

Algorithmic Trading Bot and Price Prediction

A major project report submitted in partial fulfillment of the
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in

Computer Science & Engineering / Information Technology

Submitted by

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CERTIFICATE

This is to certify that the work reported in the B.Tech project report entitled “**Algorithmic Trading Bot and Price Prediction**” which is being submitted by **Suraj Gupta & Akhil Shahni** in fulfillment for the award of Bachelor of Technology in Computer Science Engineering by the Jaypee University of Information Technology, is the record of candidate’s own work carried out by him under my supervision. This work is original and has not been submitted partially or fully anywhere else for any other degree or diploma.

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CANDIDATE'S DECLARATION

I hereby declare that the work presented in this report entitled '**Algorithmic Trading Bot and Price Prediction**' in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology in Computer Science & Engineering / Information Technology** submitted in the Department of Computer Science & Engineering and Information Technology, Jaypee University of Information Technology, Waknaghat is an authentic record of my own work carried out over a period from July 2023 to May 2024 under the supervision of **Dr. Amol Vasudeva**, Assistant Professor (Senior Grade), Department of Computer Science & Engineering and Information Technology.

The matter embodied in the report has not been submitted for the award of any other degree or diploma.

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This is to certify that the above statement made by the candidate is true to the best of my knowledge.

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TABLE OF CONTENTS

CONTENT	PAGE NO.
CERTIFICATE	i
CANDIDATE'S DECLARATION	ii
ACKNOWLEDGEMENT	iii
TABLE OF CONTENTS	iv
LIST OF FIGURES	v-vi
ABSTRACT	vii
CHAPTER 1: INTRODUCTION	1
1.1 Introduction	1
1.2 Problem Statement	2-3
1.3 Objectives	3-4
1.4 Methodology	4-8
CHAPTER 2: LITERATURE REVIEW	9-11
CHAPTER 3: SYSTEM DEVELOPMENT	12-42
3.1 Requirements and Analysis	12-16
3.2 Project Design and Architecture	16
3.3 Data Preparation	17-28
3.4 Implementation	29-42
CHAPTER 4: TESTING	43-52
CHAPTER 5: RESULTS AND EVALUATIONS	53-54
CHAPTER 6: CONCLUSION AND FUTURE SCOPES	55-56
6.1 Conclusion	55
6.2 Future Scope	56
REFERENCES	57-58

LIST OF FIGURES

FIGURE	PAGE NO.
Fig: 1 Kite connect 3.0	5
Fig: 2 Exchange Server Infrastructure	6
Fig: 3 Authentication Workflow	8
Fig: 4 Zerodha trading account	12
Fig: 5 Zerodha developer account	13
Fig: 6 Dedicated environments for Algo development	14
Fig. 7 A very basic flow chart of Algo Trading	16
Fig: 8 Real time representation of MACD indicator	19
Fig: 9 Real time representation of MACD indicator	20
Fig: 10 Real time representation of Bollinger Bands indicator	21
Fig:11 Visualization of Support	24
Fig:12 Visualization of Resistance	25
Fig:13 Doji Candlesticks	26
Fig:14 Hammer Candlesticks	27
Fig:15 Inverted Hammer candlesticks	27
Fig:16 Shooting Star Candlesticks	27
Fig.17 Sign-up interface of KiteConnect API	29
Fig.18 Creating a new app interface of KiteConnect API	29
Fig.19 Test App of KiteConnect API	30
Fig.20 Setting up the environment in Anaconda	30
Fig.21 API key and API secret	31

Fig.22 Login page of TestApp	32
Fig.23 Code snippet to start the execution	33
Fig.24 Holding Details	34
Fig.25 Last traded price	34
Fig.26 Loading all NSE instruments	35
Fig.27 Getting Historical Data	35
Fig.28 Execution of a market order	36
Fig.29 Execution of a bracket order	38
Fig.30 Execution of order	38
Fig.31 Implementation of MACD technical indicator	39
Fig.32 Real time visualization of MACD technical indicator	40
Fig.33 Implementation of Bollinger Band technical indicator	41
Fig.34 Real time visualization of MACD technical indicator	41
Fig.35 Super trend indicator	42
Fig.36. Squaring off	42
Fig.37 Code Snippets	43-52

ABSTRACT

Algorithmic trading has completely changed the face of financial markets allowing for fast implementation of the most complicated projects that would have taken time in the past. The aim of this project is to investigate the practice of Algorithmic Trading that involves the development of complex algorithms for more precise pricing predictions. The main goal is to create a strong and smart business that performs better than the traditional methods. The project uses machine learning and is implemented with an approach that includes comprehensive analysis of historical business data, integration of technical news thinking and combination of financial indicators. The main aim of the project is to create algorithms that can predict future prices and incorporate them into powerful trading strategies to achieve the best results while managing good risk. The methodology used is simple, starting with initial study and collecting various data to create a good framework for further research etc.

A variety of machine learning models, including neural networks, clustering techniques, and regression techniques, have been used to identify patterns and relationships present in a combination of data. These models have undergone extensive training and validation to ensure they are effective in understanding the complexity of business behavior. An important part of this work is good architecture practices, combining the moving average, weakness index and other factors supporting the model, predicting and increasing the accuracy and flexibility of our forecast model to cope with the changing business environment.

Another significant phase is ensuring that recovered procedures have been tested and are analyzed carefully alongside historical information in order to their efficiency. However future adjustments will enhance the algorithm to suit varying businesses. This has nothing to do with estimated costs. It seeks to make a real effect on business practices while applying the algorithmic model faster and better.

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

In financial markets, our project tries to provide a better understanding of the combination of advance technologies and the information-driven strategies. The main aim of this project is to develop an algorithmic bot that connects effortlessly, easily to advanced price prediction models and strategies. This approach aims to redefine and reconstruct traditional trading methods and replace with them the appropriate use of technological advancements of our age.

This need is motivated mainly due to the complexity of the financial markets irrespective of their nature and lack of the appropriate guidance and knowledge about the same. The core concept of algorithmic trading is for its ability to execute complex trades better and faster than human and somehow provide a better end result.

The future aspects of this project are represented by the development of cost estimation model. The main objective will be to give a slight edge to the algorithm by predicting future price movements. This integration will ensure that the bot not only responds to the growing and moving market but adapts to it as well. This step will be very important for traders who plan to stay ahead in terms of knowledge and competitive environment of the financial industry

The main purpose of our project is twofold. First, our goal is to create an algorithmic business that can operate automatically and make decisions about routing information quickly. Second, we want to create a price prediction model that learns from historical market data, constantly updates, and contributes to accurate predictions. The importance of these two goals lies in the integration of algorithmic trading robots and price prediction models that are capable of improving trading results with efficiency, and less risk.

Our work is broad and covers many important topics. We first engage in data analysis to draw conclusions from historical business data. Feature engineering is an additional process to ensure that the marketing bot has all the information it needs to make informed decisions. Predictive modeling depends on many

machine learning algorithms that enable the process to identify complex patterns and patterns in data.

Our project mainly aims at enhancing algorithmic trading through efficient information sharing among businesses in time. This keeps our trading robot updated with the latest information, hence increased responsiveness and intelligent trade decisions we make.

Additionally, we use intense means of risk management. Because of this, risk management is of utmost importance as financial markets tend to be very unstable. Our intention is to develop projects aimed at minimizing risk and sustainability of business continuity.

1.2 PROBLEM STATEMENT

When such challenges in the developed financial markets are considered, there is much more attention and observation required towards the decision-making process, predictive accuracy, and risk management. The Algorithmic Trading Bot and Price Prediction project target these challenges with a focus on the following key problem areas, integrating technical and candlestick analysis:

1. **Technical Analysis Limitations:** Traditional research methods will not be able to capture the complexity of market trends and the patterns. Individuals who are relying on traditional methods of technical analysis and traditional technical indicators face difficulties in adapting to the constantly changing market. The project identifies the need to obtain methods in algorithmic trading that have the ability to adapt to these fluctuations
2. **Candlestick Analysis Complexity:** Candlestick patterns play a major role in obtaining a deep understanding of the moving market trends. However, the changing nature of the candlestick patterns and the large number of patterns available make it very difficult to get used to candlestick analysis. The algorithm aims to solve this situation to an extent with candlestick pattern recognition and taking buy or sell calls according to it
3. **API Connectivity for the Trade Execution:** The quality of the algorithmic trading bot depends on its ability to execute quick trade decisions that are based on the algorithm. An efficient connection with the API ensures that the bot is able to do so as accurately as

possible. We aim to setup this connectivity with good algorithms that stand through all the various exceptions that might occur.

1.3 OBJECTIVES

This section explains us the common purpose and uses of algorithmic trading bots and price prediction techniques used by traders widely.

1.3.1 Primary Objectives:

1. **Development of Automatic Algorithmic Trading Bot:** The main goal of the project is to create an algorithmic trading bot that is designed to operate automatically. This will require the development of the complex algorithms that can analyze and understand the market data also identify the trading opportunities, and buy or sell orders without affecting people. The aim is to improve the business.
2. **Construction of a Robust Price Prediction Model:** This is a project that mainly focuses on strong cost modeling. It employs artificial intelligence and statistics and is meant to compare past market results with current ones for price forecasting in that case. This strategy aims at providing correct information back to algorithmic trading-bots.

1.3.2 Key Features and its Components:

1. **Integration of Technical Indicators:** Algorithmic Trading Bot will apply sophisticated technical analysis methods. Therefore, in order to make better decisions they will need to use sophisticated indicators and soft methods of reading.
2. **Candlestick Pattern Recognition:** This project is all about studying candlestick patterns to predict how the market will behave. It uses special computer programs to understand these patterns and figure out how people are feeling about the market.

3. **Real-time Market Data Integration through APIs:** However, the aim is to ensure that the Algorithmic Trading Bot uses the up-to-date data. Therefore, such APIs should be able to blend effortlessly with real-time market data feeds. This emphasizes that the project should design reliable and secure APIs which will connect with external information sources to enable the making of timely decisions.

1.3.3 Expected Outcomes:

1. **Improving the Trading Efficiency:** The Algorithmic Trading Bot will enhance the trading efficiency and it will be implemented with advanced technical analysis and candlestick pattern recognition. In turn, the company is supposed to make timely informed decisions that will optimize the entry and exit points for maximum profitability.
2. **Enhanced Predictive Accuracy:** A Price Prediction Model is used as a powerful tool towards accurate prediction of future price fluctuations. Through the use of machine learning, the model will be able to change according to changing market conditions. Consequently, traders will find it easy to get more accurate market indicators.

In summary, the goals presented in this chapter constitute the pillars of the Algorithmic Trading Bot and Price Prediction project. Incorporating auto trading, predictive modeling, and technical analysis is expected to make the project a leader in novel and other trading approaches.

1.4 METHODOLOGY

In this section, we will explain the approach taken to build algorithmic trading robots and price prediction models, highlighting the integration of Zerodha Kite Connect API as a framework.

Kite Connect is a set of REST-like HTTP APIs that unlock many of the capabilities needed to build a successful business investment and trading platform. It allows you to instantly complete orders (commodities, products, mutual funds), manage user information, publish business information to WebSocket in real time, and more.



Fig: 1 Kite connect 3.0

Trading involves numerous steps and measures and requires us to make decisions at each of the steps individually with respect to that step, using different kind of knowledge that we have through our education, training, experience, etc.

Automated Trading platform may have the following capabilities:

- Algorithm should be able to collect and display historical and real time data feeds of the market.
- Using this data, it should automatically create trading signals and guidelines.
- Consider all the complexities of the market and execute the trades effectively and efficiently without human intervention considering these complexities.

Let's know about the pointers in a simple way. When we want to trade in the Indian market using algorithms, we need to choose a broker. One of the popular brokers is Zerodha, which offers lots of services at good prices. They have different ways for us to see past and current data and to make trades. But if we want to use algorithms, it is best to use the Kite Connect interface. It's a special tool that is provided by Zerodha that lets us build our own business using their data and

tools. Now, let's understand what an API is and how it works.

What is an API?

An API also known as Application programming interface is designed to be used as an interface for developed software products to communicate with each other. It is a compilation of set rules and standards for accessing web-based software applications. Software companies like Amazon, Google, Zerodha etc. make their APIs public so that other software developers can create products from their services.

To understand things better, using the API is like driving a car. Every API comes with a user manual and once you understand and interpret it, you can use it without worrying about how the engine works inside just like any API. You just need to learn about the various or services. This type of integration is called seamless integration because users cannot see when software work is transferred from one application to another.

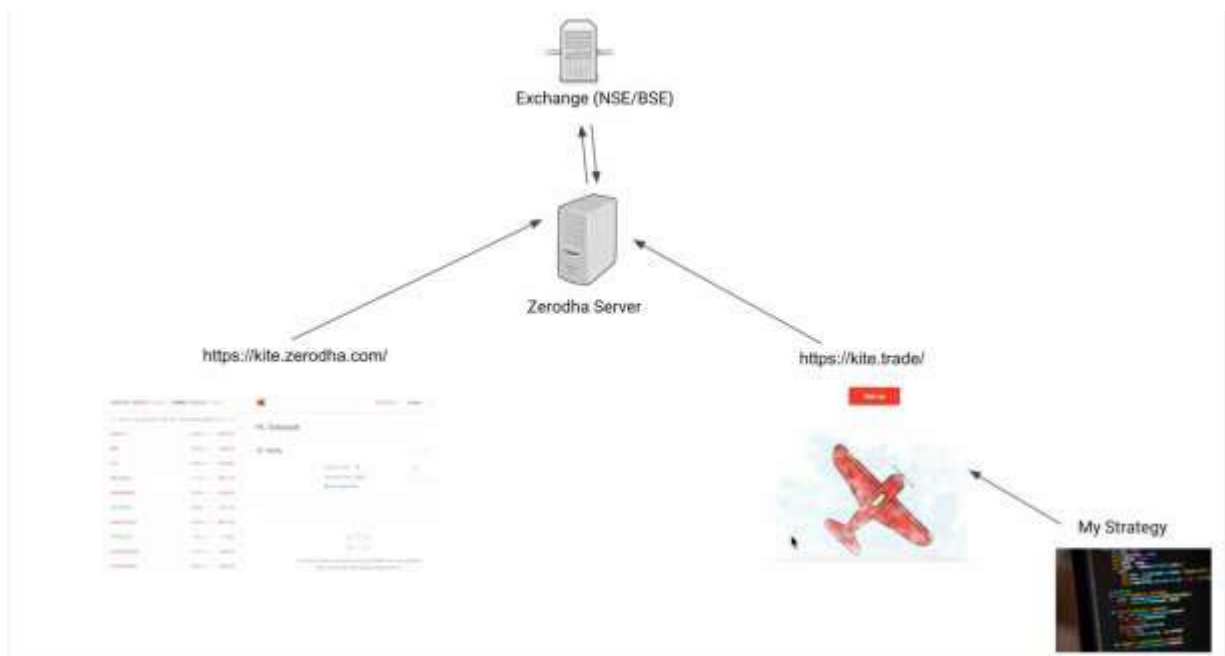


Fig: 2 Exchange Server Infrastructure

Zerodha API is available to retail customers at a monthly fee. For Kite Connect APIs, the retail users or individuals need to pay Rs 2000 per month. These charges do not include access to historical data API. The historical data API is an add-on to the Kite connect available at an additional cost of Rs 2000 per month.

Zerodha API Pricing

Kite Connect API cost - 2000/month Historical

Data API cost - 2000/month

Let's understand the methodology employed in developing the Algorithmic Trading Bot and Price Prediction model, emphasizing the integration of the Zerodha Kite Connect API as a foundational element.

1.4.1 Data Collection and Preparation:

The first stage involves collecting detailed information from financial markets. Collect historical price data, trading volume, and other metrics to establish a basis for analysis. Zerodha Kite Connect API supports the connection of historical business data, providing a solid foundation for the next phase of the project.

1.4.2 Technical Analysis Integration:

We have provided an advanced analysis system to improve the decision-making process of the algorithmic trading robot. We retrieve live market data using Zerodha Kite Connect API and use indicators like Moving Averages, Relative Strength Index (RSI) and Bollinger Bands. The API helps extract new values and packet data important for analysis.

1.4.3 Candlestick Pattern Recognition:

The data of machine learning-based candlestick patterns can be found in this price prediction model. Various models for different candlesticks are trained using data of past prices collected from Zerodha Kite Link API. In real time, this allows the model to be correctly recognized to make its interpretation a remote model through the API instantaneous datastream.

There is a history API that keeps up with data (most recent at the time of access) for different devices. This change has been in the works for several years. The history is displayed as candles (time stamp, open price, high price, low price, close price, traded volume, and open interest) and one can present the information at a different interval of time such as minutes, three minutes, five minutes, and hours, anytime, anyday.

1.4.4 Algorithmic Trading Bot Development:

The main part of the project is the creation of an Algorithmic Trading Bot. The Zerodha Kite Connect API enables the instant execution of buy and sell orders by exploiting the technical analysis findings and forecasts from the Price Prediction Model. A trading bot is configured to autonomously evaluate markets, spot trading opportunities and act upon them by precisely placing trade orders using the Zerodha trading platform.

Authentication workflow - once per day



Fig: 3 Authentication Work

CHAPTER 2

LITERATURE SURVEY

2.1 OVERVIEW OF RELEVANT LITERATURE

Algorithmic trading bots and price prediction are being used a lot in the Indian stock market. These bots use special instructions to make trades faster and more accurately than humans. Price prediction helps traders decide when to buy or sell stocks by using different techniques like looking at past patterns or using computers to learn from data. Zerodha, a company in India, has made a tool called Kite Connect API that helps traders use these bots and make trades easily. People have done studies to see how well these bots and price prediction work in India, and they have found that it can be successful, but it also depends on the specific bot, the market conditions, and how much risk the trader is willing to take.

Evaluating the Performance of Algorithmic Trading and Price Forecasting in Indian Markets:

There is an increasing trend of research into the efficiency of algorithmic trading and price prediction in the Indian markets. A study titled as Algorithmic Trading in Indian Stock Market examines different algorithmic trading strategies used in India. The study tells the importance of algorithm design and market conditions in the performance of algorithmic trading strategies. Another study tells that algorithmic trading can indeed be profitable. However, there is some risk associated that one needs to be aware of.

Kite Connect API: Platform for the algorithmic trading.

The Kite Connect API has been an effective platform for algorithmic trading in the Indian market. It is a very complex trading tool and has a wide feature that includes real time market data, order placement and execution plus portfolio management. It has a user-friendly interface and it works well with various platforms therefore, it is convenient for both individual and institutional investors. Kite Connect API helps traders in their trading by providing information that is very essential for trading.

Technical Analysis:

Technical analysis is amongst the oldest and popular techniques for price prediction. This involves studying the past market prices, the chart patterns to detect the trends and forecast the prices movements in the future. Technical analysts use moving averages, support and resistance levels and a variety of other technical indicators to understand the possible market directions for trading which will help the traders during buying and selling.

Fundamental Analysis:

Whereas technical analysis considers historical data on price, fundamental analysis is a more thorough examination of the company's strengths and weaknesses in order to discover the actual value. It is based on considering different financial ratios like earnings, revenue, the debt levels and the expertise of the management in order to get information about the company's prospects in the future.

Complementary Methods: Technical Analysis and Fundamental Analysis

Technical and fundamental analysis are different but can be used together to get better precision in price predictions. Nevertheless, technical analysis serves as an indication for short-term trading signals whereas fundamental analysis provides a long-term growth prospect of a company. Using the two approaches together, algorithmic trading bots can get an insight of the company's value and trade upon the short-term trading opportunities and long-term investment strategies.

Reinforcement Learning in Algorithmic Trading:

One of the emerging areas in algorithmic trading is called reinforcement learning. Reinforcement learning algorithms learn in doing; interacting with the environment and receiving feedback. In 2019, Li Xucheng and Peng Zhihao proposed a new algorithmic trading model combining artificial intelligent into it. While this study demonstrated the profitability of applying reinforcement learning algorithms towards algorithmic trading, albeit marginal, net profit.

Event-Based Algorithmic Trading:

Ye and Dejun (2018) developed event-based algorithmic trading strategies involving the stock news, earnings reports, and sentiment changes, all leading to stock price motion. According to the authors, they put forward a trading system that applies moving average, searches for candlestick patterns in search of reversal points and places orders automatically. They however stressed on the importance of contingency planning, risk management and the complexity associated therein while accurately predicting the market reaction.

Risks Associated with Algorithmic Trading:

The risks involve regulatory risks, financial risk, reputational risk, operational risk, and technological risk. The ever-changing landscape of algorithmic trading regulatory frameworks constitute regulatory risks. Traders should observe all the legal regulations to be legally safe. Financial risks have their origin from the volatile nature of the stock exchange. In particular, high-frequency trading using algorithmic trading strategies can make losses worse.

Reputational risks may ensue from negative public image and unsanctioned trading activities in algorithmic trading. Therefore, traders should abide by ethical standards and promote transparency so as to guard their reputation. The operational risks include software malfunctions and network outages. Operational risks need to be dealt with by traders using strong risk management practices. In addition, technological risks are related to future developments or obsolescence of the algorithmic trading technologies. In order to remain competent, traders ought to be updated on new technologies all the time.

2.2 KEY GAPS IN THE LITERATURE

1. **Performance Of the Algorithm in Different Market Conditions:** There not enough studies that evaluate the performance and working of algorithmic trading strategies across various different market conditions such as bull market, bear market, or sideways markets.
2. **Impact of Regulatory Changes by the Governing Body:** Further studies are required on how changes and/or modifications in regulatory framework affect the performance of algorithmic trading over the years.

CHAPTER 3

SYSTEM DEVELOPMENT

3.1 REQUIREMENTS AND ANALYSIS

Taking into account technical and operative aspects of Zerodha Kite Connect API for algorithmic trading. Here's a detailed list of requirements to guide the development and deployment of an algorithmic trading system using the Zerodha Kite Connect API:

1. Zerodha Trading Account:

- Have a trading account and use it with Zerodha. Make sure there is adequate money in the account and it's open ready for trading.

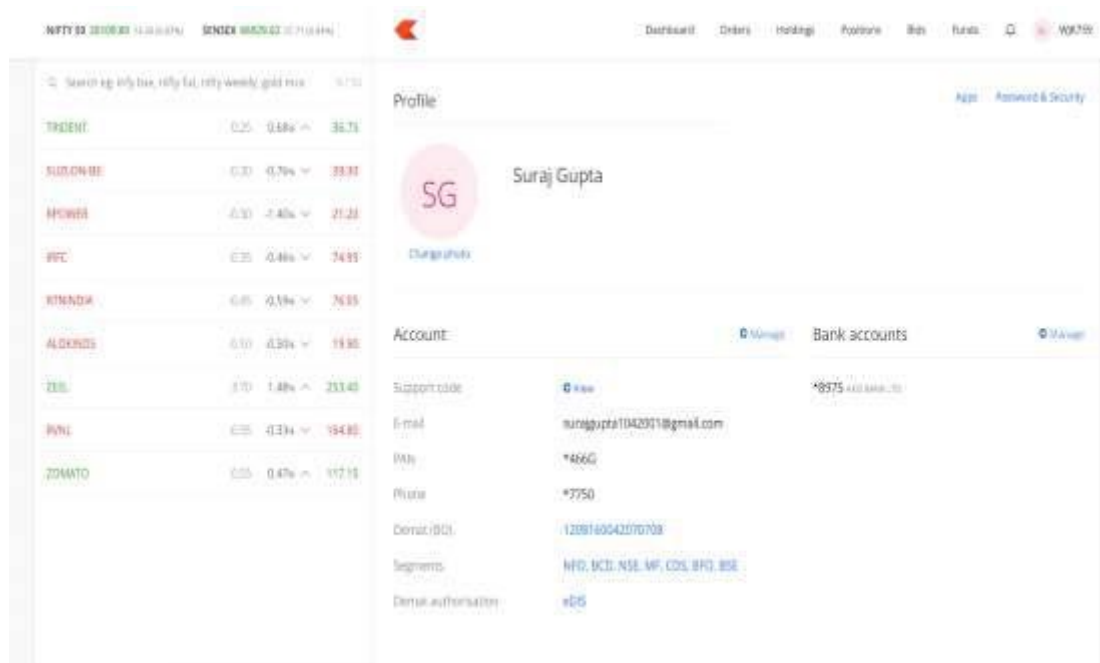


Fig: 4 Zerodha trading account

2. Developer Account and API Key:

- Create a developer account on the Zerodha Developer Portal and generate API keys. The API keys are essential for authenticating requests made to the Kite Connect API.

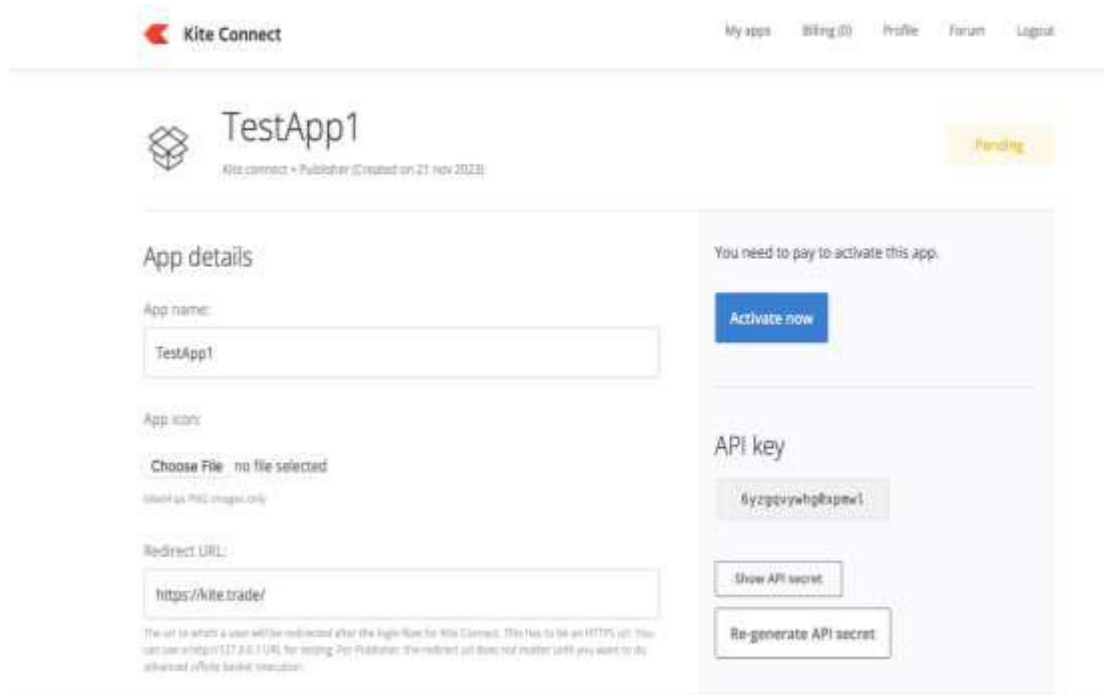


Fig: 5 Zerodha developer account

3. Programming Language and Environment:

- Choose a programming language that is compatible with the Zerodha Kite Connect API. Popular languages like Python, Java, and .NET. Set up the development environment with the necessary libraries and dependencies.

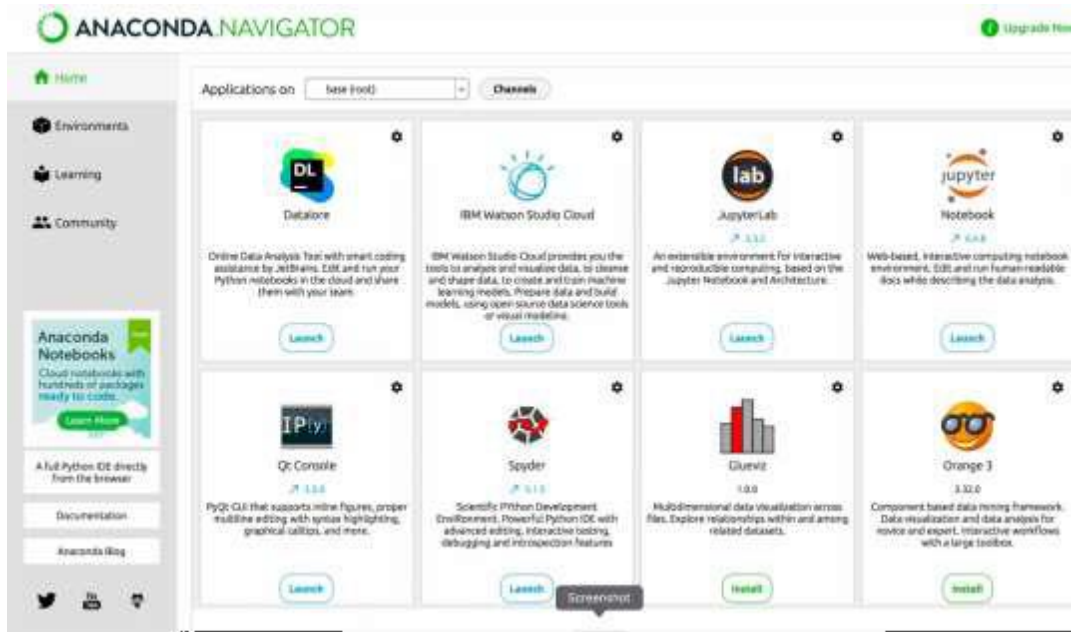


Fig: 6 Dedicated environments for Algo development

4. API Documentation:

- Familiarize yourself with the Zerodha Kite Connect API documentation. Understand the available endpoints, request and response formats, error handling, and any specific nuances of the API.

5. Access to Real-Time Market Data:

- Determine the types of real-time market data needed for your algorithmic trading strategy. This may include live price quotes, order book details, and trade data. Ensure that the Zerodha Kite Connect API provides access to the required data.

6. Historical Data for Backtesting:

- Obtain historical market data for backtesting purposes. After that evaluate the historical data that is provided by the Api for the simulation on the basis of the condition of the past market.

7. Technical Analysis Indicators:

- We have to know the technical analysis indicators that are required for our algorithm. We will check if the Kite connect Api supports the retrieval of the technical indicators for eg - Moving Averages, RSI and the Bollinger Bands.

8. Order Placement and Execution:

- Now for the placement of orders and execution we have to understand the process that how to place and execute orders by using the api. We have to define the order types like market orders, limit orders etc for making the strategy for trading.

9. Web sockets for Streaming of Data:

- As we know that the real time streaming data is very important for trading, we have to make sure that the Kite Connect Api supports Websockets. Websockets will enable the streaming of the live market data and keeps us updated to whether to sell or buy currently.

10. Risk Management Parameters:

- Risk Management parameters are very important in the trading. We have to establish the risk management parameters like position sizing, stop loss etc. Also, we have to understand the risk management strategies that are of real time market.

11. Security Measures:

- Security measures are very important. we have to implement the security measures to protect the sensitive information for eg the Api keys etc. We have to use secure connections like Https and also code safely. Also, the security mechanisms that are being provided to us by the zerodha needs to be followed strictly.

12. Order Status and Account Information:

- Also, we have to ensure that the Api provides us the functionality to check order status, retrieve account information, and monitor portfolio positions. Real time updates are very important for algorithmic trading.

13. Back testing Framework:

- Also, we have to implement a back testing framework to evaluate the performance of our algorithm using the historical data. We have to make sure that the backtesting environment is accurately simulating the real market conditions and providing us the important insights.

By considering these requirements, we can seamlessly integrate the Zerodha Kite Connect API into the algorithmic trading systems, creating a good and efficient platform for executing the automated trading strategies.

3.2 PROJECT DESIGN AND ARCHITECTURE

3.2.1 PROJECT DESIGN:

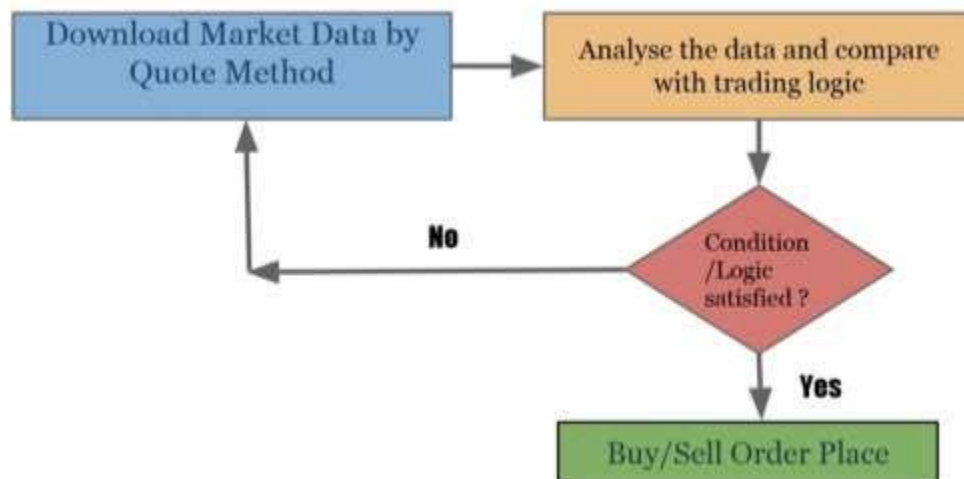


Fig. 7 A very basic flow chart of Algo Trading

3.3 DATA PREPARATION

3.3.1 UNDERSTANDING TECHNICAL INDICATORS

Technical indicators are a term used for technical signals generated from the price, volume or any other property of the security employed by technical analysts. Technical analysts to some extent may rely on historical data and some indicators to predict what the future price movements can be. Technical indicators include things such as the MFI (Money flow index), RSI (Relative strength Index), MACD (Moving average convergence divergence) and Bollinger Bands, Stochastic etc.

How Technical Indicators Work

Technical analysis is a trading practice that involves examining statistical trends derived from trading activity, which includes price movement and volume, in order to evaluate investments and locate trading chances. Technical analysts are different from the fundamental analysts who evaluate a security's intrinsic value using the financial or economic data. They look at prices, trading signals, and other analytical charting tools to gauge whether a security is strong or weak.

Technical analysis applies to any security that has previous trading statistics. This includes stocks, futures, commodities, currencies, corporate bonds, as well as many other securities. In most cases, the analysis will focus on stocks. It should be noted, however, that these principles are applicable to every security. Commodity and forex dealers prefer technical analysis more than those dealing in equities who concentrate on long-term values.

Technical indicators, or “technical,” use historical trading data such as price, volume, and open interest as their focus and are often utilized by active traders. Nevertheless, long-term investors can also use technicals to spot buy and sell opportunities.

Types of Indicators

The two most widely understood types of indicators are:

1. **Oscillators:** Indicators that oscillate about a local minimum and maximum are called oscillators. These are graphed above and below the price chart. For instance, the stochastic oscillator, MACD or RSI.
2. **Overlays:** When stock chart is constructed by plotting technical indicators that have the same scale as the prices at the top of the prices, they are called overlays. They include moving averages and Bollinger Bands.

Let's briefly understand some of the above mentioned and widely used indicators used in the Indian stock market.

3. MACD:

The MACD (Moving average convergence/divergence) is a type of trend following momentum indicator that computes the difference between two EMAs (Exponential Moving Averages) for the prices of a security. In most cases the MACD line is produced from the arithmetic subtraction of the 26 and the 12-period exponential moving averages.

In this scenario, the 9-day EMA of the MACD line serves as the signal line and is set to intersect with the MACD line. The trader may or may not buy security when the MACD line is above the signal line and open short/sell position at the time when the MACD line is below the signal line. The three main components of technical interpretation for the MACD are trend, divergence, and up/down momentum.

MACD Crossovers

As depicted in the chart below, when the MACD flows below the signal line, it is a bearish signal that it may be time to sell the security. On the contrary, the MACD moving above the signal line is a bullish signal and indicates that the asset will continue to gain momentum for a brief period. Some traders will wait for a

clear crossover above the signal line before opening a position to reduce fraud and open the position early.

Crossovers work best when they are on-trend. A positive trend continues when the MACD breaks above the signal line after a short downtrend within a long-term trend.



Fig: 8 Real time representation of MACD indicator



Fig: 9 Real time representation of MACD indicator

4. Bollinger Bands

Technical analysis tool Bollinger Band is defined by a set of trendlines. They may be plotted by two standard deviations either above or below an SMA of a security's price (which can be easily changed by the trader). John Bollinger developed a tool known as Bollinger Bands in order to give investors a higher chance of detecting oversold or overbought assets.

One of the most popular techniques used in the stock-market is Bollinger Bands®. For instance, many traders think that when the prices approach the upper band, the market is overbought while when they go to the lower band, the market is oversold. John Bollinger has a system of 22 rules to follow when dealing with bands as a trading system.

The Squeeze

Bollinger Bands are based on the central concept of “the squeeze”. A squeeze occurs when the bands come together in such a way that they are converging and hence contracting the moving average. It is taken as a sign of low volatility that indicates further increased volatility and possible trade in the future. On the other hand, the bands become wider, the chances of lowering volatility are higher while the chances that one can exit with a trade increase. They are not trading signals under these conditions. These bands do not signify the point of time for the occurrence of the change or in what direction the prices can change.

Breakouts

Price action takes place around 90% between the two bands. Any breakout over or under the bands is significant. Many investors believe that the breakout, which occurs when the security price hits or surpasses one of the bands constitutes a trading signal. There are no predictive values to breakouts as they may result in price increases or decreases, regardless of magnitude.

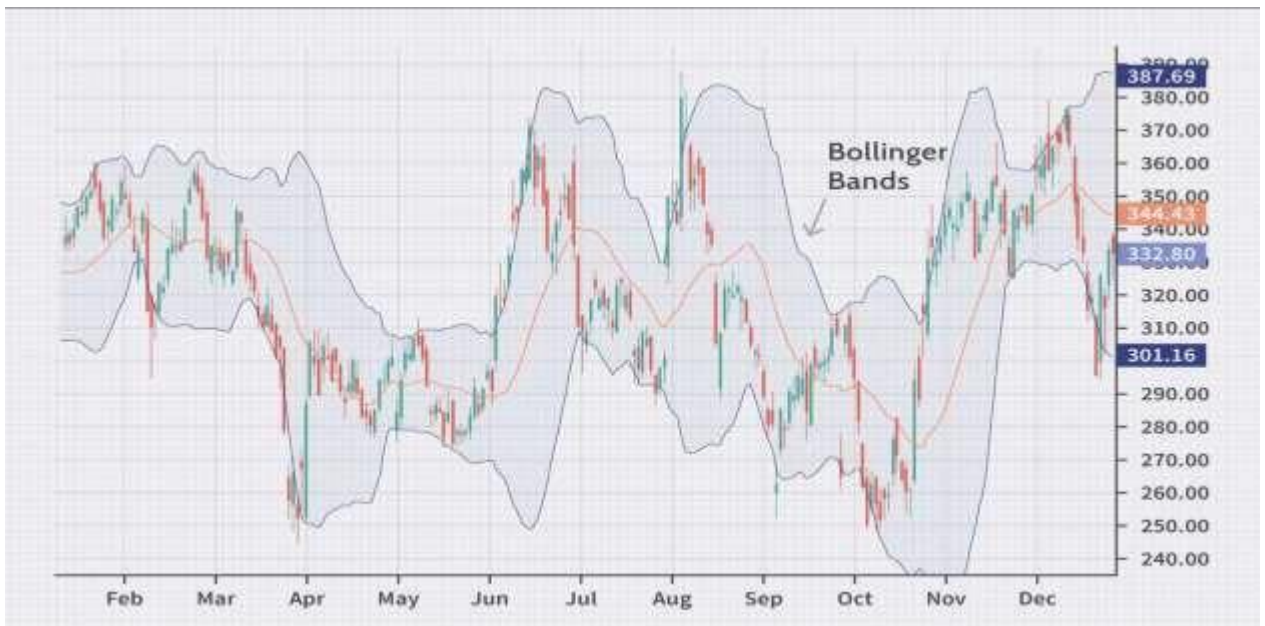


Fig: 10 Real time representation of Bollinger Bands indicator

5. RENKO CHARTS:

Renko charts are a type of trading chart that filter out and remove small price movements so that traders can focus on the larger trend. They are created by something called Renko bricks. The price must move a pre-specified amount only to create a Renko brick properly. When the price is rising or in an uptrend, the Renko bricks are shown in white / green. When the price starts falling or starts a downtrend, the bricks are black / red. This makes it quite easy to spot the direction in which the stock price is moving and changing.

After obtaining much experience, if used correctly, Renko charts can help to eliminate uncertainty based on price direction and can be used into a trend trading strategy.

Here the timeframe on the chart is generally set to one day. This means that new Renko bricks will only form based on the closing price of the day.

3.3.2 UNDERSTANDING THE PRICE ACTION

Price action is referred to the way a stock's price behaves. This movement is mainly analyzed in terms of price movements from the past. Price action trading is a term used to describe trading that allows a trader to interpret and visualize the market and make independent trading decisions with the help of current and actual price movements rather than technical indicators alone.

Price action trading relies on technical analysis tools since it does not focus on the basic analysis criterias and concentrates more on recent and historical price movement.

The trader may use simple price bars, break-outs, price bands, or trend lines as tools and patterns.

Another key aspect of price action trading is trader's psychological and behavioral maturity, interpretations and understandings, and the resulting actions taken by the said trader.

For example, the trader has a personal level of 1000 for a stock. Should a given stock hovering at nearly 980 cross the stipulated level at 1000, the trader assumes a further upward move and takes a long position.

Some other traders on the other hand may have the opposite view of the stock and as soon as the

stock hits 1000, they take a short position as they think that there is a price reversal or correction on the stock.

Every trader will understand the same price action differently according to their respective trading mindset. Every trader has their own meaning, the set of written and unwritten rules, and understanding of the consequences.

Price action trading is a technical type of trading, which is systematic utilizing various technical tools, measures and recent price history of every stock. Such traders are left with more freedom to make various decisions within certain situations. The price action traders take their trading positions subjectively based on their personal analysis, assumptions about behavior, and their psychological state.

3.3.3 SUPPORT AND RESISTANCE BASICS

Support and resistance are the fundamental and the most important concepts in technical analysis. Understanding what these terms really mean and their practical application in live market is essential to correct reading and analysis of the price charts.

What Is Support?

In a downtrend, prices fall due to the surplus of supply, or in simpler words, when supply is greater than the demand. The lower the price of the stock, the more attractive it is to people waiting on the sidelines to buy the stock. To some extent, demand, which was previously growing slowly, will grow to match supply in some time. At this point the price will

stop falling as the demand and supply have attained a temporary balance. This is support. Support lines can be price levels or price zones on the chart.

At this level, sometimes, demand typically exceeds supply, halting and reversing price declines.



Fig:11 Visualization of Support

What Is Resistance?

Resistance is the opposite of what we understood for support. Prices move up because demand exceeds the supply. As prices move higher and higher, there will come a point when selling of the security will overpower the desire to buy. This happens for a variety of reasons. It could be that traders may have analyzed that the prices are too high or have met their target over the time period. It could be the reluctance of buyers to open new positions at such rich valuations or high prices. It could be for any other numbers of reasons. But a technical trader will clearly see a level at which supply begins to overwhelm demand.



Fig:12 Visualization of Resistance

A major component of price action analysis is the understanding and recognizing of candlestick patterns. Let's understand a couple of candlestick patterns and types

1. DOJI CANDLE

In Japanese, “doji” means “the same thing”.

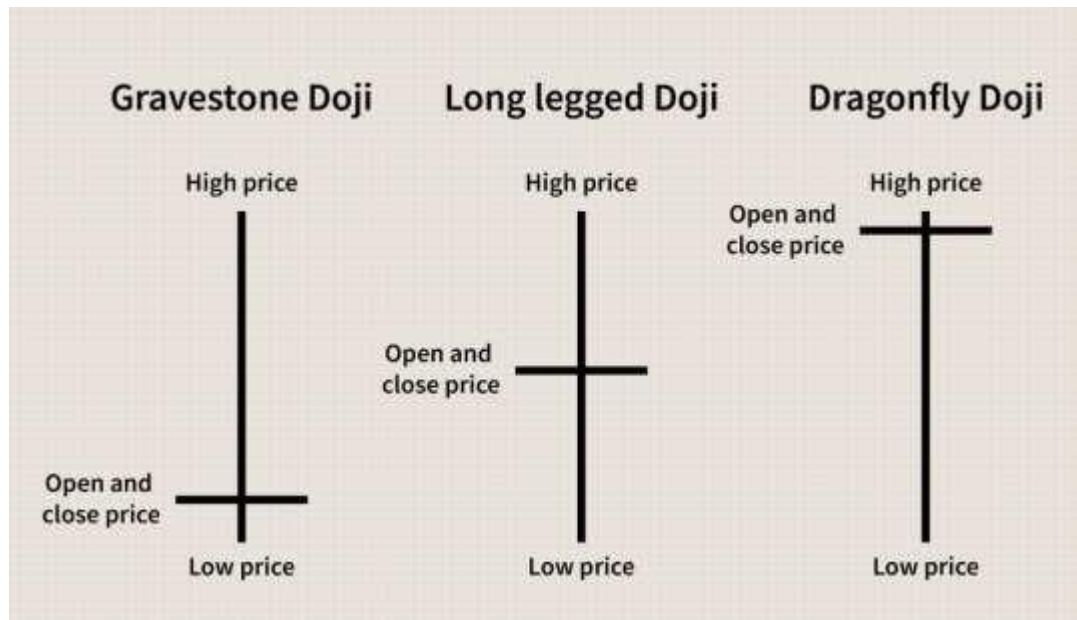


Fig:13 Doji Candlesticks

2. HAMMER CANDLE

A hammer is a candlestick price pattern, which forms when a security trades extremely below the opening price, but rallies within the candle time period and closes near the opening. This pattern creates a candlestick which resembles the shape of a hammer and its lower shadow is at least twice the size of the real body. The candlestick body is the difference between the opening and close prices whereas the shadow reflects high and low prices for the candlestick time-period.

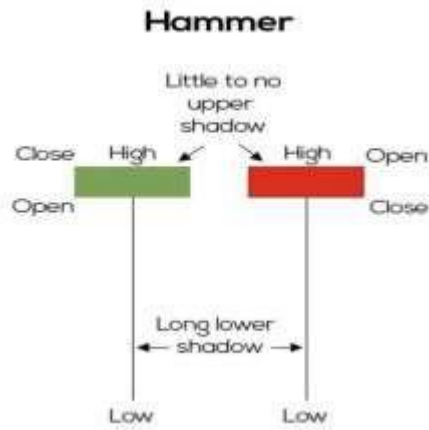


Fig:14 Hammer Candlesticks

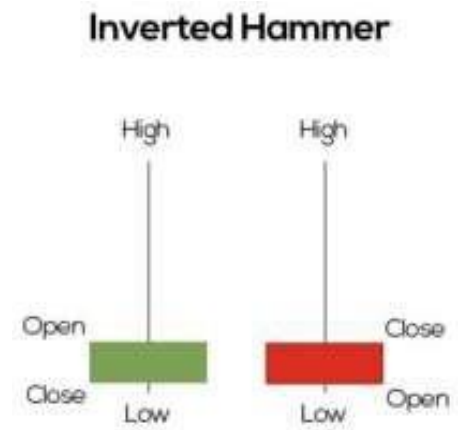


Fig:15 Inverted Hammer candlesticks

3. SHOOTING STAR CANDLE

One of the most common bearish candles is the shooting star that comprises a tall upper shadow, no lower shadow, and a tiny real body close to that day's low. A shooting star comes after an uptrend. It occurs when a security opens, moves up quite significantly, but then closes the day very close to where it opened. A candle to be called a shooting star has to form its pattern in the course of price increase. Secondly, the shooting star's body has to be more than the multiple of the difference between the opening and the highest price of that particular day. The shadow should not extend much beyond the true figure.



Fig:16 Shooting Star Candlesticks

3.3.4 SUPER-TREND INDICATOR:

A common technical analysis tool, super trend indicator helps investors in recognizing market trends. First introduced by Olivier Seban, the indicator is helpful for understanding the direction of momentum the security carries and is widely used when screening and understanding stocks, and commodities. It plots a line on the price chart, which acts as a dynamic level of support or resistance, enabling traders and investors make informed decisions about entry and exit points respectively.

The Supertrend Indicator is quite straightforward. Its line is calculated by adjusting the stocks's closing price with a value derived from multiplying the average true range (ATR), which is a measure of market volatility, and a specified multiplier.

3.3.5 SQUARING OFF:

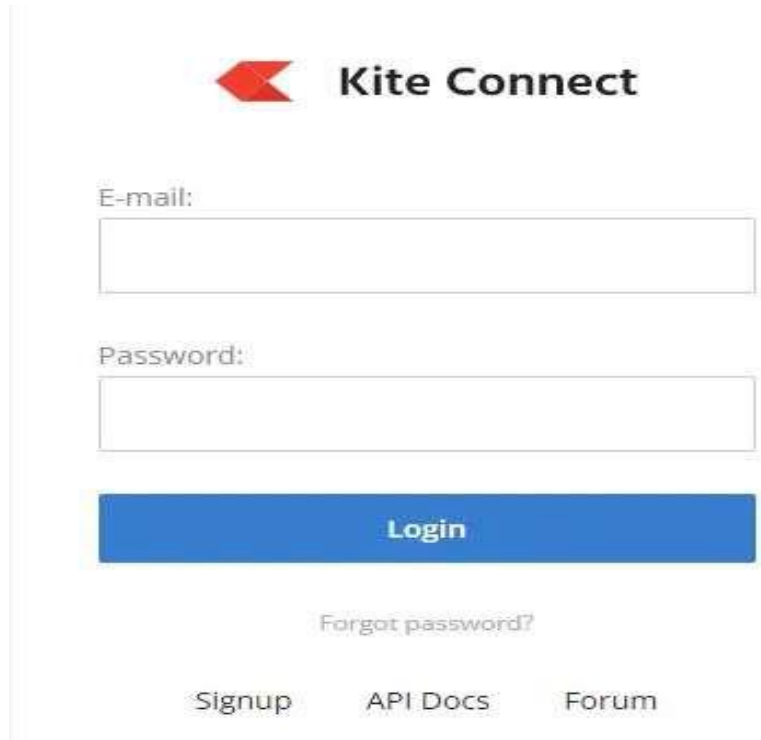
Squaring off is an agreement, where all the shares bought by the investor are entirely sold or “squared off”, generally to make a profit from the change in price at which the shares were bought in the first place. It's also a squared off position when the dealer sells off the stocks at a price, only to buy the same number of shares back at a lower price than before. Squaring off helps to cut down on losses if that's the case or help make gains on the current position.

Intraday trading refers to the session of trading of stocks and other securities on the stock exchange that dealers partake in during the time the session stays open for that particular day. This is carried out by knowledgeable and experienced investors who aim to make profit off of the short-term changes. The square off deals is automated in an intraday trading session, so that if the investors themselves don't square off their holding position, the broker they are using will do it for them. The first position doesn't require the broker to transfer the bought shares to the investor's Demat account, but rather are held until squaring off takes place, following which the gains and losses from the squaring off are transferred to the said demat account.

3.4 IMPLEMENTATION

3.4.3 CREATING KITE CONNECT APP

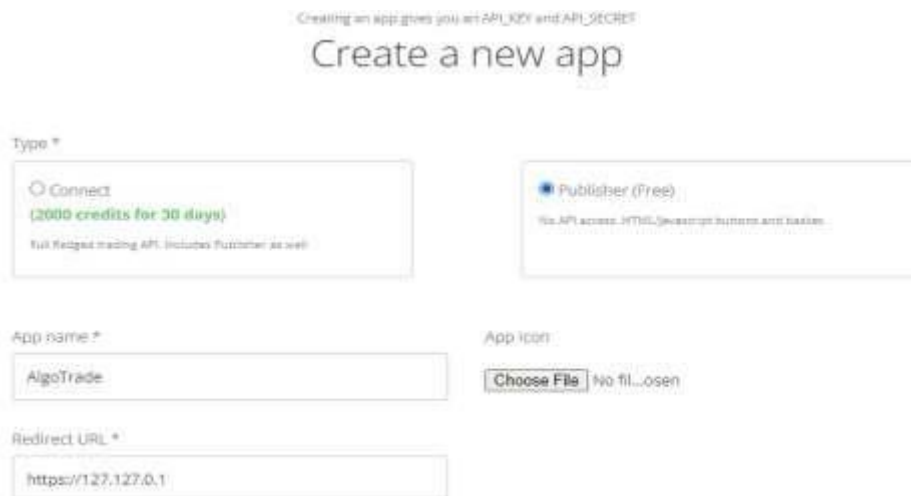
Step 1: Sign up to <https://developers.kite.trade/login> to create a developer account.



The image shows the Kite Connect login/sign-up interface. At the top, there is a red arrow logo followed by the text "Kite Connect". Below the logo, there are two input fields: "E-mail:" and "Password:". A blue "Login" button is positioned below the password field. Underneath the button, there is a link for "Forgot password?". At the bottom of the form, there are three links: "Signup", "API Docs", and "Forum".

Fig.17 Sign-up interface of KiteConnect API

Step 2: Create a new app and subscribe for 30-days to get access to Kite Connect.



The image shows the "Create a new app" interface. At the top, it says "Creating an app gives you an API_KEY and API_SECRET" followed by "Create a new app". Below this, there are two radio button options for "Type *": "Connect (2000 credits for 30 days) Full KiteConnect trading API. Includes Publisher as well." and "Publisher (Free) No API access. HTML/javascript buttons and styles.". Below the "Type" options, there are three input fields: "App name *" with the value "AlgoTrade", "App icon:" with a "Choose File" button and "No file chosen", and "Redirect URL *" with the value "https://127.127.0.1".

Fig.18 Creating a new app interface of KiteConnect API

Step 3: Upon subscribing, you will get your own API Key and API Secret. These two, namely, API key and API secret, will be used to generate the request token and access token.

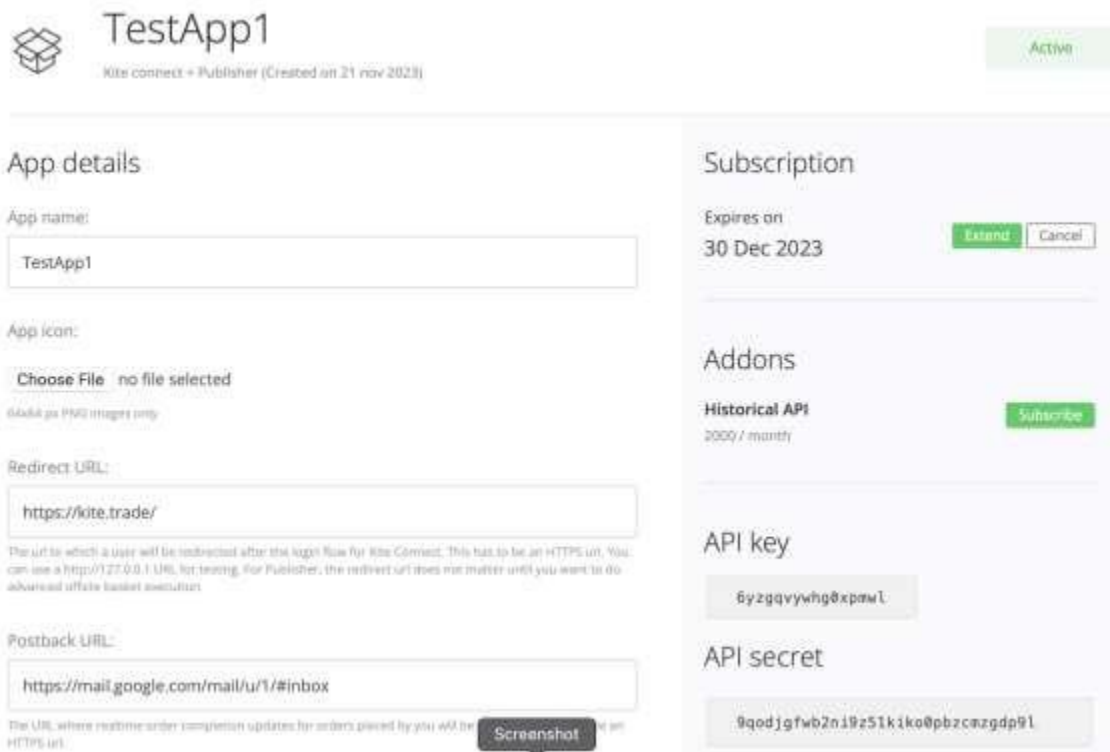


Fig.19 Test App of KiteConnect API

3.4.4 SETTING UP THE ENVIRONMENT TO CODE

Create a new python environment to process all the codes and install all the necessary libraries.

base (root):	Name	Description	Version
kiteconnect:	<input checked="" type="checkbox"/> pandas	High-performance, easy-to-use data structures and data analysis tools.	2.1.1
base (root):	Name	Description	Version
kiteconnect:	<input checked="" type="checkbox"/> kiteconnect		5.0.0
base (root):	Name	Description	Version
kiteconnect:	<input checked="" type="checkbox"/> matplotlib	Publication quality figures in python	3.8.2

Fig.20 Setting up the environment in Anaconda

3.4.5 MANUAL LOGIN PROCESS

User has to log in at least once a day. However, you can still continue using Access Token for the entire day. Generate Access token post 7: 30 AM.

After making your app on the Kite Connect developer console and having obtained the API key and secret, you can use these credentials to connect to the Kite Connect API and perform manual logins for your app's users. Below is a general overview of the process:

1. Obtain API Key and Secret:

Log in to the Kite Connect developer console.

Obtain the API key and secret provided for your app.



Fig.21 API key and API secret

2. Generate Authorization URL:

Use the obtained API key and redirect URL to generate the authorization URL.

Redirect the user to this URL to start the login process.

3. User Authentication:

The user will be directed to log in to their Kite connect account and grant permission for the app to access their account.

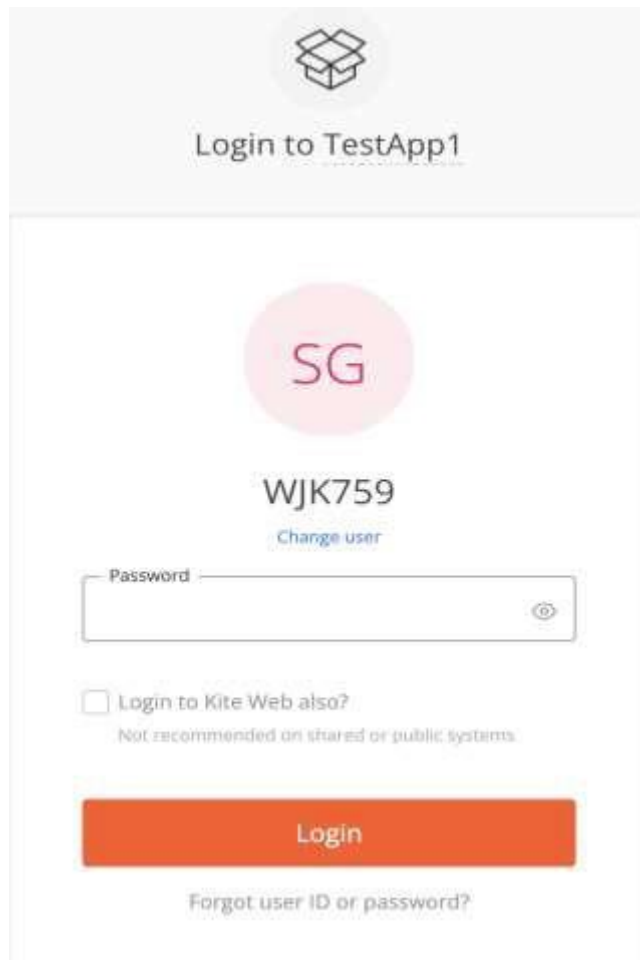


Fig.22 Login page of TestApp

4. Redirect Back to Your App:

After successful authentication, Kite Connect will redirect the user back to the specified redirect URL along with a temporary code.

5. Exchange Code for Access Token:

Your app server should receive the temporary code from the redirect URL and exchange it for an access token by making a POST request to Kite Connect's token endpoint.

Include the API key, secret, and the received code in the request.

6. Store Access Token:

Once you obtain the access token, store it securely. This token will be used to authenticate subsequent requests on behalf of the user.

7. API Requests:

Use the obtained access token to make authenticated API requests to Kite Connect on behalf of the user.

You can fetch market data, place orders, and perform other operations using the Kite Connect API

```
[35]: from kiteconnect import KiteConnect
import pandas as pd

[36]: api_key = "6yzgqvvywhg0xpmwl"
api_secret = "9qodjgfw2ni9z51kiko0pbzcmzgd9l"
kite = KiteConnect(api_key=api_key)
print(kite.login_url())

https://kite.zerodha.com/connect/login?api_key=6yzgqvvywhg0xpmwl&v=3

[37]: kite.set_access_token(data="access_token")

[38]: request_token = "G4XId9U0KtmXKoUKGlxSeSynkVwhw1Jf"
data = kite.generate_session(request_token, api_secret=api_secret)
```

Fig.23 Code snippet to start the execution

Now, we can start implementing and useful API calls on our connected portfolio

3.4.6 BASIC API CALLS

1. Holding Details

A portfolio is a collection of various holdings i.e. the contents held by a single investor or entity such as the mutual fund and the pension fund. Portfolio holdings may consist of many investment instruments like stocks, bonds, mutual funds, options, futures and ETFs (Exchange trading Funds).

```
[58]: # Fetch holding details
holdings = kite.holdings()
holdings_df=pd.DataFrame(holdings)
holdings_df
```

	tradingsymbol	exchange	instrument_token	isin	product	price	quantity	used_quantity	tt_quantity	realised_quantity	...	short_quantity	col
0	ADANIPORTS	BSE	136427780	INE742F01042	CNC	0	35	0	0	35	...	0	
1	ASHOKLEY	BSE	128122116	INE208A01029	CNC	0	100	0	0	100	...	0	
2	AWL	BSE	139125252	INE699HD1024	CNC	0	50	0	0	50	...	0	
3	COALINDIA	BSE	136519172	INE522F01014	CNC	0	150	0	0	150	...	0	
4	EXIDEIND	NSE	173057	INE302AD1020	CNC	0	150	0	0	150	...	0	
5	INFY	BSE	128053508	INE009AD1021	CNC	0	35	0	0	35	...	0	
6	ITC	BSE	128224004	INE154AD1025	CNC	0	100	0	0	100	...	0	
7	LICI	NSE	2426881	INE0J1Y01017	CNC	0	40	0	0	40	...	0	
8	NATIONALUM	BSE	136251908	INE139A01034	CNC	0	100	0	0	100	...	0	
9	RELIANCE	BSE	128083204	INE002AD1018	CNC	0	15	0	0	15	...	0	
10	RVNL	BSE	138918148	INE415G01027	CNC	0	180	0	0	180	...	0	
11	SAIL	NSE	758529	INE114AD1011	CNC	0	140	0	0	140	...	0	
12	SBIN	BSE	128028676	INE062AD1020	CNC	0	55	0	0	55	...	0	
13	TATAMOTORS	BSE	128145924	INE155AD1022	CNC	0	140	0	0	140	...	0	
14	TATAMTRDVR	NSE	4343041	IN9155AD1020	CNC	0	75	0	0	75	...	0	
15	TATAPOWER	NSE	877057	INE245AD1021	CNC	0	135	0	0	135	...	0	
16	TATASTEEL	BSE	128120324	INE081AD1020	CNC	0	292	0	0	292	...	0	

Fig.24 Holding Details

2. Last Trading Price

The final price at which the futures contract was traded. The appearance of the Last Trade Price or LTP depends on the liquidity in the market, based on which the Last Trade Price may occur seconds or even a day ahead.

```
[52]: # Fetch last trading price of an instrument
ltp = kite.ltp("NSE:INFY")
ltp
```

```
[52]: {'NSE:INFY': {'instrument_token': 408065, 'last_price': 1459.6}}
```

Fig.25 Last traded price

3.4.7 LOAD NSE INSTRUMENTS IN THE FORM OF DATAFRAME

```
[39]: instrument_dump = kite.instruments("NSE")
instrument_df = pd.DataFrame(instrument_dump)
instrument_df
```

	instrument_token	exchange_token	tradingsymbol	name	last_price	expiry	strike	tick_size	lot_size	instrument_type	segment	exchange
0	284713	1034	HANGSENG BEES-NAV	HANGSENG BEES-NAV	0.0		0.0	0.00	0	EQ	INDICES	NSE
1	264969	1035	INDIA VIX	INDIA VIX	0.0		0.0	0.00	0	EQ	INDICES	NSE
2	260617	1018	NIFTY 100	NIFTY 100	0.0		0.0	0.00	0	EQ	INDICES	NSE
3	264457	1033	NIFTY 200	NIFTY 200	0.0		0.0	0.00	0	EQ	INDICES	NSE
4	256265	1001	NIFTY 50	NIFTY 50	0.0		0.0	0.00	0	EQ	INDICES	NSE
...
5694	2916865	11394	ZOTA	ZOTA HEALTH CARE	0.0		0.0	0.05	1	EQ	NSE	NSE
5695	7436801	29050	ZUARI	ZUARI AGRO CHEMICALS	0.0		0.0	0.05	1	EQ	NSE	NSE

```
[40]: ltp=kite.ltp('NSE:ALOKINDS')
ltp=ltp['NSE:ALOKINDS']['last_price']
ltp
```

```
[40]: 28
```

Fig.26 Loading all NSE instruments

3.4.8 GETTING HISTORICAL DATA

In general, the following steps will be required of you in order to fetch historical data with the use of the Kite Connect API after creating your app.

1. Authenticate Your App:

Authenticate your app and get the access token through the OAuth 2.0 authorization flow as described in the previous responses.

2. Get Historical Data:

Once you have an access token you can use this for making the historical market data from Kite Connect API.

3. Specify Parameters:

Use the instrument token of the instrument for which you prefer historical data in place of

{instrument_token}. These instrument tokens are available in other API calls or Zerodha instrument dump.

Choose the appropriate time interval to be used for the historical data and replace {interval} with it (e.g., 'day', 'minute', etc.).

```
def instrumentLookup(instrument_df,symbol):
    """Looks up instrument token for a given script from instrument dump"""
    try:
        return instrument_df[instrument_df.tradingsymbol==symbol].instrument_token.values[0]
    except:
        return -1

def fetchOHLC(ticker,interval,duration):
    """extracts historical data and outputs in the form of dataframe"""
    instrument = instrumentLookup(instrument_df,ticker)
    data = pd.DataFrame(kite.historical_data(instrument,dt.date.today()-dt.timedelta(duration), dt.date.today(),interval))
    data.set_index("date",inplace=True)
    return data

fetchOHLC("NIFTY20MAYFUT","5minute",4)
```

Fig.27 Getting Historical Data

3.4.7 PLACING ORDERS USING ALGORITHMS

An order is a set of directions to a broker or brokerage house, asking it to buy or sell securities in a stock account on an investor's behalf. The basic trading unit of a securities market is an order. The orders are normally placed through a phone call or over a trading platform which may now involve more trading systems and algorithms. It is the order execution cycle that follows once the orders have been placed.

There are several categories of orders, from which investors can place the restrictions to the price and time that the order can be executed. These are simply conditional order instructions that can specify a particular price limit (limit order) or dictate the duration the order can remain effective (valid until) as well as order triggers.

Let's discuss two major types of orders:

1. MARKET ORDERS

A market order involves buying and selling a stock at the best price for the market at that time. A market order is typically an execution, but not necessarily at a specified price. Such orders are the best fit when the intention is to execute the trade as quickly as possible. A market order is most appropriate when you think that a stock is correctly valued, when you are sure you want a fill, or when you want immediate execution.

A few important things to remember with market orders: Often, a quote of a stock contains the maximum potential price that buyers are prepared to pay for the stock, the least potential price which sellers are ready to sell the stock for and the last price that the stock was previously sold for. Nevertheless, the last trade price may not be current, especially with respect to less-liquid stocks, where the last trade could have occurred minutes or hours ago. This may also be true in high-speed markets, where stock prices often change dramatically within a short period of time. As such, current bid and offer prices matter more than the last trade price when placing a market order.

In general, market orders should typically be placed when the market is already open. In such a case, a market order would be executed when the market reopens, whose price can be different from the prior close level. Before market sessions there is always the possibility of factors affecting the stock prices like earnings releases, company news, economic data and unforeseen events that impact the entire industry, sector or market all together.

```

45: def placeMarketOrder(symbol,buy_sell,quantity):
    # Place an intraday market order on NSE
    if buy_sell == "buy":
        t_type=kite.TRANSACTION_TYPE_BUY
    elif buy_sell == "sell":
        t_type=kite.TRANSACTION_TYPE_SELL
    kite.place_order(tradingsymbol=symbol,
                    exchange=kite.EXCHANGE_NSE,
                    transaction_type=t_type,
                    quantity=quantity,
                    order_type=kite.ORDER_TYPE_MARKET,
                    product=kite.PRODUCT_MIS,
                    variety=kite.VARIETY_REGULAR)

58: placeMarketOrder("ALOKINDS","buy",1)

59: placeMarketOrder("ALOKINDS","sell",1)

```

Executed orders (2) Q Search[] [Contract note](#) [View history](#) [Download](#)

Time	Type	Instrument	Product	Qty	Avg. price	Status
09:22:02	SELL	ALOKINDS <small>NSE</small>	MIS	1 / 1	19.90	COMPLETE
09:21:14	BUY	ALOKINDS <small>NSE</small>	MIS	1 / 1	20.00	COMPLETE

Fig.28 Execution of a market order

3.4.8 MACD IMPLEMENTATION USING API:

```

def MACD(DF,a,b,c):
    """function to calculate MACD
    typical values a(fast moving average) = 12;
                   b(slow moving average) =26;
                   c(signal line ma window) =9"""
    df = DF.copy()
    df["MA_Fast"]=df["close"].ewm(span=a,min_periods=a).mean()
    df["MA_Slow"]=df["close"].ewm(span=b,min_periods=b).mean()
    df["MACD"]=df["MA_Fast"]-df["MA_Slow"]
    df["Signal"]=df["MACD"].ewm(span=c,min_periods=c).mean()
    df.dropna(inplace=True)
    return df

```

Fig.30 Execution of order

```
[96]: macd=MACD(ohlc, 12, 26, 9)
      macd

[96]:
```

	open	high	low	close	volume	MA_Fast	MA_Slow	MACD	Signal
date									
2023-11-28 12:00:00+05:30	19.95	19.95	19.90	19.90	130444	19.994054	20.051051	-0.056997	-0.042048
2023-11-28 12:05:00+05:30	19.90	20.00	19.90	19.95	185220	19.987257	20.043023	-0.055766	-0.045121
2023-11-28 12:10:00+05:30	19.95	20.00	19.95	19.95	42723	19.981511	20.035672	-0.054161	-0.047099
2023-11-28 12:15:00+05:30	19.95	20.00	19.95	20.00	22969	19.984361	20.032867	-0.048506	-0.047401
2023-11-28 12:20:00+05:30	19.95	20.05	19.95	20.00	115312	19.986772	20.030294	-0.043523	-0.046580
...
2023-11-30 12:30:00+05:30	19.65	19.70	19.65	19.70	61172	19.683716	19.691969	-0.008252	-0.020012
2023-11-30 12:35:00+05:30	19.65	19.70	19.60	19.65	143800	19.678529	19.688860	-0.010331	-0.018076
2023-11-30 12:40:00+05:30	19.65	19.65	19.60	19.60	104233	19.666448	19.682278	-0.015830	-0.017627
2023-11-30 12:45:00+05:30	19.60	19.65	19.60	19.65	63615	19.663917	19.679887	-0.015969	-0.017295
2023-11-30 12:50:00+05:30	19.65	19.65	19.60	19.65	1741	19.661776	19.677673	-0.015897	-0.017016

161 rows x 9 columns

Fig.31 Implementation of MACD technical indicator



Fig.32 Real time visualization of MACD technical indicator

3.4.9 BOLLINGER BANDS IMPLEMENTATION USING API:

```
[99]: def bollBnd(Df,n):
    """function to calculate Bollinger Band"""
    df = Df.copy()
    df["MA"] = df['close'].rolling(n).mean()
    #df["MA"] = df['close'].ewm(span=n,min_periods=n).mean()
    df["BB_up"] = df["MA"] + 2*df['close'].rolling(n).std(ddof=0)
    df["BB_dn"] = df["MA"] - 2*df['close'].rolling(n).std(ddof=0)
    df["BB_width"] = df["BB_up"] - df["BB_dn"]
    df.dropna(inplace=True)
    return df
```



```
[98]: ohlc = fetchOHLC("ALOKINDS","5minute",5)
bollBnd = bollBnd(ohlc,28)
bollBnd
```

```
[98]:
```

	open	high	low	close	volume	MA	BB_up	BB_dn	BB_width
date									
2023-11-28 10:50:00+05:30	20.15	20.20	20.10	20.15	288260	20.1550	20.268578	20.041422	0.227156
2023-11-28 10:55:00+05:30	20.15	20.15	20.10	20.15	37063	20.1575	20.268293	20.046707	0.221585
2023-11-28 11:00:00+05:30	20.15	20.15	20.10	20.15	68523	20.1650	20.249261	20.080739	0.168523
2023-11-28 11:05:00+05:30	20.15	20.15	20.10	20.15	36545	20.1700	20.236332	20.103668	0.132665
2023-11-28 11:10:00+05:30	20.10	20.15	20.10	20.10	14422	20.1675	20.240129	20.094871	0.145258
...
2023-11-30 12:45:00+05:30	19.60	19.65	19.60	19.65	83615	19.6650	19.729031	19.600969	0.128062
2023-11-30 12:50:00+05:30	19.65	19.65	19.60	19.60	35138	19.6625	19.732321	19.592679	0.139642
2023-11-30 12:55:00+05:30	19.65	19.65	19.55	19.60	130283	19.6600	19.734833	19.585167	0.149666
2023-11-30 13:00:00+05:30	19.60	19.60	19.55	19.60	38197	19.6575	19.736715	19.578285	0.158430
2023-11-30 13:05:00+05:30	19.60	19.60	19.55	19.60	139	19.6550	19.738066	19.571934	0.166132

178 rows x 9 columns

Fig.33 Implementation of Bollinger Band technical indicator



Fig.34 Real time visualization of MACD technical indicator

3.4.10 SUPER-TREND INDICATOR:

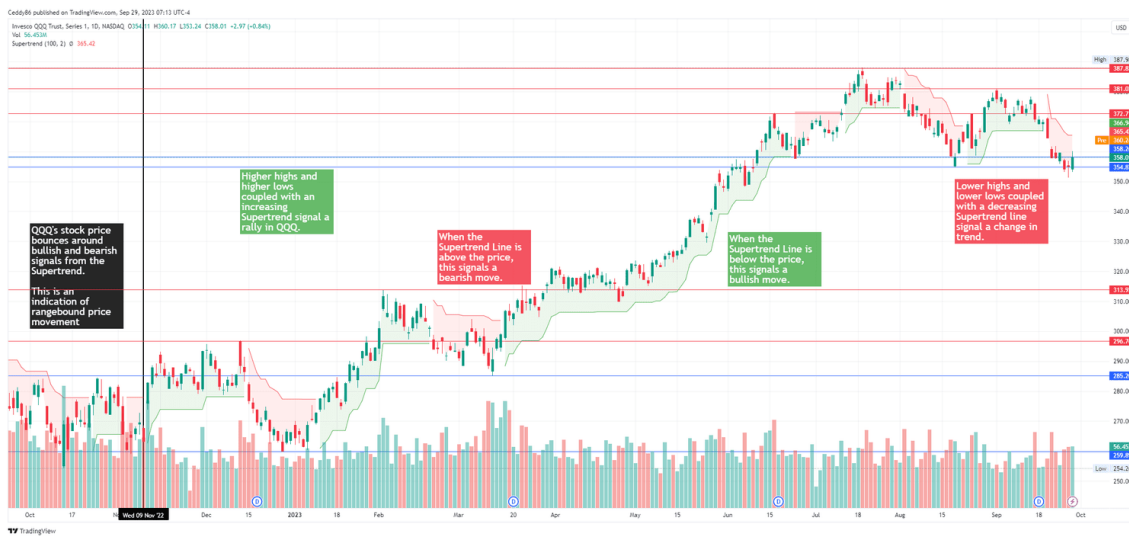


Fig 35. Super-trend indicator

3.4.11 SQUARING OFF POSITIONS:

```

23
24 def placeMarketOrder(symbol,buy_sell,quantity):
25     if buy_sell == "buy":
26         t_type=kite.TRANSACTION_TYPE_BUY
27     elif buy_sell == "sell":
28         t_type=kite.TRANSACTION_TYPE_SELL
29     kite.place_order(tradingsymbol=symbol,
30                     exchange=kite.EXCHANGE_NSE,
31                     transaction_type=t_type,
32                     quantity=quantity,
33                     order_type=kite.ORDER_TYPE_MARKET,
34                     product=kite.PRODUCT_MIS,
35                     variety=kite.VARIETY_REGULAR)
36
37 def CancelOrder(order_id):
38     # Modify order given order id
39     kite.cancel_order(order_id=order_id,
40                       variety=kite.VARIETY_REGULAR)
41 a,b = 0,0
42 while a < 10:
43     try:
44         pos_df = pd.DataFrame(kite.positions()["day"])
45         break
46     except:
47         print("can't extract position data..retrying")
48         a+=1
49 while b < 10:
50     try:
51         ord_df = pd.DataFrame(kite.orders())
52         break
53     except:
54         print("can't extract order data..retrying")
55         b+=1
56 for i in range(len(pos_df)):
57     ticker = pos_df["tradingsymbol"].values[i]
58     if pos_df["quantity"].values[i] >0:
59         quantity = pos_df["quantity"].values[i]
60         placeMarketOrder(ticker,"sell", quantity)
61     if pos_df["quantity"].values[i] <0:
62         quantity = abs(pos_df["quantity"].values[i])
63         placeMarketOrder(ticker,"buy", quantity)
64
65 pending = ord_df[ord_df['status'].isin(["TRIGGER_PENDING","OPEN"])]["order_id"].tolist()
66 drop = []
67 attempt = 0
68 while len(pending)>0 and attempt<5:
69     pending = [j for j in pending if j not in drop]
70     for order in pending:
71         try:
72             CancelOrder(order)
73             drop.append(order)
74         except:
75             print("unable to delete order id : ",order)
76             attempt+=1
77

```

Fig 36. Squaring off

CHAPTER 4

TESTING

4.1 CANDLESTICK PATTERN SCANNER

```
[28]: import time

[29]: def doji(ohlc_df):
    """returns dataframe with doji candle column"""
    df = ohlc_df.copy()
    avg_candle_size = abs(df["close"] - df["open"]).median()
    df["doji"] = abs(df["close"] - df["open"]) <= (0.05 * avg_candle_size)
    return df

def maru_bozu(ohlc_df):
    """returns dataframe with maru bozu candle column"""
    df = ohlc_df.copy()
    avg_candle_size = abs(df["close"] - df["open"]).median()
    df["h-c"] = df["high"] - df["close"]
    df["l-o"] = df["low"] - df["open"]
    df["h-o"] = df["high"] - df["open"]
    df["l-c"] = df["low"] - df["close"]
    df["maru_bozu"] = np.where((df["close"] - df["open"]) > 2*avg_candle_size & \
        (df[["h-c", "l-o"]].max(axis=1) < 0.005*avg_candle_size), "maru_bozu_green",
        np.where((df["open"] - df["close"]) > 2*avg_candle_size & \
        (abs(df[["h-o", "l-c"]]).max(axis=1) < 0.005*avg_candle_size), "maru_bozu_red", False))
    df.drop(["h-c", "l-o", "h-o", "l-c"], axis=1, inplace=True)
    return df

def hammer(ohlc_df):
    """returns dataframe with hammer candle column"""
    df = ohlc_df.copy()
    df["hammer"] = ((df["high"] - df["low"]) > 3*(df["open"] - df["close"])) & \
        ((df["close"] - df["low"]) / (.001 + df["high"] - df["low"]) > 0.6) & \
        ((df["open"] - df["low"]) / (.001 + df["high"] - df["low"]) > 0.6) & \
        (abs(df["close"] - df["open"]) > 0.1 * (df["high"] - df["low"]))

    return df

def shooting_star(ohlc_df):
    """returns dataframe with shooting star candle column"""
    df = ohlc_df.copy()
    df["sstar"] = ((df["high"] - df["low"]) > 3*(df["open"] - df["close"])) & \
        ((df["high"] - df["close"]) / (.001 + df["high"] - df["low"]) > 0.6) & \
        ((df["high"] - df["open"]) / (.001 + df["high"] - df["low"]) > 0.6) & \
        (abs(df["close"] - df["open"]) > 0.1 * (df["high"] - df["low"]))

    return df
```

Fig.37a

```

def candle_pattern(ohlc_df, ohlc_day):
    """returns the candle pattern identified"""
    pattern = None
    signi = "low"
    avg_candle_size = abs(ohlc_df["close"] - ohlc_df["open"]), median()
    sup, res = res_sup(ohlc_df, ohlc_day)

    if (sup - 1.5*avg_candle_size) < ohlc_df["close"][-1] < (sup + 1.5*avg_candle_size):
        signi = "HIGH"

    if (res - 1.5*avg_candle_size) < ohlc_df["close"][-1] < (res + 1.5*avg_candle_size):
        signi = "HIGH"

    if candle_type(ohlc_df) == 'doji' \
        and ohlc_df["close"][-1] > ohlc_df["close"][-2] \
        and ohlc_df["close"][-1] > ohlc_df["open"][-1]:
        pattern = "doji_bullish"

    if candle_type(ohlc_df) == 'doji' \
        and ohlc_df["close"][-1] < ohlc_df["close"][-2] \
        and ohlc_df["close"][-1] < ohlc_df["open"][-1]:
        pattern = "doji_bearish"

    if candle_type(ohlc_df) == "maru_bozu_green":
        pattern = "maru_bozu_bullish"

    if candle_type(ohlc_df) == "maru_bozu_red":
        pattern = "maru_bozu_bearish"

    if trend(ohlc_df.iloc[:1, :], 7) == "uptrend" and candle_type(ohlc_df) == "hammer":
        pattern = "hanging_man_bearish"

    if trend(ohlc_df.iloc[:1, :], 7) == "downtrend" and candle_type(ohlc_df) == "hammer":
        pattern = "hammer_bullish"

    if trend(ohlc_df.iloc[:1, :], 7) == "uptrend" and candle_type(ohlc_df) == "shooting_star":
        pattern = "shooting_star_bearish"

```

Fig.37b

```

def candle_type(ohlc_df):
    """returns the candle type of the last candle of an OHLC DF"""
    candle = None
    if doji(ohlc_df) == True:
        candle = "doji"
    if maru_bozu(ohlc_df) == "maru_bozu_green":
        candle = "maru_bozu_green"
    if maru_bozu(ohlc_df) == "maru_bozu_red":
        candle = "maru_bozu_red"
    if shooting_star(ohlc_df) == True:
        candle = "shooting_star"
    if hammer(ohlc_df) == True:
        candle = "hammer"
    return candle

```

Fig.37c

```

def candle_pattern(ohlc_df, ohlc_day):
    """returns the candle pattern identified"""
    pattern = None
    sign1 = "low"
    avg_candle_size = abs(ohlc_df["close"] - ohlc_df["open"]).median()
    sup, res = res_sup(ohlc_df, ohlc_day)

    if (sup - 1.5*avg_candle_size) < ohlc_df["close"][-1] < (sup + 1.5*avg_candle_size):
        sign1 = "HIGH"

    if (res - 1.5*avg_candle_size) < ohlc_df["close"][-1] < (res + 1.5*avg_candle_size):
        sign1 = "HIGH"

    if candle_type(ohlc_df) == 'doji' \
        and ohlc_df["close"][-1] > ohlc_df["close"][-2] \
        and ohlc_df["close"][-1] > ohlc_df["open"][-1]:
        pattern = "doji_bullish"

    if candle_type(ohlc_df) == 'doji' \
        and ohlc_df["close"][-1] < ohlc_df["close"][-2] \
        and ohlc_df["close"][-1] < ohlc_df["open"][-1]:
        pattern = "doji_bearish"

    if candle_type(ohlc_df) == "maru_bozu_green":
        pattern = "maru_bozu_bullish"

    if candle_type(ohlc_df) == "maru_bozu_red":
        pattern = "maru_bozu_bearish"

    if trend(ohlc_df.iloc[:-1,:],7) == "uptrend" and candle_type(ohlc_df) == "hammer":
        pattern = "hanging_man_bearish"

    if trend(ohlc_df.iloc[:-1,:],7) == "downtrend" and candle_type(ohlc_df) == "hammer":
        pattern = "hammer_bullish"

    if trend(ohlc_df.iloc[i-1,:],7) == "uptrend" and candle_type(ohlc_df) == "shooting_star":
        pattern = "shooting_star_bearish"

```

Fig.37d

```

def main():
    for ticker in tickers:
        try:
            ohlc = fetchOHLC(ticker, '5minute',5)
            ohlc_day = fetchOHLC(ticker, 'day',30)
            ohlc_day = ohlc_day.iloc[:-1,:].
            cp = candle_pattern(ohlc,ohlc_day)
            print(ticker, ":", cp)
        except:
            print("skipping for ", ticker)

# Continuous execution
starttime=time.time()
timeout = time.time() + 60*60*1 # 60 seconds times 60 meaning the script will run for 1 hr.
while time.time() <= timeout:
    try:
        print("passthrough at ", time.strftime('NY-%m-%d %H:%M:%S', time.localtime(time.time())))
        main()
        time.sleep(300 - ((time.time() - starttime) % 300.0)) # 300 second interval between each new execution
    except KeyboardInterrupt:
        print('\n\nKeyboard exception received, Exiting.')
        exit()

```

passthrough at 2023-11-30 15:06:29

Fig.37e

```

if trend(ohlc_df.iloc[:1,:],7) == "uptrend" \
    and candle_type(ohlc_df) == "doji" \
    and ohlc_df["high"][-1] < ohlc_df["close"][-2] \
    and ohlc_df["low"][-1] > ohlc_df["open"][-2]:
    pattern = "harahi_cross_bearish"

if trend(ohlc_df.iloc[:1,:],7) == "downtrend" \
    and candle_type(ohlc_df) == "doji" \
    and ohlc_df["high"][-1] < ohlc_df["open"][-2] \
    and ohlc_df["low"][-1] > ohlc_df["close"][-2]:
    pattern = "harahi_cross_bullish"

if trend(ohlc_df.iloc[:1,:],7) == "uptrend" \
    and candle_type(ohlc_df) != "doji" \
    and ohlc_df["open"][-1] > ohlc_df["high"][-2] \
    and ohlc_df["close"][-1] < ohlc_df["low"][-2]:
    pattern = "engulfing_bearish"

if trend(ohlc_df.iloc[:1,:],7) == "downtrend" \
    and candle_type(ohlc_df) != "doji" \
    and ohlc_df["close"][-1] > ohlc_df["high"][-2] \
    and ohlc_df["open"][-1] < ohlc_df["low"][-2]:
    pattern = "engulfing_bullish"

return "Significance - {}, Pattern - {}".format(signi,pattern)

```

Fig.37f

```

ons is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a val
ue by position, use 'ser.iloc[pos]'
    level = (ohlc_df["close"][-1] + ohlc_df["open"][-1])/2 + (ohlc_df["high"][-1] + ohlc_df["low"][-1])/2)/2
/var/folders/9r/h6xsvkp92dzgh8j5c91qqt00000gn/T/ipykernel_57189/557838254.py:44: FutureWarning: Series.__getitem__ treating keys as positi
ons is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a val
ue by position, use 'ser.iloc[pos]'
    high = round(ohlc_day["high"][-1],2)
/var/folders/9r/h6xsvkp92dzgh8j5c91qqt00000gn/T/ipykernel_57189/557838254.py:45: FutureWarning: Series.__getitem__ treating keys as positi
ons is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a val
ue by position, use 'ser.iloc[pos]'
    low = round(ohlc_day["low"][-1],2)
/var/folders/9r/h6xsvkp92dzgh8j5c91qqt00000gn/T/ipykernel_57189/557838254.py:46: FutureWarning: Series.__getitem__ treating keys as positi
ons is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a val
ue by position, use 'ser.iloc[pos]'
    close = round(ohlc_day["close"][-1],2)
/var/folders/9r/h6xsvkp92dzgh8j5c91qqt00000gn/T/ipykernel_57189/2807705594.py:8: FutureWarning: Series.__getitem__ treating keys as positi
ons is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a val
ue by position, use 'ser.iloc[pos]'
    if (sup - 1.5*avg_candle_size) < ohlc_df["close"][-1] < (sup + 1.5*avg_candle_size):
/var/folders/9r/h6xsvkp92dzgh8j5c91qqt00000gn/T/ipykernel_57189/2807705594.py:11: FutureWarning: Series.__getitem__ treating keys as positi
ons is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a val
ue by position, use 'ser.iloc[pos]'
    if (res - 1.5*avg_candle_size) < ohlc_df["close"][-1] < (res + 1.5*avg_candle_size):
/var/folders/9r/h6xsvkp92dzgh8j5c91qqt00000gn/T/ipykernel_57189/557838254.py:89: FutureWarning: Series.__getitem__ treating keys as positi
ons is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a val
ue by position, use 'ser.iloc[pos]'
    if doji(ohlc_df)[:-1] == True:
skipping for RELAXO
passthrough at 2023-11-30 15:11:29

```

Fig.37g: Code Snippets

4.2 SUPER-TREND STRATEGY IMPLEMENTATION:

```

def fetchOHL(ticker, interval, duration):
    """extracts historical data and outputs in the form of dataframe"""
    instrument = instrumentLookup(instrument_df, ticker)
    data = pd.DataFrame(kite.historical_data(instrument, dt.date.today()-dt.timedelta(duration), dt.date.today(), interval))
    data.set_index("date", inplace=True)
    return data

def atr(DF, n):
    "function to calculate True Range and Average True Range"
    df = DF.copy()
    df['H-L'] = abs(df['high'] - df['low'])
    df['H-PC'] = abs(df['high'] - df['close'].shift(1))
    df['L-PC'] = abs(df['low'] - df['close'].shift(1))
    df['TR'] = df[['H-L', 'H-PC', 'L-PC']].max(axis=1, skipna=False)
    df['ATR'] = df['TR'].ewm(com=n, min_periods=n).mean()
    return df['ATR']

def supertrend(DF, n, m):
    """function to calculate Supertrend given historical candle data
    n = n day ATR - usually 7 day ATR is used
    m = multiplier - usually 2 or 3 is used"""
    df = DF.copy()
    df['ATR'] = atr(df, n)
    df['B-U'] = (df['high'] + df['low']) / 2 + m * df['ATR']
    df['B-L'] = (df['high'] + df['low']) / 2 - m * df['ATR']
    df['U-B'] = df['B-U']
    df['L-B'] = df['B-L']
    ind = df.index
    for i in range(n, len(df)):
        if df['close'][i-1] <= df['U-B'][i-1]:
            df.loc[ind[i], 'U-B'] = min(df['B-U'][i], df['U-B'][i-1])
        else:
            df.loc[ind[i], 'U-B'] = df['B-U'][i]
    for i in range(n, len(df)):
        if df['close'][i-1] >= df['L-B'][i-1]:
            df.loc[ind[i], 'L-B'] = max(df['B-L'][i], df['L-B'][i-1])
        else:
            df.loc[ind[i], 'L-B'] = df['B-L'][i]

```

Fig.37g

```

df['Strend'] = np.nan
for test in range(n, len(df)):
    if df['close'][test-1] <= df['U-B'][test-1] and df['close'][test] > df['U-B'][test]:
        df.loc[ind[test], 'Strend'] = df['L-B'][test]
        break
    if df['close'][test-1] >= df['L-B'][test-1] and df['close'][test] < df['L-B'][test]:
        df.loc[ind[test], 'Strend'] = df['U-B'][test]
        break
for i in range(test+1, len(df)):
    if df['Strend'][i-1] == df['U-B'][i-1] and df['close'][i] <= df['U-B'][i]:
        df.loc[ind[i], 'Strend'] = df['U-B'][i]
    elif df['Strend'][i-1] == df['U-B'][i-1] and df['close'][i] > df['U-B'][i]:
        df.loc[ind[i], 'Strend'] = df['L-B'][i]
    elif df['Strend'][i-1] == df['L-B'][i-1] and df['close'][i] >= df['L-B'][i]:
        df.loc[ind[i], 'Strend'] = df['L-B'][i]
    elif df['Strend'][i-1] == df['L-B'][i-1] and df['close'][i] <= df['L-B'][i]:
        df.loc[ind[i], 'Strend'] = df['U-B'][i]
return df['Strend']

def st_dir_refresh(ohlc, ticker):
    """function to check for supertrend reversal"""
    global st_dir
    if ohlc["st1"][-1] > ohlc["close"][-1] and ohlc["st1"][-2] < ohlc["close"][-2]:
        st_dir[ticker][0] = "red"
    if ohlc["st2"][-1] > ohlc["close"][-1] and ohlc["st2"][-2] < ohlc["close"][-2]:
        st_dir[ticker][1] = "red"
    if ohlc["st3"][-1] > ohlc["close"][-1] and ohlc["st3"][-2] < ohlc["close"][-2]:
        st_dir[ticker][2] = "red"
    if ohlc["st1"][-1] < ohlc["close"][-1] and ohlc["st1"][-2] > ohlc["close"][-2]:
        st_dir[ticker][0] = "green"
    if ohlc["st2"][-1] < ohlc["close"][-1] and ohlc["st2"][-2] > ohlc["close"][-2]:
        st_dir[ticker][1] = "green"
    if ohlc["st3"][-1] < ohlc["close"][-1] and ohlc["st3"][-2] > ohlc["close"][-2]:
        st_dir[ticker][2] = "green"

```

Fig.37h

```

def sl_price(ohlc):
    """function to calculate stop loss based on supertrends"""
    st = ohlc.iloc[-1,[-3,-2,-1]]
    if st.min() > ohlc["close"][-1]:
        sl = (0.6*st.sort_values(ascending = True)[0]) + (0.4*st.sort_values(ascending = True)[1])
    elif st.max() < ohlc["close"][-1]:
        sl = (0.6*st.sort_values(ascending = False)[0]) + (0.4*st.sort_values(ascending = False)[1])
    else:
        sl = st.mean()
    return round(sl,1)

def placeSLOrder(symbol,buy_sell,quantity,sl_price):
    # Place an intraday stop loss order on NSE
    if buy_sell == "buy":
        t_type=kite.TRANSACTION_TYPE_BUY
        t_type_sl=kite.TRANSACTION_TYPE_SELL
    elif buy_sell == "sell":
        t_type=kite.TRANSACTION_TYPE_SELL
        t_type_sl=kite.TRANSACTION_TYPE_BUY
    kite.place_order(tradingsymbol=symbol,
                    exchange=kite.EXCHANGE_NSE,
                    transaction_type=t_type,
                    quantity=quantity,
                    order_type=kite.ORDER_TYPE_MARKET,
                    product=kite.PRODUCT_MIS,
                    variety=kite.VARIETY_REGULAR)
    kite.place_order(tradingsymbol=symbol,
                    exchange=kite.EXCHANGE_NSE,
                    transaction_type=t_type_sl,
                    quantity=quantity,
                    order_type=kite.ORDER_TYPE_SL,
                    price=sl_price,
                    trigger_price = sl_price,
                    product=kite.PRODUCT_MIS,
                    variety=kite.VARIETY_REGULAR)

```

Fig.37i

```

def ModifyOrder(order_id,price):
    # Modify order given order id
    kite.modify_order(order_id=order_id,
                    price=price,
                    trigger_price=price,
                    order_type=kite.ORDER_TYPE_SL,
                    variety=kite.VARIETY_REGULAR)

def main(capital):
    a,b = 0,0
    while a < 10:
        try:
            pos_df = pd.DataFrame(kite.positions()["day"])
            break
        except:
            print("can't extract position data..retrying")
            a+=1
    while b < 10:
        try:
            ord_df = pd.DataFrame(kite.orders())
            break
        except:
            print("can't extract order data..retrying")
            b+=1

    for ticker in tickers:
        print("starting passthrough for.....",ticker)
        try:
            ohlc = fetchOHLC(ticker,"5minute",4)
            ohlc["st1"] = supertrend(ohlc,7,3)
            ohlc["st2"] = supertrend(ohlc,10,3)
            ohlc["st3"] = supertrend(ohlc,11,2)
            st_dir_refresh(ohlc,ticker)
            quantity = int(capital/ohlc["close"][-1])
            if len(pos_df.columns)==0:
                if st_dir[ticker] == ["green","green","green"]:
                    placeSLOrder(ticker,"buy",quantity,sl_price(ohlc))
                if st_dir[ticker] == ["red","red","red"]:
                    placeSLOrder(ticker,"sell",quantity,sl_price(ohlc))
            if len(pos_df.columns)!=0 and ticker not in pos_df["tradingsymbol"].tolist():
                if st_dir[ticker] == ["green","green","green"]:
                    placeSLOrder(ticker,"buy",quantity,sl_price(ohlc))

```

Fig.37j


```

if len(pos_df.columns)!=0 and ticker not in pos_df["tradingsymbol"].tolist():
    if st_dir[ticker] == ["green","green","green"]:
        placeSLOrder(ticker,"buy",quantity,s_l_price(ohlc))
    if st_dir[ticker] == ["red","red","red"]:
        placeSLOrder(ticker,"sell",quantity,s_l_price(ohlc))
if len(pos_df.columns)!=0 and ticker in pos_df["tradingsymbol"].tolist():
    if pos_df[pos_df["tradingsymbol"]==ticker]["quantity"].values[0] == 0:
        if st_dir[ticker] == ["green","green","green"]:
            placeSLOrder(ticker,"buy",quantity,s_l_price(ohlc))
        if st_dir[ticker] == ["red","red","red"]:
            placeSLOrder(ticker,"sell",quantity,s_l_price(ohlc))
    if pos_df[pos_df["tradingsymbol"]==ticker]["quantity"].values[0] != 0:
        order_id = ord_df.loc[(ord_df["tradingsymbol"] == ticker) & (ord_df['status'].isin(["TRIGGER PENDING","OPEN"]))]["order_id"].values[0]
        ModifyOrder(order_id,s_l_price(ohlc))
except:
    print("API error for ticker :",ticker)

tickers = ["SUNPHARMA","CIPLA","NTPC","INDUSINDBK","HEROMOTOCO","BAJFINANCE",
           "HCLTECH","DRREDDY","VEDL","SHREECEM","TITAN","TCS"]

capital = 3000 #position size
st_dir = {}
for ticker in tickers:
    st_dir[ticker] = ["None","None","None"]

starttime=time.time()
timeout = time.time() + 60*60*1
while time.time() <= timeout:
    try:
        main(capital)
        time.sleep(300 - ((time.time() - starttime) % 300.0))
    except KeyboardInterrupt:
        print('\n\nKeyboard exception received. Exiting.')
        exit()

```

Fig.37k

4.3 SQUARING OFF IMPLEMENTATION:

```

23
24 def placeMarketOrder(symbol,buy_sell,quantity):
25     if buy_sell == "buy":
26         t_type=kite.TRANSACTION_TYPE_BUY
27     elif buy_sell == "sell":
28         t_type=kite.TRANSACTION_TYPE_SELL
29     kite.place_order(tradingsymbol=symbol,
30                     exchange=kite.EXCHANGE_NSE,
31                     transaction_type=t_type,
32                     quantity=quantity,
33                     order_type=kite.ORDER_TYPE_MARKET,
34                     product=kite.PRODUCT_MIS,
35                     variety=kite.VARIETY_REGULAR)
36
37 def CancelOrder(order_id):
38     # Modify order given order id
39     kite.cancel_order(order_id=order_id,
40                      variety=kite.VARIETY_REGULAR)
41 a,b = 0,0
42 while a < 10:
43     try:
44         pos_df = pd.DataFrame(kite.positions()["day"])
45         break
46     except:
47         print("can't extract position data..retrying")
48         a+=1
49 while b < 10:
50     try:
51         ord_df = pd.DataFrame(kite.orders())
52         break
53     except:
54         print("can't extract order data..retrying")
55         b+=1
56 for i in range(len(pos_df)):
57     ticker = pos_df["tradingsymbol"].values[i]
58     if pos_df["quantity"].values[i] >0:
59         quantity = pos_df["quantity"].values[i]
60         placeMarketOrder(ticker,"sell", quantity)
61     if pos_df["quantity"].values[i] <0:
62         quantity = abs(pos_df["quantity"].values[i])
63         placeMarketOrder(ticker,"buy", quantity)
64
65 pending = ord_df[ord_df['status'].isin(["TRIGGER PENDING","OPEN"])]["order_id"].tolist()
66 drop = []
67 attempt = 0
68 while len(pending)>0 and attempt<5:
69     pending = [j for j in pending if j not in drop]
70     for order in pending:
71         try:
72             CancelOrder(order)
73             drop.append(order)
74         except:
75             print("unable to delete order id : ",order)
76             attempt+=1
77

```

Fig.37l

4.4 REAL TIME RENKO INDICATOR IMPLEMENTATION:

```

[ ]: def tokenLookup(instrument_df, symbol_list):
    """Looks up instrument token for a given script from instrument dump"""
    token_list = []
    for symbol in symbol_list:
        token_list.append(int(instrument_df[instrument_df.tradingsymbol==symbol].instrument_token.values[0]))
    return token_list

def tickerLookup(token):
    global instrument_df
    return instrument_df[instrument_df.instrument_token==token].tradingsymbol.values[0]

def instrumentLookup(instrument_df, symbol):
    """Looks up instrument token for a given script from instrument dump"""
    try:
        return instrument_df[instrument_df.tradingsymbol==symbol].instrument_token.values[0]
    except:
        return -1

def fetchOHLC(ticker, interval, duration):
    """extracts historical data and outputs in the form of dataframe"""
    instrument = instrumentLookup(instrument_df, ticker)
    data = pd.DataFrame(kite.historical_data(instrument, dt.date.today()-dt.timedelta(duration), dt.date.today(), interval))
    data.set_index("date", inplace=True)
    return data

def atr(DF, n):
    """function to calculate True Range and Average True Range"""
    df = DF.copy()
    df['H-L'] = abs(df['high'] - df['low'])
    df['H-PC'] = abs(df['high'] - df['close'].shift(1))
    df['L-PC'] = abs(df['low'] - df['close'].shift(1))
    df['TR'] = df[['H-L', 'H-PC', 'L-PC']].max(axis=1, skipna=False)
    df['ATR'] = df['TR'].ewm(com=n, min_periods=n).mean()
    return df['ATR'][-1]

def renkoOperation(ticks):
    for tick in ticks:
        try:
            ticker = tickerLookup(int(tick['instrument_token']))
            if renko_param[ticker]['upper_limit'] == None:
                renko_param[ticker]['upper_limit'] = float(tick['last_price']) + renko_param[ticker]['brick_size']
                renko_param[ticker]['lower_limit'] = float(tick['last_price']) - renko_param[ticker]['brick_size']
            if float(tick['last_price']) > renko_param[ticker]['upper_limit']:
                gap = (float(tick['last_price']) - renko_param[ticker]['upper_limit']) // renko_param[ticker]['brick_size']
                renko_param[ticker]['lower_limit'] = renko_param[ticker]['upper_limit'] + (gap * renko_param[ticker]['brick_size'])
                renko_param[ticker]['upper_limit'] = renko_param[ticker]['upper_limit'] + ((1+gap) * renko_param[ticker]['brick_size'])
                renko_param[ticker]['brick'] = max(1, renko_param[ticker]['brick'] + (1+gap))
            if float(tick['last_price']) < renko_param[ticker]['lower_limit']:
                gap = (renko_param[ticker]['lower_limit'] - float(tick['last_price'])) // renko_param[ticker]['brick_size']
                renko_param[ticker]['upper_limit'] = renko_param[ticker]['lower_limit'] - (gap * renko_param[ticker]['brick_size'])
                renko_param[ticker]['lower_limit'] = renko_param[ticker]['lower_limit'] - ((1+gap) * renko_param[ticker]['brick_size'])
                renko_param[ticker]['brick'] = min(-1, renko_param[ticker]['brick'] - (1+gap))
            print("{}: brick number = {}, last price = {}, upper bound = {}, lower bound = {}".format(ticker, renko_param[ticker]['brick'], tick['last_price'], renko_param[ticker]['upper_limit'], renko_param[ticker]['lower_limit']))
        except:
            pass

```

Fig.37m

```

except Exception as e:
    print(e)
    pass

tickers = ["ZEEL", "WIPRO", "VEDL", "ULTRACEMCO", "UPL", "TITAN", "TECHM", "TATASTEEL",
           "TATAMOTORS", "TCS", "SUNPHARMA", "SBIN", "SHREECEM", "RELIANCE", "POWERGRID",
           "ONGC", "NESTLEIND", "NTPC", "MARUTI", "MGM", "LT", "KOTAKBANK", "JSWSTEEL", "INFY",
           "INDUSINDBK", "IOC", "ITC", "ICICIBANK", "HDFC", "HINDUNILVR", "HINDALCO",
           "HEROMOTOCO", "HDFCBANK", "HCLTECH", "GRASIM", "GAIL", "EICHERMOT", "DRREDDY",
           "COALINDIA", "CIPLA", "BRITANNIA", "BHARTIARTL", "BPCL", "BAJAJFINSV",
           "BAJFINANCE", "BAJAJ-AUTO", "AXISBANK", "ASIANPAINT", "ADANIEXPORTS"]

renko_param = {}
for ticker in tickers:
    renko_param[ticker] = {"brick_size": round(atr(fetchOHLC(ticker, "5minute", 15), 200), 2), "upper_limit": None, "lower_limit": None, "brick": 0}

#create KiteTicker object
kws = KiteTicker(key_secret[0], kite.access_token)
tokens = tokenLookup(instrument_df, tickers)

def on_ticks(ws, ticks):
    renkoOperation(ticks)
    #print(ticks)

def on_connect(ws, response):
    ws.subscribe(tokens)
    ws.set_mode(ws.MODE_LTP, tokens)

kws.on_ticks=on_ticks
kws.on_connect=on_connect
kws.connect()

```

Fig.37n

4.4 REAL TIME RENKO + MACD INDICATORS IMPLEMENTATION:

```
[ ]: def tokenLookup(instrument_df,symbol_list):
    """Looks up instrument token for a given script from instrument dump"""
    token_list = []
    for symbol in symbol_list:
        token_list.append(int(instrument_df[instrument_df.tradingsymbol==symbol].instrument_token.values[0]))
    return token_list

def tickerLookup(token):
    global instrument_df
    return instrument_df[instrument_df.instrument_token==token].tradingsymbol.values[0]

def instrumentLookup(instrument_df,symbol):
    """Looks up instrument token for a given script from instrument dump"""
    try:
        return instrument_df[instrument_df.tradingsymbol==symbol].instrument_token.values[0]
    except:
        return -1

def fetchOHLC(ticker,interval,duration):
    """extracts historical data and outputs in the form of dataframe"""
    instrument = instrumentLookup(instrument_df,ticker)
    data = pd.DataFrame(kite.historical_data(instrument,dt.date.today()-dt.timedelta(duration), dt.date.today(),interval))
    data.set_index("date",inplace=True)
    return data

def atr(DF,n):
    """function to calculate True Range and Average True Range"""
    df = DF.copy()
    df['H-L'] = abs(df['high']-df['low'])
    df['H-PC'] = abs(df['high']-df['close'].shift(1))
    df['L-PC'] = abs(df['low']-df['close'].shift(1))
    df['TR'] = df[['H-L','H-PC','L-PC']].max(axis=1,skipna=False)
    df['ATR'] = df['TR'].ewm(com=n,min_periods=n).mean()
    return df['ATR'][-1]

def MACD(DF,a,b,c):
    """function to calculate MACD
    typical values a(fast moving average) = 12;
    b(slow moving average) = 26;
    c(signal line ma window) = 9"""
    df = DF.copy()
    df['MA_Fast'] = df['close'].ewm(span=a,min_periods=a).mean()
    df['MA_Slow'] = df['close'].ewm(span=b,min_periods=b).mean()
    df['MACD'] = df['MA_Fast']-df['MA_Slow']
    df['Signal'] = df['MACD'].ewm(span=c,min_periods=c).mean()
    df.dropna(inplace=True)
    return df
```

Fig.37o

```
def macd_xover_refresh(macd,ticker):
    global macd_xover
    if macd["MACD"][-1]>macd["Signal"][-1]:
        macd_xover[ticker]="bullish"
    elif macd["MACD"][-1]<macd["Signal"][-1]:
        macd_xover[ticker]="bearish"

def renkoOperation(ticks):
    for tick in ticks:
        try:
            ticker = tickerLookup(int(tick['instrument_token']))
            if renko_param[ticker]["upper_limit"] == None:
                renko_param[ticker]["upper_limit"] = float(tick['last_price']) + renko_param[ticker]["gap"]
                renko_param[ticker]["lower_limit"] = float(tick['last_price']) - renko_param[ticker]["gap"]
            if float(tick['last_price']) > renko_param[ticker]["upper_limit"]:
                gap = (float(tick['last_price']) - renko_param[ticker]["upper_limit"])/renko_param[ticker]["brick"]
                renko_param[ticker]["lower_limit"] = renko_param[ticker]["upper_limit"] + (gap*renko_param[ticker]["brick"])
                renko_param[ticker]["upper_limit"] = renko_param[ticker]["upper_limit"] + ((1+gap)*renko_param[ticker]["brick"])
                renko_param[ticker]["brick"] = max(1,renko_param[ticker]["brick"]+(1+gap))
            if float(tick['last_price']) < renko_param[ticker]["lower_limit"]:
                gap = (renko_param[ticker]["lower_limit"] - float(tick['last_price']))/renko_param[ticker]["brick"]
                renko_param[ticker]["upper_limit"] = renko_param[ticker]["lower_limit"] - (gap*renko_param[ticker]["brick"])
                renko_param[ticker]["lower_limit"] = renko_param[ticker]["lower_limit"] - ((1+gap)*renko_param[ticker]["brick"])
                renko_param[ticker]["brick"] = min(-1,renko_param[ticker]["brick"]-(1+gap))
            print("{}: brick number = {},last price ={}, upper bound ={}, lower bound ={}".format(ticker,renko_param[ticker]["brick"],tick['last_price'],renko_param[ticker]["upper_limit"],renko_param[ticker]["lower_limit"]))
        except Exception as e:
            print(e)
            pass

def main(capital):
    global renko_param
    a,b = 0,0
    while a < 10:
        try:
            pos_df = pd.DataFrame(kite.positions()["day"])
            break
        except:
            print("can't extract position data..retrying")
            a+=1
    while b < 10:
        try:
            ord_df = pd.DataFrame(kite.orders())
            break
        except:
            print("can't extract order data..retrying")
            b+=1
```

Fig.37p

```

for ticker in tickers:
    print("starting passthrough for....",ticker)
    try:
        ohlc = fetchOHLC(ticker,"minute",4)
        macd = MACD(ohlc,12,26,9)
        macd_xover_refresh(macd,ticker)
        quantity = int(capital/ohlc["close"][-1])
        if len(pos_df.columns)==0:
            if macd_xover[ticker] == "bullish" and renko_param[ticker]["brick"] >=2:
                print("buy order placed for {}".format(ticker))
            if macd_xover[ticker] == "bearish" and renko_param[ticker]["brick"] <=-2:
                print("sell order placed for {}".format(ticker))
            if len(pos_df.columns)!=0 and ticker not in pos_df["tradingymbol"].tolist():
                if macd_xover[ticker] == "bullish" and renko_param[ticker]["brick"] >=2:
                    print("buy order placed for {}".format(ticker))
                if macd_xover[ticker] == "bearish" and renko_param[ticker]["brick"] <=-2:
                    print("sell order placed for {}".format(ticker))
            if len(pos_df.columns)!=0 and ticker in pos_df["tradingymbol"].tolist():
                if pos_df[pos_df["tradingymbol"]==ticker]["quantity"].values[0] == 0:
                    if macd_xover[ticker] == "bullish" and renko_param[ticker]["brick"] >=2:
                        print("buy order placed for {}".format(ticker))
                    if macd_xover[ticker] == "bearish" and renko_param[ticker]["brick"] <=-2:
                        print("sell order placed for {}".format(ticker))
                if pos_df[pos_df["tradingymbol"]==ticker]["quantity"].values[0] > 0:
                    print("buy order modified for {}".format(ticker))
                if pos_df[pos_df["tradingymbol"]==ticker]["quantity"].values[0] < 0:
                    print("sell order modified for {}".format(ticker))
        except Exception as e:
            print("API error for ticker :",ticker)
            print(e)

tickers = ["ZEEL","WIPRO","VEDL","ULTRACEMCO","UPL","TITAN","TECHM","TATASTEEL",
           "TATAMOTORS","TCS","SUNPHARMA","SBIN","SHREECEM","RELIANCE","POWERGRID",
           "ONGC","NESTLEIND","NTPC","MARUTI","M&M","LT","KOTAKBANK","JSWSTEEL","INFY",
           "INDUSINDBK","IOC","ITC","ICICIBANK","HDFC","HINDUNILVR","HINDALCO",
           "HEROMOTOCO","HDFCBANK","HCLTECH","GRASIM","GAIL","EICHERMOT","DRREDDY",
           "COALINDIA","CIPLA","BRITANNIA","BHARTIARTL","BPCL","BAJAJFINSV",
           "BAJFINANCE","BAJAJ-AUTO","AXISBANK","ASIANPAINT","ADANIEXPORTS"]

capital = 3000 #position size
macd_xover = {}
renko_param = {}
for ticker in tickers:
    renko_param[ticker] = {"brick_size":round(0.2*atr(fetchOHLC(ticker,"5minute",15),200),2),"upper_
    macd_xover[ticker] = None

```

Fig.37q

```

kws = KiteTicker(key_secret[0],kite.access_token)
tokens = tokenLookup(instrument_df,tickers)

start_minute = dt.datetime.now().minute
def on_ticks(ws,ticks):
    global start_minute
    renkoOperation(ticks)
    now_minute = dt.datetime.now().minute
    if abs(now_minute - start_minute) >= 1:
        start_minute = now_minute
        main(capital)

def on_connect(ws,response):
    ws.subscribe(tokens)
    ws.set_mode(ws.MODE_LTP,tokens)

while True:
    now = dt.datetime.now()
    if (now.hour >= 9 and now.minute >= 15 ):
        kws.on_ticks=on_ticks
        kws.on_connect=on_connect
        kws.connect()
    if (now.hour >= 14 and now.minute >= 30):
        sys.exit()

```

Fig.37r

CHAPTER 5

RESULTS AND EVALUATION

Algorithmic trading is the tool of both traders and investors in today's speeding financial market where even every second is important. This project was mainly focused on developing a new algorithmic trading bot, a pricing bot and simple user interface based on kite connect API. Then, the last part of the chapter deals with the outcome of the project depicting what was done, how it was done, and whether the algorithmic trading system worked.

The following are what we came across after evolving this project.

1. App Development on KiteConnect

First of all, we had developed an app on KiteConnect. This entailed a journey into the complexities of KiteConnect developer console, which gave us a vital API key and secret for our software. This key and secret were used as a security measure for obtaining market information and conducting securities transactions at NSE. This was important for the remaining steps in the project to be carried out successfully.

2. Environment Setup for Algorithmic Trading

Our project was aimed at creating an excellent environment for the trading algorithm. We carefully established our infrastructure dealing with data storage, processing capacities and continuous integration.

3. Technical Indicators Integration

To make our decision-making process better, we have used two important things called as MACD and Bollinger Bands. MACD helps us to notice when things are changing quickly, while Bollinger Bands help us see when prices might go up or down.

4. Candlestick Patterns Analysis

Technical analysts have utilized candlestick patterns for a long time now. In our project we carried out thorough analysis of these patterns, looking for meaning behind them as market signals. We utilized a sophisticated candlestick pattern detector which could specifically scan for certain patterns using particular parameters. The tool turned out to be precious – it helped to forecast the future shift in price and the possible change of direction of the trend.

5. Support and Resistance Analysis

For every trader making right strategies it is very important to be aware of support and resistance levels. Therefore, we looked at those levels and identified locations where people normally buy and sell stocks. This is what we had fed into our systems to make intelligent trades. Our robot was very effective in generating money here too!

6. Implementation of API Functionalities

An important part of our project was the effective use of KiteConnect API functionalities. This included various activities such as obtaining historical market data all the way to the detailed list of NSE instruments. We also built the capacity of executing buy-and-sell orders automatically which constitute the basic needs for algorithmic trading.

7. Retrieving Historical data

We then applied our algorithmic trading system on live testing, moving from historical data to real-time market conditions. We could test the adaptability and responsiveness of our algorithm in this phase crucial for the validation. Real-time testing helped us see how the bot responded in the unpredictable world of live markets.

5.1 Results and Observations:

Thus, the outcome from the evaluation shows that our algorithmic trading system was efficient. The backtesting results gives positive outcomes with profitable trades, adjusted risk returns and conformity to trading plans. This real time testing enabled us to appreciate how the system would function in a market environment and therefore helped us to quickly address any arising issues.

We implemented into our algorithmic models and risk management mechanism that ensured minimal losses during the unfavorable market conditions. The system turned out to be flexible its response to changing market situations revealed the adaptability of the algorithmic approach.

CHAPTER 6

CONCLUSIONS AND FUTURE SCOPES

6.1 CONCLUSION

Building an algorithmic trade bot for our project will be a huge milestone in automating the financial sector. By including technical indicators, candlestick pattern analysis, and support and resistance analysis, our trading algorithms have become stronger and can make smart decisions even in a difficult environment.

The KiteConnect API allowed our system to process the trades with accuracy using the National Stock Exchange. A very effective candlestick pattern scanner helped us to locate markets opportunities and execute better trades.

The backtesting, real-time testing, and risk management assessments ensured that the system was properly evaluated and provided an indication of the system's reliability and robustness. These assessments reiterated the fact that our algorithms were profitable, flexible, and scalable.

In this regard, iterative improvement and flexibility will be vital components as we chart our way through the changing terrain of algorithmic trading. This project provides us with knowledge and foundation on which we are ready to meet future technological challenges and other innovations in the financial markets. The journey highlights the power of algorithm trading in modern finance, offering new frontiers to investigate and improve upon this growing area. As the market is changing, we must also have a very useful and futuristic mechanism for trading that will be very easy to use for the normal people as well.

6.2 FUTURE SCOPES

As we plan to continue the development of this project during the course of our next semester, we have planned the following outlooks to continue our journey with:

1. Automating the login process and introduction of selenium python library
2. WebSocket Streaming
3. Streaming live tick data
4. Introduction to some more technical indicators like
 - a. ATR
 - b. ADX
 - c. RSI
5. Deploying Strategies on cloud.

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APPENDIX

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