899X/928/3/032043

Dar, A. N. (2021). PRINCIPAL COMPONENT ANALYSIS (PCA) (Using Eigen Decomposition). *Gsj*, *9*(7), 240–252. www.globalscientificjournal.com

Elbialy, B. A. (2019). The Effect of Using Technical and Fundamental Analysis on the Effectiveness of Investment Decisions of Traders on the Egyptian Stock Exchange. *International Journal of Applied Engineering Research*, *14*(24), 4492–4501. http://www.ripublication.com

Faijareon, C., & Sornil, O. (2019). Evolving and combining technical indicators to generate trading strategies. *Journal of Physics: Conference Series*, *1195*(1). https://doi.org/10.1088/1742-6596/1195/1/012010

Hafeez, M. A., Rashid, M., Tariq, H., Abideen, Z. U., Alotaibi, S. S., & Sinky, M. H. (2021). Performance improvement of decision tree: A robust classifier using tabu search algorithm. *Applied Sciences (Switzerland)*, *11*(15). https://doi.org/10.3390/app11156728

Hansen, K. B. (2020). The virtue of simplicity: On machine learning models in algorithmic trading. *Big Data and Society*, *7*(1). https://doi.org/10.1177/2053951720926558

Huang, Y., Capretz, L. F., & Ho, D. (2021). Machine Learning for Stock Prediction Based on Fundamental Analysis. *2021 IEEE Symposium Series on Computational Intelligence, SSCI 2021 - Proceedings*. https://doi.org/10.1109/SSCI50451.2021.9660134

Jena, M., & Dehuri, S. (2020). Decision tree for classification and regression: A state-of-the art review. *Informatica (Slovenia)*, *44*(4), 405–420. https://doi.org/10.31449/INF.V44I4.3023

Kimbonguila, A., Matos, L., Petit, J., Scher, J., & Nzikou, J.-M. (2019). Effect of Physical Treatment on the Physicochemical, Rheological and Functional Properties of Yam Meal of the Cultivar “Ngumvu” From Dioscorea Alata L. of Congo. *International Journal of Recent Scientific Research*, *10*, 30693–30695. https://doi.org/10.24327/IJRSR

Magner, N., Lavin, J. F., Valle, M., & Hardy, N. (2021). The predictive power of stock market’s expectations volatility: A financial synchronization phenomenon. *PLoS ONE*, *16*(5 May), 1–21. https://doi.org/10.1371/journal.pone.0250846

Markoulidakis, I., Kopsiaftis, G., Rallis, I., & Georgoulas, I. (2021). Multi-Class Confusion Matrix Reduction method and its application on Net Promoter Score classification problem. *ACM International Conference Proceeding Series*, 412–419. https://doi.org/10.1145/3453892.3461323

Mohapatra, S., & Misra, A. K. (2020). Momentum returns: A portfolio-based empirical study to establish evidence, factors and profitability in Indian stock market. *IIMB Management Review*, *32*(1), 75–84. https://doi.org/10.1016/j.iimb.2019.07.007

moneycontrol. (n.d.). *HDFC Bank Ltd.TECHNICALS*. https://www.moneycontrol.com/technical-analysis/hdfcbank/HDF01/weekly

Mukerji, P., Chung, C., Walsh, T., & Xiong, B. (2019). The Impact of Algorithmic Trading in a Simulated Asset Market. *Journal of Risk and Financial Management*, *12*(2), 68. https://doi.org/10.3390/jrfm12020068

Omta, W. A., van Heesbeen, R. G., Shen, I., de Nobel, J., Robers, D., van der Velden, L. M., Medema, R. H., Siebes, A. P. J. M., Feelders, A. J., Brinkkemper, S., Klumperman, J. S., Spruit, M. R., Brinkhuis, M. J. S., & Egan, D. A. (2020). Combining Supervised and Unsupervised Machine Learning Methods for Phenotypic Functional Genomics Screening. *SLAS Discovery*, *25*(6), 655–664. https://doi.org/10.1177/2472555220919345

Rajkar, A., Kumaria, A., Raut, A., & Kulkarni, N. (2021). Stock Market Price Prediction and Analysis. *International Journal of Engineering Research & Technology*, *10*(06), 115–119.

Rouf, N., Malik, M. B., Arif, T., Sharma, S., Singh, S., Aich, S., & Kim, H. C. (2021). Stock market prediction using machine learning techniques: A decade survey on methodologies, recent developments, and future directions. *Electronics (Switzerland)*, *10*(21). https://doi.org/10.3390/electronics10212717

Schonlau, M., & Zou, R. Y. (2020). The random forest algorithm for statistical learning. *Stata Journal*, *20*(1), 3–29. https://doi.org/10.1177/1536867X20909688

Shah, D., Isah, H., & Zulkernine, F. (2019). Stock market analysis: A review and taxonomy of prediction techniques. *International Journal of Financial Studies*, *7*(2). https://doi.org/10.3390/ijfs7020026

Silva, I., & Naranjo, J. E. (2020). A systematic methodology to evaluate prediction models for driving style classification. *Sensors (Switzerland)*, *20*(6), 1–21. https://doi.org/10.3390/s20061692

Sonkiya, P., Bajpai, V., & Bansal, A. (2021). *Stock price prediction using BERT and GAN*. http://arxiv.org/abs/2107.09055

Thanekar, G. S., & Shaikh, Z. S. (2021). Analysis and Evaluation of Technical Indicators for Prediction of Stock Market. *International Journal of Engineering Research & Technology (IJERT)*, *10*(May), 341–344.

Wang, L. (2019). Research and Implementation of Machine Learning Classifier Based on KNN. *IOP Conference Series: Materials Science and Engineering*, *677*(5), 0–5. https://doi.org/10.1088/1757-899X/677/5/052038

Zhang, P., Jia, Y., & Shang, Y. (2022). Research and application of XGBoost in imbalanced data. *International Journal of Distributed Sensor Networks*, *18*(6). https://doi.org/10.1177/15501329221106935

**Appendix**

## Plagiarism Report[[1]](#footnote-1)

## Publications in a Journal/Conference Presented/White Paper[[2]](#footnote-2)

The publication of this work has been planned after the future work of deployment of state-of-the-art API with dashboard.

## Any Additional Details

**The implementation for the capstone project can be accessed at the link below:**

<https://github.com/Embedded-org/ACCOMPLISHMENTS/tree/master/RACE_CAPSTONE_PROJECT2>

1. Turnitin report to be attached from the University. [↑](#footnote-ref-1)
2. URL of the white paper/Paper published in a Journal/Paper presented in a Conference/Certificates to be provided. [↑](#footnote-ref-2)