RESEARCH TREATISE (SEM II)

A Dissertation Submitted to

SVKM's NMIMS (Demmed to Be University)

In Partial Fulfilment for the Degree of

M.Sc. Statistics and Data Science 2023-2025

INTRADAY TRADING: NAVIGATING THE MARKET WAVES

By: Group 2

ROLL NO.	NAME	SAP ID
A021	Sahil Satish Jadhav	86062300007
A045	Himanshu Pal	86062300021
A063	Ashwini Shetty	86062300005
A070	Ansh Tyagi	86062300049
A035	Akash Lalwani	86062300024

Project Supervisor:

Mr. Nikhil Pawanikar

Nilkamal School of Mathematics, Applied Statistics and Analytics, SVKM's Narsee Monjee Institute of Management Studies (Deemed-To-Be-University) V.L. Mehta Rd, Vile Parle (West), Mumbai – 4000

ACKNOWLEDGEMENT

First and foremost, we would like to express our heartfelt gratitude towards the Programme chairperson M.Sc. Statistics and Data Science, Prof. (Dr.) Dr. Pradnya Khandeparker, for your constant support and guidance throughout this project on Intraday Trading: Navigating the Market Waves. Your encouragement and feedback have been instrumental in helping us achieve our goals and complete this project successfully.

We would also like to thank our mentor, Mr Nikhil Pawanikar, for his valuable insights and assistance in navigating the complexities of this project. His expertise in the field of, Machine Learning has been a tremendous asset to us, and we all have learned so much under his guidance.

We would like to express our appreciation to other faculty members, our friends, and family members who have supported us throughout this project with their words of encouragement and motivation.

Sincerely,

Sahil Jadhav

Ansh Tyagi

Ashwini Shetty

Himanshu Pal

Akash Lalwani

TABLE OF CONTENTS

ABSTRACT

Intraday trading in financial markets demands swift decision-making, relying on a combination of technical and sentiment analysis for effective trade execution. In today's dynamic financial landscape, the ability to swiftly adapt to market fluctuations is paramount for successful intraday trading. This project delves into the fusion of technical analysis and sentiment analysis, presenting a comprehensive approach to understanding and capitalizing on market movements. By leveraging advanced analytical techniques, we aim to provide traders with actionable insights in real time. Furthermore, the integration of automation technology revolutionizes trading strategies, allowing for rapid execution and optimization of trades. Through the development of a live trading visualization system, this project facilitates intuitive decision-making by providing a clear, concise representation of market data and trends.With a focus on agility and innovation, this endeavour seeks to empower traders to navigate the complexities of intraday trading with confidence and precision.

INTRODUCTION

The execution of a country’s financial market is a critical determinant of its overall economic condition, authorizing economists and financial experts to compute the country’s ongoing economic health. Among the several financial markets, the stock market stands out as a central driving force. Intraday trading stands at the intersection of opportunity and volatility in the financial markets. The ability to swiftly navigate these market waves, capturing fleeting opportunities while mitigating risks, is a hallmark of successful traders. In this era of technological advancement and data proliferation, traders are presented with an unprecedented array of tools and techniques to analyze and interpret market dynamics. As financial markets evolve and become increasingly interconnected, the ability to navigate the ebbs and flows of market dynamics has never been more critical. Against this backdrop, our project seeks to delve deep into the intricacies of intraday trading, combining technical analysis, sentiment analysis, and cutting-edge automation to empower traders with actionable insights and tools for success.

This project, titled "Intraday Trading: Navigating the Market Waves," embarks on a journey to explore the intricate realm of intraday trading through the lens of technical analysis, sentiment analysis, and automation. By combining these methodologies, we aim to provide traders with a holistic understanding of market movements and equip them with the tools necessary to make informed decisions in real time.

Complementing the quantitative rigor of technical analysis, sentiment analysis introduces a qualitative dimension to our trading strategy. By leveraging natural language processing and machine learning algorithms, we analyze vast troves of textual data—from financial news articles and social media posts to earnings reports and analyst opinions—to gauge market sentiment accurately. Understanding the prevailing sentiment among traders and investors allows us to anticipate shifts in market sentiment and sentiment-driven price movements, providing invaluable insights into market psychology.

However, our project does not stop at analysis alone. Recognizing the need for agility and efficiency in today's hypercompetitive markets, we have integrated automation technology into our trading framework. Through the development of automated trading algorithms and execution systems, we aim to streamline the trading process, enabling rapid decision-making and seamless execution of trading strategies.

Moreover, our live trading visualization system provides traders with real-time access to market data and insights, fostering a dynamic feedback loop between analysis and action. At its core, our project is driven by a commitment to innovation and a passion for empowering traders with the tools and knowledge necessary to thrive in the ever-changing landscape of intraday trading. By combining the art and science of trading, we aspire to redefine the boundaries of possibility and unlock new avenues for success in the financial markets. Through the development of a live trading visualization system, this project aims to enhance traders' ability to interpret and act upon market data intuitively, fostering a seamless synergy between human insight and technological prowess.

In summation, this project represents a convergence of innovation, expertise, and technology in the realm of intraday trading. By synthesizing technical and sentiment analysis methodologies with the power of automation, we aspire to redefine the boundaries of intraday trading, ushering in a new era of efficiency, profitability, and success in the financial markets.

LITERATURE REVIEW

Many investors invest their funds in the finance sector, especially in the stock market for elevated returns. Some of them utilize news stories or moving averages to acknowledge market trends and produce trading decisions, but only a few earn elevated(high) returns. The reason for this unsatisfactory performance is the non-linearity and random aspect of the stock market Han et al. [2023].

Technical analysis, rooted in the study of historical market data and price patterns, remains a cornerstone of intraday trading strategies. Researchers such as Lo et al. (2000) have investigated the efficacy of technical indicators such as moving averages, Relative Strength Index (RSI), and Bollinger Bands in predicting short-term price movements. Additionally, studies by Brock et al. (1992) and Lee et al. (2004) have examined the profitability of various trading rules based on technical indicators, shedding light on their potential as actionable trading signals.

Subsequent studies by Zhang et al. (2011) and Sprenger et al. (2013) further explored the relationship between news sentiment and intraday stock returns, highlighting the role of sentiment analysis in uncovering hidden market dynamics.

Moreover, the advent of automation technologies has revolutionized intraday trading, enabling traders to execute trades swiftly and efficiently. High-frequency trading (HFT) algorithms, as studied by Menkveld (2013) and Hasbrouck (2013), leverage automation to capitalize on fleeting market opportunities, driving liquidity and price efficiency. Furthermore, the development of algorithmic trading platforms and application programming interfaces (APIs) has democratized access to automated trading strategies, empowering individual traders to compete in the global marketplace.

OBJECTIVES

- Leverage technical analysis techniques to identify market patterns and trends.
- Incorporate sentiment analysis tools to gauge market sentiment from news.
- Develop automated trading systems to execute strategies with precision.
- Develop a real-time visualization system for intraday trading that provides comprehensive insights into market dynamics, and price movements.

DATA DESCRIPTION

For Technical Analysis:

The dataset comprises historical stock data of SBIN (State Bank of India) extracted from the Kite-Zerodha trading app in the 3-minute time frame, spanning a period of five years from 2019 to 2024. As one of the largest and most prominent public sector banks in India, SBIN serves as a pivotal entity within the country's financial landscape, making its stock an object of significant interest and scrutiny among traders and investors alike.

The Dataset consists of:

Open: The price at which a financial instrument (in this case, SBIN stock) begins trading at the opening of a trading session. It represents the first transaction of the day.

High: The highest price reached by the stock during the trading session. It indicates the peak value attained by the stock price within the given time frame.

Low: The lowest price reached by the stock during the trading session. It signifies the lowest value attained by the stock price within the given time frame.

Close: The price at which the stock ends trading at the closing of the trading session. It represents the last transaction of the day.

Volume: It refers to the total number of shares of SBIN stock that were traded during a given trading session. It indicates the level of activity or liquidity in the market for SBIN stock on that particular day

Snapshot of the data:

	A	B	C	D	E	F	G	H
1	Date	Open	High	Low	Close	Volume	% Change	% Change vs Average
2	Tue Jan 01 2019 09:15:00 GMT+0530	297.5	297.55	296.05	296.35	1,90,958	0.19	0.18
3	Tue Jan 01 2019 09:18:00 GMT+0530	296.3	296.4	295.45	295.9	1,65,295	-0.15	-0.15
4	Tue Jan 01 2019 09:21:00 GMT+0530	295.8	295.9	295.4	295.8	76,629	-0.03	-0.04
5	Tue Jan 01 2019 09:24:00 GMT+0530	295.8	295.9	295.25	295.4	98,605	-0.14	-0.14
6	Tue Jan 01 2019 09:27:00 GMT+0530	295.3	295.8	295.2	295.75	83,583	0.12	0.12
7	Tue Jan 01 2019 09:30:00 GMT+0530	295.75	295.8	295.5	295.6	50,320	-0.05	-0.05
8	Tue Jan 01 2019 09:33:00 GMT+0530	295.6	295.6	294.95	295.05	1,29,371	-0.19	-0.19
9	Tue Jan 01 2019 09:36:00 GMT+0530	295.05	295.6	295.05	295.4	45,365	0.12	0.12
10	Tue Jan 01 2019 09:39:00 GMT+0530	295.4	295.55	295.3	295.45	37,982	0.02	0.02
11	Tue Jan 01 2019 09:42:00 GMT+0530	295.45	295.5	295.1	295.2	65,469	-0.08	-0.09
12	Tue Jan 01 2019 09:45:00 GMT+0530	295.2	295.25	294.4	294.45	1,53,993	-0.25	-0.26
13	Tue Jan 01 2019 09:48:00 GMT+0530	294.45	294.9	294.4	294.65	86,627	0.07	0.07
14	Tue Jan 01 2019 09:51:00 GMT+0530	294.65	295.1	294.6	294.65	99,758	0	0
15	Tue Jan 01 2019 09:54:00 GMT+0530	294.65	294.65	293.85	294.15	1,68,783	-0.17	-0.17
16	Tue Jan 01 2019 09:57:00 GMT+0530	294.15	294.35	294	294.15	81,625	0	0
17	Tue Jan 01 2019 10:00:00 GMT+0530	294.15	294.5	293.95	294.45	1,14,850	0.1	0.1
18	Tue Jan 01 2019 10:03:00 GMT+0530	294.45	294.45	294.3	294.35	30,103	-0.03	-0.04
19	Tue Jan 01 2019 10:06:00 GMT+0530	294.35	294.7	294.3	294.3	50,192	-0.02	-0.02
20	Tue Jan 01 2019 10:09:00 GMT+0530	294.3	294.5	294.2	294.35	32,174	0.02	0.02
21	Tue Jan 01 2019 10:12:00 GMT+0530	294.35	294.7	294.3	294.7	34,210	0.12	0.12
22	Tue Jan 01 2019 10:15:00 GMT+0530	294.7	294.75	294.5	294.75	38,436	0.02	0.02
23	Tue Jan 01 2019 10:18:00 GMT+0530	294.75	294.75	294.5	294.65	39,766	-0.03	-0.04
24	Tue Jan 01 2019 10:21:00 GMT+0530	294.65	294.95	294.6	294.65	34,951	0	0
25	Tue Jan 01 2019 10:24:00 GMT+0530	294.65	294.8	294.6	294.75	26,461	0.03	0.03
26	Tue Jan 01 2019 10:27:00 GMT+0530	294.7	295.1	294.7	295.05	56,271	0.1	0.1
27	Tue Jan 01 2019 10:30:00 GMT+0530	295.05	295.05	294.85	294.95	42,304	-0.03	-0.04
28	Tue Jan 01 2019 10:33:00 GMT+0530	294.95	295	294.55	294.8	48,272	-0.05	-0.05
29	Tue Jan 01 2019 10:36:00 GMT+0530	294.8	295.15	294.6	295.1	55,501	0.1	0.1
30	Tue Jan 01 2019 10:39:00 GMT+0530	295.05	295.5	294.9	295.45	1,42,767	0.12	0.12
31	Tue Jan 01 2019 10:42:00 GMT+0530	295.45	295.75	295.25	295.7	2,07,771	0.08	0.08
32	Tue Jan 01 2019 10:45:00 GMT+0530	295.7	296.1	295.7	295.95	1,95,918	0.08	0.08
33	Tue Jan 01 2019 10:48:00 GMT+0530	295.9	296.1	295.8	296.1	89,589	0.05	0.05

For Sentiment Analysis:

The gathered news headlines serve as the textual data input for sentiment analysis. Each headline represents a snippet of information that may contain positive, negative, or neutral sentiments toward SBIN stock. Sentiment analysis algorithms analyze the language and context of these headlines to determine the overall sentiment expressed.

Sentiments are labeled as 1 for positive, -1 for negative, and 0 for Neutral.

Positive: Sentiments expressing favorable opinions or emotions

Negative: Sentiments expressing unfavorable opinions or emotions

Neutral: Sentiments that do not convey strong positive or negative opinions

Snapshot of the data:

cleaned senti	pred_lab
sbi can never match electoral bond donor to party ex finance secy	-1
electoral bond case sc to hear sbi is plea seeking extension of time on march 11	-1
adr move sc on delay by sbi in poll bond data	-1
adr move sc on delay by sbi in poll bond data	-1
electoral bond case ngo call for contempt proceeding against sbi	-1
electoral bond plea seek contempt action against sbi for disobeying sc is order	-1
fund pick franklin india el tax saver	1
international woman is day 2024 former sbi chair arundhati bhattacharya do not wait for female role model	0
adr file contempt petition against sbi in supreme court	-1
electoral bond case live news update adr file contempt petition against sbi sc asks lawyer prashant bhushan representing ngo to send e mail assures listing	-1
electoral bond disclosure contempt plea in supreme court against sbi over time extension	-1
vocabulary made easy series boost your word power to crack competitive exam	1
electoral bond case adr move supreme court after sbi fails to disclose data by march 6	-1
electoral bond case adr file plea in sc seeking contempt proceeding against sbi	-1
adr move supreme court seeking contempt proceeding against sbi in electoral bond case	-1
sensex nifty hit fresh record peak in early trade jsw steel tata steel among top gainer	1
a curious plea	0
bharatpe may appoint ceo in next 2 month rajnish kumar	1
icici bank federal bank sbi among top banking stock expert believe are all set to outperform	1
banking veteran rajnish kumar is 5 big commandment for fintech to survive and thrive	1
trader diary buy sell or hold strategy on maruti suzuki tata steel hindalco sbi axis bank exide over a dozen other stock today	1

METHODOLOGY

SENTIMENT ANALYSIS:

LLMs are based on transformer neural network architectures, specifically the encoder-decoder. These uses an attention mechanism that allows the model to weigh different parts of the input sequence when processing each part of the output. This architecture is well-suited for modelling sequential data like text. One of the popular examples of LLMs include OpenAI's GPT (Generative Pre-trained Transformer) models and Google's BERT (Bidirectional Encoder Representations from Transformers), etc.

Pre-Training is a key aspect of LLMs, the pre-training process on massive text corpora (corpora in NLP meanings the entire dataset) and using a popular technique i.e.
Causal Language Modelling: Training to predict the next token given the previous tokens. This unsupervised pre-training on broad data allows LLMs to build general language understanding before any task-specific fine-tuning.
LLMs can rapidly learn new tasks by being shown some examples in the input prompt, without any explicit fine-tuning (few-shot learning). Their general knowledge allows rapid adaptation.

Out data is a semi labelled dataset. Using the provided labels we iteratively. Performed sentiment analysis using the Gemini API, an LLM using the 'gemini-pro' argument passed to the GenerativeModel class from genai library in python which generates predicted labels and the perform unsupervised learning with labels as Good (1), Bad (-1) and Neutral (0).

TECHNICAL INDICATORS:

Technical indicators are mathematical calculations applied to price and volume data of financial assets to provide insights into market behaviour and potential future price movements. They are widely used by traders and analysts to make informed decisions about buying, selling, or holding assets. The origins of technical analysis and technical indicators can be traced back to the late 19th and early 20th centuries. Charles Dow, one of the founders of Dow Jones & Company and the Wall Street Journal, developed the Dow Theory, which laid the foundation for modern technical analysis. Dow's theory emphasized the importance of market trends, cycles, and patterns in predicting future price movements.

Below is the list of indicators which we have used in our model for analysis:

- Moving Average Convergence Divergence
- Supertrend
- Relative Strength Index

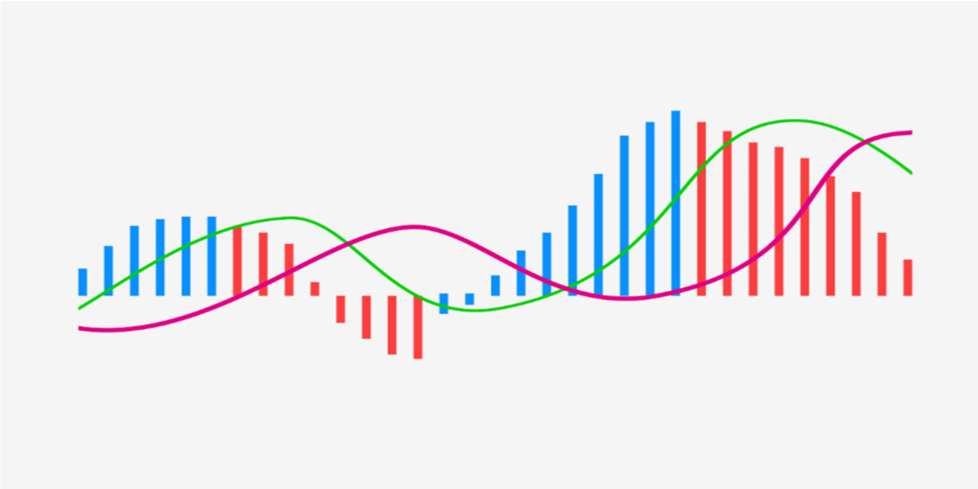
- Triple Exponential Moving Average
- Double Exponential Moving Average
- Average Directional Index
- Williams %
- Bollinger Bands
- Central Pivot Range
- Pivot Points
- Trailing Stoploss
- Ascending Triangle Pattern

Technical indicators are indispensable tools in the arsenal of traders, designed to provide nuanced insights into market dynamics by considering multiple factors influencing price changes. Central Pivot Range (CPR) and Pivot Points stand out as pivotal references, guiding traders with precision amidst the tumult of market trends. Acting as beacons of support and resistance, these indicators delineate key price levels and provide a framework for anticipating price reversals and navigating market sentiment. Whether identifying entry and exit points or managing risk, the strategic use of CPR and Pivot Points empowers traders to navigate the complexities of financial markets with confidence and agility, enabling informed decision-making in real-time trading scenarios.

1. **<u>MACD</u>**

   The Moving Average Convergence Divergence (MACD) is a versatile technical indicator extensively used by traders to analyse market trends and potential trading opportunities. Consisting of three key components—the MACD Line, Signal Line, and MACD Histogram—it provides valuable insights into momentum, trend strength, and potential trend reversals. The MACD Line is derived by subtracting a longer-term Exponential Moving Average (EMA) from a shorter-term EMA, typically calculated using 12 and 26 periods, respectively. The Signal Line, a 9-period EMA of the MACD Line, acts as a smoothing mechanism, offering a clearer view of the underlying trend. The MACD Histogram, representing the difference between the MACD Line and Signal Line, visually illustrates the convergence or divergence between these two lines.

   In our case we have combined each and every indicator with our support and resistances such as if the MACD values are indicating "1" and you are also currently in a position then combining with CPR and Pivot Points means my strategy would indicate a sell signal or a different signal when either the market direction is going to fall or be in the range within it, which would still give us loss.



2. **<u>SUPERTREND</u>**

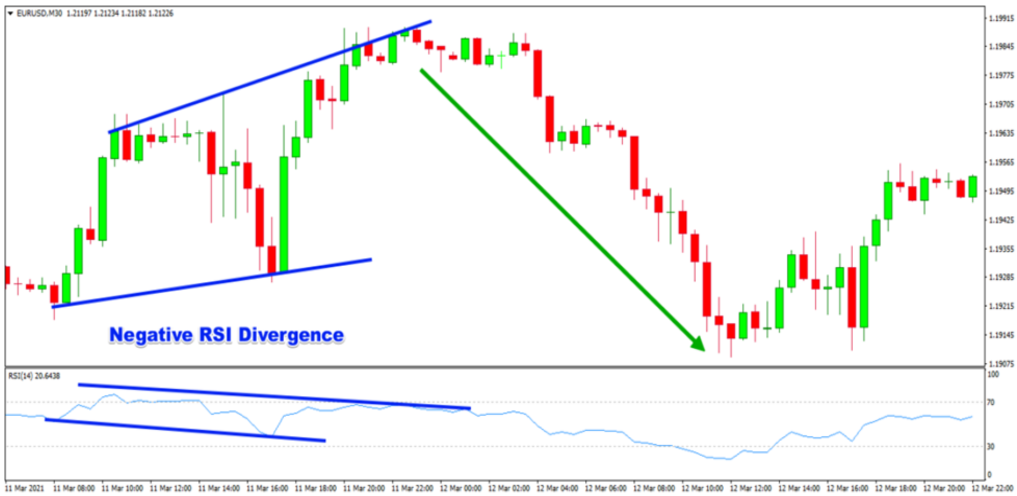
Supertrend is a popular trend-following technical indicator used by traders to identify trends and potential entry or exit points in financial markets. It's based on the concept of moving averages and volatility, providing a clear visual representation of trend direction and strength. Here's a detailed breakdown of Supertrend:

<u>Calculation</u>: The Supertrend indicator is calculated using the Average True Range (ATR) and a multiplier factor. The ATR measures market volatility by calculating the average range between high and low prices over a specified period. The multiplier factor determines the distance of the Supertrend line from the price. The formula for calculating Supertrend is: **Supertrend (Upper Band) = High + (Multiplier * ATR)Supertrend (Lower Band) = Low - (Multiplier * ATR)**

3. **<u>Relative Strength Index</u> (RSI)**

Understanding RSI: RSI is a momentum oscillator that measures the speed and change of price movements. It oscillates between 0 and 100 and is typically calculated using the average gains and losses over a specified period, often 14 periods. RSI values above 70 are considered overbought, suggesting a potential reversal to the downside, while values below 30 are considered oversold, indicating a potential reversal to the upside. Types of Divergence: There are two main types of RSI divergence—bullish divergence and bearish divergence. Bullish Divergence: Bullish divergence occurs when the price forms a lower low, but the RSI indicator forms a higher low. This discrepancy suggests that while the price is weakening, momentum is building to the upside, indicating a potential bullish reversal.

Bearish Divergence: Bearish divergence occurs when the price forms a higher high, but the RSI indicator forms a lower high. This discrepancy suggests that while the price is rising, momentum is weakening, indicating a potential bearish reversal. Confirmation: RSI divergence is often used in conjunction with other technical indicators or price action analysis to confirm signals. Traders may look for additional signs of reversal, such as candlestick patterns, trendline breaks, or support/resistance levels, to strengthen the validity of the divergence signal. Timeframes: RSI divergence can occur on different timeframes, ranging from intraday to longer-term charts. Traders may choose to focus on specific timeframes based on their trading style and preferences. Divergence signals on higher timeframes are generally considered more significant but may require patience to materialize.



4. **<u>Triple Exponential Moving Average (TEMA) / Double Exponential Moving Average</u>**

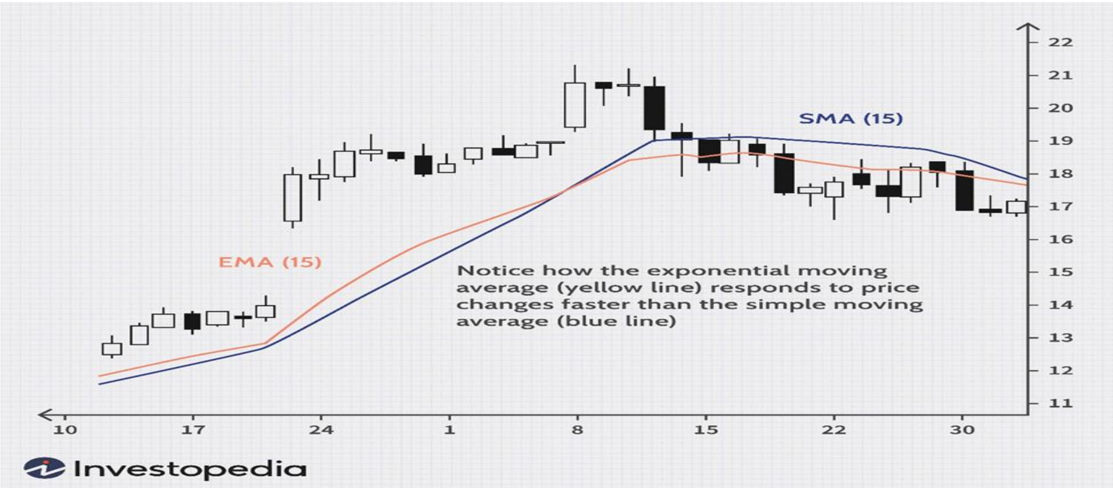
The exponential Moving Average (EMA) is a popular technical indicator used by traders to analyze price trends. It gives more weight to recent prices, making it more responsive to current price movements compared to simple moving averages (SMAs). EMAs are calculated by giving more weight to recent data points, which makes them better suited for capturing short-term trends and momentum shifts in the market.

Now, let's delve into two other types of moving averages: Triple Exponential Moving Average (TEMA) and Double Exponential Moving Average (DEMA).

Triple Exponential Moving Average (TEMA): TEMA goes a step further than EMA by applying triple smoothing to the price data. This means that TEMA reacts even faster to recent price changes, making it highly sensitive to short-term trend movements. By smoothing the data three times, TEMA aims to reduce noise and provide clearer signals of trend direction. However, its increased sensitivity can also lead to more false signals in choppy or range-bound markets.

Double Exponential Moving Average (DEMA): DEMA is another variant of the EMA that applies double smoothing to the price data. It strikes a balance between the responsiveness of EMA and the smoothing effect of SMA. DEMA attempts to filter out noise and provide smoother trend lines while still reacting relatively quickly to price changes. This makes DEMA a versatile tool for traders looking for a balance between responsiveness and stability in their moving average analysis.

In our model we have used three different periods of moving average based on its capability to indicate the signal which are 9,12,26.



5. **<u>Average Directional Index</u>**

The Average Directional Index (ADX) is a technical indicator used to measure the strength of a trend in financial markets. Developed by J. Welles Wilder Jr., the ADX does not indicate the direction of the trend but rather quantifies its strength regardless of direction. Here's some key information about ADX:

Calculation: The ADX is calculated based on the smoothed average of price movements over a specified period, typically 14 periods. It consists of three lines:

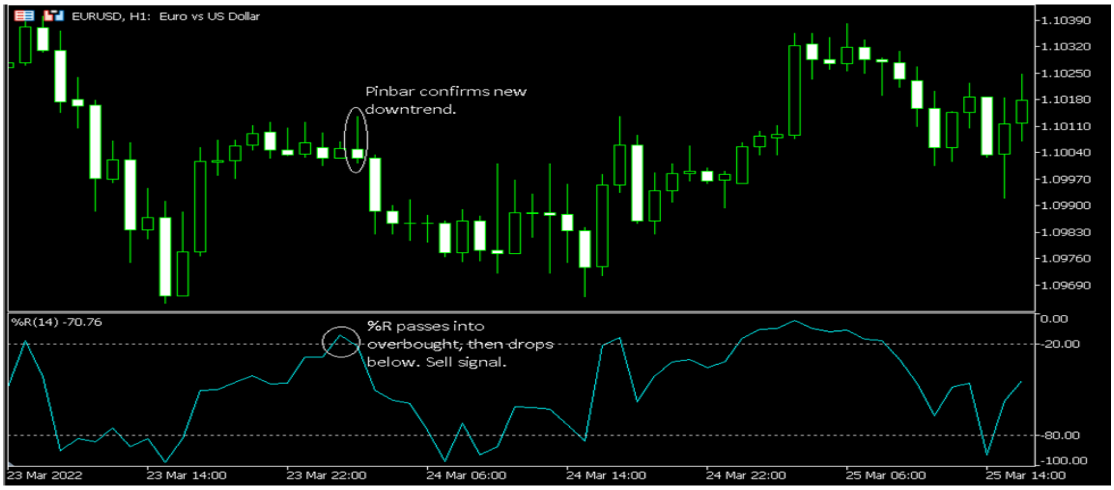
The ADX line itself, which represents the strength of the trend.
The Positive Directional Index (+DI), which measures the strength of upward price movements.
The Negative Directional Index (-DI), which measures the strength of downward price movements.
Interpretation: The ADX line oscillates between 0 and 100. A low ADX value suggests a weak or absent trend, while a high ADX value indicates a strong trend. Traders often look for ADX values above 25 to confirm the presence of a significant trend. Values above 40 are considered very strong trends.
Directional Movement: The +DI and -DI lines are used to determine the direction of the trend. When the +DI line crosses above the -DI line, it suggests an uptrend, while a crossover below indicates a downtrend. Traders may also look for the strength of these directional movements relative to each other to gauge trend momentum.
Just entering a trade is not important it is also important to capture momentum to reduce trade time so that's when Average Directional Index comes into picture. In our Model we have used two different periods of ADX namely 8 and 14.

6. **<u>Williams %</u>**
The Williams %R, also known as Williams Percent Range, is a technical indicator developed by Larry Williams to measure overbought or oversold conditions in financial markets. It oscillates between 0 and -100 and is primarily used to identify potential reversal points in price trends. Here's some key information about Williams %R:

Calculation: Williams's %R is calculated using the highest high and lowest low prices over a specified period, typically 14 periods. The formula is as follows: %R = [(Highest High - Close) / (Highest High - Lowest Low)] * -100

Interpretation: Williams's %R values above -20 typically indicate that an asset is overbought, suggesting that prices may be due for a reversal to the downside.

Conversely, values below -80 suggest that an asset is oversold, indicating that prices may be due for a reversal to the upside.
Range-Bound Conditions: When the Williams %R reaches extreme levels (above -20 or below -80), it may suggest that the market is in a range-bound condition, with prices likely to revert to the mean. Traders may look for potential trading opportunities when %R moves back within the -20 to -80 range.
Williams %R is a key component of our arsenal, particularly when combined with other indicators. This synergistic blend not only provides optimal signals but also significantly reduces lag, enhancing our ability to make timely and informed trading decisions.

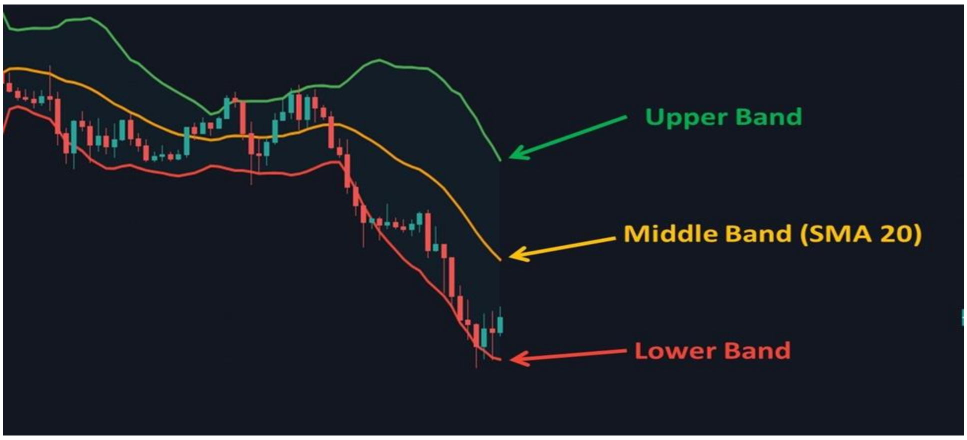


7. **Bollinger Bands**

Bollinger Bands are a popular technical analysis tool developed by John Bollinger in the 1980s. They consist of three lines: a middle line, typically a simple moving average (SMA), and two outer bands that are standard deviations away from the middle line. Here's a concise overview of Bollinger Bands:

Calculation: The middle line, or the "Bollinger Band," is usually calculated as a 20-period SMA. The upper and lower bands are placed a certain number of standard deviations away from the middle line, typically two standard deviations. Interpretation: Bollinger Bands are used to measure volatility and identify potential overbought or oversold conditions in the market. When prices touch or exceed the outer bands, it suggests that the market is either overbought (when touching the upper band) or oversold (when touching the lower band). Range Contraction and Expansion: Bollinger Bands expand, and contract based on market volatility. During periods of low volatility, the bands narrow, indicating a potential upcoming increase in volatility. Conversely, during periods of high volatility, the bands widen, reflecting increased market activity.

Bollinger bands acts as our lower control limit and upper control limit which helps us to take trade with respecting the boundaries and always be in that specific range and also helps us in taking reversal trades. Now our goal while constructing this trading model was to capture long trades and directional trends and not pullbacks so we have used the logics of Bollinger bands to have a sense of direction of the price and to what extent it can go from that specific point, and not for reversal trades.



8. **<u>Central Pivot Range</u>**
The Central Pivot Range (CPR) is a technical analysis tool used by traders to identify potential support and resistance levels in financial markets. It is derived from the calculation of pivot points and provides a range within which price movements are expected to occur. Here's a concise overview of the Central Pivot Range: Calculation: The Central Pivot Range is calculated using the previous day's high, low, and close prices. The central pivot point is the average of the previous day's high, low, and close. The upper and lower boundaries of the CPR are then calculated based on a percentage of the central pivot point.
Interpretation: The central pivot point serves as a key reference level. It is considered a neutral point, with prices expected to fluctuate around it
Central Pivot Range, imagine it as a center of Gravity every time the price moves away from CPR it will return to CPR, when that's not sure but yes it will return.

9. **<u>Pivot Points</u>**
Pivot Points are a widely used technical analysis tool in trading, particularly in the realm of intraday trading. They serve as key reference levels for identifying potential support and resistance levels and determining market sentiment. Here's a concise overview of Pivot Points:

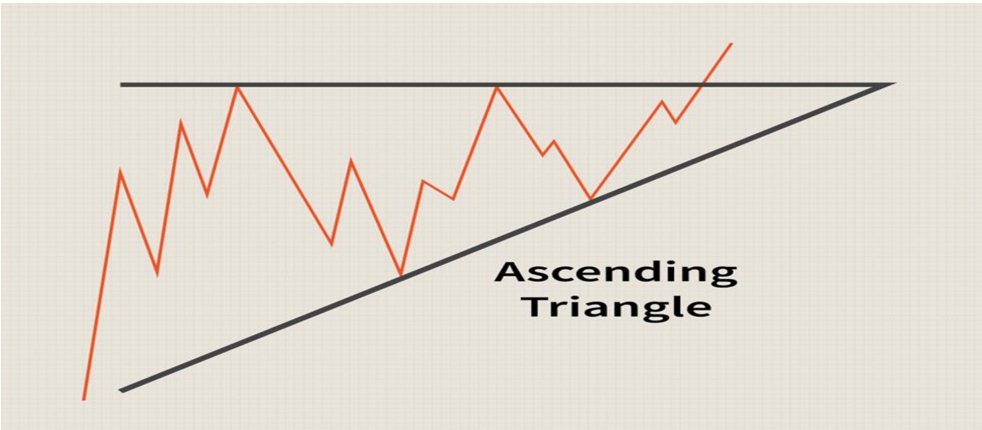
Calculation: Pivot Points are calculated based on the high, low, and close prices of the previous trading session. The central pivot point (PP) is calculated as the average of the previous day's high, low, and close. Other support and resistance levels are derived from this central pivot point.
Key Levels: The primary Pivot Points include the central pivot point (PP), as well as support levels **(S1, S2, S3)** below the PP and resistance levels **(R1, R2, R3)**

above the PP. These levels are calculated using various formulas, such as adding or subtracting a multiple of the daily trading range from the PP.
Interpretation: Pivot Points serve as significant levels where price action is expected to react. If the price is trading above the central pivot point, it is considered bullish, with the next resistance levels (R1, R2, R3) serving as potential targets. Conversely, if the price is trading below the central pivot point, it is considered bearish, with the next support levels (S1, S2, S3) serving as potential targets

10. <u>Trailing Stoploss</u>

Trailing Stop Loss is a risk management technique used by traders to protect profits while allowing for potential further gains in a trade. Unlike a traditional stop-loss order, which remains fixed at a predetermined price level, a trailing stop-loss order adjusts dynamically as the price moves in the trader's favor.
Here's a concise overview of Trailing Stop Loss:
Function: A Trailing Stop Loss order automatically adjusts the stop-loss level as the price moves in the trader's Favor. If the price moves in the desired direction, the stop-loss level trails behind the current price by a specified distance or percentage. This allows traders to lock in profits if the price reverses while still giving the trade room to potentially capture further gains.
Implementation: Traders typically set a trailing stop distance or percentage based on their risk tolerance and trading strategy. For example, a trader might set a trailing stop 20 cents below the highest price reached since entry, ensuring that profits are protected if the price reverses by at least that amount.
If you are in profit you should exit in profit, trailing stop loss helps you to exit in profit by making you understand to what point you should ride the trend.

11. **Ascending Triangle Pattern**
    The Ascending Triangle pattern is a bullish continuation pattern commonly observed in technical analysis. It is formed by two trendlines: a horizontal resistance line and an ascending support line. Here's a concise overview of the Ascending Triangle pattern:



All these indicator logics basically strategic functions were applied to our 5 years of stock data of State Bank of India for generating signals as 1, -1 and 0 based on its nature. Our current data is

BACKTESTING

Backtesting is a critical component of evaluating trading strategies before deploying them in live markets. It involves testing a strategy against historical data to simulate how it would have performed in the past. we performed backtesting on an intraday stock prediction strategy using the backtesting library in Python

Backtesting allows us to assess the viability of a trading strategy by simulating its performance on historical data. It helps in identifying potential strengths and weaknesses of the strategy, refining parameters, and gaining confidence before deploying it in real trading environments. However, it's crucial to note that past performance does not guarantee future results, and continuous monitoring and adaptation are essential in live trading scenarios.

Backtest Execution

The backtesting process was executed using the Backtest class provided by the backtesting library. We defined a custom strategy class (Signal) that inherits from backtesting.Strategy to implement our trading logic. Within the Signal class, we utilized the various indicator values to generate buy and sell signals based on predefined conditions

Backtest Parameters:

• Initial capital: $10,000

• Strategy implementation: Implemented using the Strategy class from the backtesting library

• Trading frequency: Intraday

Performance Metrics

After running the backtest, we obtained performance statistics using the stats object. These metrics provide insights into the effectiveness of the trading strategy during the backtesting period. Typical performance metrics include:

• Start/End Date: The dates of the backtest period (here, they seem to be placeholders).

• Duration: Duration of the backtest period.

• Exposure Time [%]: Percentage of time the strategy was active in the market.

• Equity Final [$]: Final equity value after running the strategy.

• Return [%]: Percentage return achieved by the strategy.

• Buy & Hold Return [%]: Return percentage for a buy-and-hold strategy over the same period.

• Max. Drawdown [%]: Maximum percentage loss experienced from a peak to a trough.

• Trades: Total number of trades executed during the backtest.

• Win Rate [%]: Percentage of winning trades.

• Profit Factor: Ratio of gross profits to gross losses.

• SQN: System Quality Number, a measure of trading system quality considering the ratio of expectancy to risk.

The output helps evaluate the strategy's performance, risk-adjusted returns, trade frequency, and effectiveness in generating profits compared to a passive buy-and-hold approach.

MACD Strategy

```
Start                          1970-01-01 00:00:00
End                            1970-01-01 00:00...
Duration                       0 days 00:00:00....
Exposure Time [%]                        82.780558
Equity Final [$]                           25815.7
Equity Peak [$]                           37048.95
Return [%]                                 158.157
Buy & Hold Return [%]                   156.571621
Return (Ann.) [%]                              0.0
Volatility (Ann.) [%]                          NaN
Sharpe Ratio                                   NaN
Sortino Ratio                                  NaN
Calmar Ratio                                   0.0
Max. Drawdown [%]                       -33.986751
Avg. Drawdown [%]                        -1.227258
Max. Drawdown Duration         0 days 00:00:00....
Avg. Drawdown Duration         0 days 00:00:00....
# Trades                                      8665
Win Rate [%]                             45.343335
Best Trade [%]                            7.073462
Worst Trade [%]                          -5.246495
Avg. Trade [%]                            0.010985
Max. Trade Duration            0 days 00:00:00....
Avg. Trade Duration            0 days 00:00:00....
Profit Factor                             1.070239
Expectancy [%]                             0.01311
SQN                                        1.27401
_strategy                              tema_Signal
_equity_curve                                  ...
_trades                                Size  Entr...
dtype: object
```

Supertrend Strategy :

```
Start                          1970-01-01 00:00:00
End                            1970-01-01 00:00...
Duration                       0 days 00:00:00....
Exposure Time [%]                        99.990486
Equity Final [$]                          25356.55
Equity Peak [$]                           25934.05
Return [%]                                153.5655
Buy & Hold Return [%]                   156.571621
Return (Ann.) [%]                              0.0
Volatility (Ann.) [%]                          NaN
Sharpe Ratio                                   NaN
Sortino Ratio                                  NaN
Calmar Ratio                                   0.0
Max. Drawdown [%]                       -58.475815
Avg. Drawdown [%]                        -1.396315
Max. Drawdown Duration         0 days 00:00:00....
Avg. Drawdown Duration         0 days 00:00:00....
# Trades                                         1
Win Rate [%]                                 100.0
Best Trade [%]                          158.201598
Worst Trade [%]                         158.201598
Avg. Trade [%]                          158.201598
Max. Trade Duration            0 days 00:00:00....
Avg. Trade Duration            0 days 00:00:00....
Profit Factor                                  NaN
Expectancy [%]                          158.201598
SQN                                            NaN
_strategy                                   Signal
_equity_curve                                  ...
_trades                           Size  EntryBa...
dtype: object
```

RSI Strategy :

```
Start                          1970-01-01 00:00:00
End                            1970-01-01 00:00...
Duration                       0 days 00:00:00....
Exposure Time [%]                       4.880787
Equity Final [$]                        10248.05
Equity Peak [$]                         11075.15
Return [%]                                2.4805
Buy & Hold Return [%]                 156.571621
Return (Ann.) [%]                            0.0
Volatility (Ann.) [%]                        NaN
Sharpe Ratio                                 NaN
Sortino Ratio                                NaN
Calmar Ratio                                 0.0
Max. Drawdown [%]                     -11.168246
Avg. Drawdown [%]                      -0.925211
Max. Drawdown Duration         0 days 00:00:00....
Avg. Drawdown Duration         0 days 00:00:00....
# Trades                                     405
Win Rate [%]                           40.246914
Best Trade [%]                          4.461998
Worst Trade [%]                        -3.795507
Avg. Trade [%]                          0.005895
Max. Trade Duration            0 days 00:00:00....
Avg. Trade Duration            0 days 00:00:00....
Profit Factor                           1.038329
Expectancy [%]                          0.008506
SQN                                      0.16773
_strategy                                 Signal
_equity_curve                                ...
_trades                              Size  Entry...
dtype: object
```

DEMA Strategy :

```
Start                          1970-01-01 00:00:00
End                            1970-01-01 00:00...
Duration                       0 days 00:00:00....
Exposure Time [%]                      75.286536
Equity Final [$]                             0.0
Equity Peak [$]                         14813.05
Return [%]                                -100.0
Buy & Hold Return [%]                 156.571621
Return (Ann.) [%]                            0.0
Volatility (Ann.) [%]                        NaN
Sharpe Ratio                                 NaN
Sortino Ratio                                NaN
Calmar Ratio                                 0.0
Max. Drawdown [%]                         -100.0
Avg. Drawdown [%]                      -1.874984
Max. Drawdown Duration         0 days 00:00:00....
Avg. Drawdown Duration         0 days 00:00:00....
# Trades                                       1
Win Rate [%]                                 0.0
Best Trade [%]                       -110.160609
Worst Trade [%]                      -110.160609
Avg. Trade [%]                                 0
Max. Trade Duration            0 days 00:00:00....
Avg. Trade Duration            0 days 00:00:00....
Profit Factor                                0.0
Expectancy [%]                       -110.160609
SQN                                          NaN
_strategy                                 Signal
_equity_curve                                ...
_trades                          Size  EntryBa...
dtype: object
```

TEMA Strategy

```
Start                          1970-01-01 00:00:00
End                            1970-01-01 00:00...
Duration                       0 days 00:00:00....
Exposure Time [%]                      82.780558
Equity Final [$]                         18710.8
Equity Peak [$]                         23323.15
Return [%]                                87.108
Buy & Hold Return [%]                 156.571621
Return (Ann.) [%]                            0.0
Volatility (Ann.) [%]                        NaN
Sharpe Ratio                                 NaN
Sortino Ratio                                NaN
Calmar Ratio                                 0.0
Max. Drawdown [%]                     -28.260044
Avg. Drawdown [%]                      -1.234545
Max. Drawdown Duration         0 days 00:00:00....
Avg. Drawdown Duration         0 days 00:00:00....
# Trades                                    8665
Win Rate [%]                            43.21985
Best Trade [%]                          7.073462
Worst Trade [%]                        -5.806452
Avg. Trade [%]                          0.007346
Max. Trade Duration            0 days 00:00:00....
Avg. Trade Duration            0 days 00:00:00....
Profit Factor                           1.050259
Expectancy [%]                          0.009472
SQN                                     1.034112
_strategy                                 Signal
_equity_curve                                ...
_trades                             Size  Entr...
dtype: object
```

ADX Strategy 1

```
Start                          1970-01-01 00:00:00
End                            1970-01-01 00:00...
Duration                       0 days 00:00:00....
Exposure Time [%]                        48.410811
Equity Final [$]                           50709.2
Equity Peak [$]                            51548.5
Return [%]                                 407.092
Buy & Hold Return [%]                   156.571621
Return (Ann.) [%]                              0.0
Volatility (Ann.) [%]                          NaN
Sharpe Ratio                                   NaN
Sortino Ratio                                  NaN
Calmar Ratio                                   0.0
Max. Drawdown [%]                       -17.864977
Avg. Drawdown [%]                        -1.233493
Max. Drawdown Duration         0 days 00:00:00....
Avg. Drawdown Duration         0 days 00:00:00....
# Trades                                      7698
Win Rate [%]                             34.060795
Best Trade [%]                           14.148921
Worst Trade [%]                           -8.07632
Avg. Trade [%]                            0.021265
Max. Trade Duration            0 days 00:00:00....
Avg. Trade Duration            0 days 00:00:00....
Profit Factor                             1.155108
Expectancy [%]                            0.023077
SQN                                       2.798849
_strategy                                   Signal
_equity_curve                                  ...
_trades                             Size  Entr...
dtype: object
```

ADX Strategy 2

```
Start                          1970-01-01 00:00:00
End                            1970-01-01 00:00...
Duration                       0 days 00:00:00....
Exposure Time [%]                         5.649535
Equity Final [$]                           12656.4
Equity Peak [$]                            13801.0
Return [%]                                  26.564
Buy & Hold Return [%]                   156.571621
Return (Ann.) [%]                              0.0
Volatility (Ann.) [%]                          NaN
Sharpe Ratio                                   NaN
Sortino Ratio                                  NaN
Calmar Ratio                                   0.0
Max. Drawdown [%]                         -8.87327
Avg. Drawdown [%]                        -0.575229
Max. Drawdown Duration         0 days 00:00:00....
Avg. Drawdown Duration         0 days 00:00:00....
# Trades                                      4433
Win Rate [%]                             44.822919
Best Trade [%]                            3.156049
Worst Trade [%]                          -1.116972
Avg. Trade [%]                            0.005327
Max. Trade Duration            0 days 00:00:00....
Avg. Trade Duration            0 days 00:00:00....
Profit Factor                             1.101624
Expectancy [%]                             0.00551
SQN                                       1.810069
_strategy                                   Signal
_equity_curve                                  ...
_trades                             Size  Entr...
dtype: object
```

ADX Strategy 3

```
Start                          1970-01-01 00:00:00
End                            1970-01-01 00:00...
Duration                       0 days 00:00:00....
Exposure Time [%]                        42.388953
Equity Final [$]                           13522.0
Equity Peak [$]                           16011.35
Return [%]                                   35.22
Buy & Hold Return [%]                   156.571621
Return (Ann.) [%]                              0.0
Volatility (Ann.) [%]                          NaN
Sharpe Ratio                                   NaN
Sortino Ratio                                  NaN
Calmar Ratio                                   0.0
Max. Drawdown [%]                       -25.138417
Avg. Drawdown [%]                         -1.07775
Max. Drawdown Duration         0 days 00:00:00....
Avg. Drawdown Duration         0 days 00:00:00....
# Trades                                      9304
Win Rate [%]                             44.260533
Best Trade [%]                            8.739627
Worst Trade [%]                          -4.972376
Avg. Trade [%]                            0.003268
Max. Trade Duration            0 days 00:00:00....
Avg. Trade Duration            0 days 00:00:00....
Profit Factor                             1.033741
Expectancy [%]                            0.004335
SQN                                       0.710498
_strategy                                   Signal
_equity_curve                                  ...
_trades                             Size  Entr...
dtype: object
```

William %R Strategy

```
Start                        1970-01-01 00:00:00
End                          1970-01-01 00:00...
Duration                     0 days 00:00:00....
Exposure Time [%]                      50.838836
Equity Final [$]                          8780.7
Equity Peak [$]                         12198.15
Return [%]                               -12.193
Buy & Hold Return [%]                 156.571621
Return (Ann.) [%]                            0.0
Volatility (Ann.) [%]                        NaN
Sharpe Ratio                                 NaN
Sortino Ratio                                NaN
Calmar Ratio                                 0.0
Max. Drawdown [%]                     -45.409755
Avg. Drawdown [%]                      -0.667382
Max. Drawdown Duration       0 days 00:00:00....
Avg. Drawdown Duration       0 days 00:00:00....
# Trades                                   21305
Win Rate [%]                           63.384182
Best Trade [%]                          6.024379
Worst Trade [%]                       -12.338936
Avg. Trade [%]                         -0.000641
Max. Trade Duration          0 days 00:00:00....
Avg. Trade Duration          0 days 00:00:00....
Profit Factor                           0.998691
Expectancy [%]                         -0.000108
SQN                                    -0.271124
_strategy                                 Signal
_equity_curve                                ...
_trades                               Size  Ent...
dtype: object
```

Heikin-Ashi Strategy

```
Start                        1970-01-01 00:00:00
End                          1970-01-01 00:00...
Duration                     0 days 00:00:00....
Exposure Time [%]                      94.114513
Equity Final [$]                          3173.9
Equity Peak [$]                          13054.3
Return [%]                               -68.261
Buy & Hold Return [%]                 156.571621
Return (Ann.) [%]                            0.0
Volatility (Ann.) [%]                        NaN
Sharpe Ratio                                 NaN
Sortino Ratio                                NaN
Calmar Ratio                                 0.0
Max. Drawdown [%]                     -77.623082
Avg. Drawdown [%]                      -2.807088
Max. Drawdown Duration       0 days 00:00:00....
Avg. Drawdown Duration       0 days 00:00:00....
# Trades                                   20508
Win Rate [%]                           37.370782
Best Trade [%]                         12.717087
Worst Trade [%]                        -9.001041
Avg. Trade [%]                         -0.005728
Max. Trade Duration          0 days 00:00:00....
Avg. Trade Duration          0 days 00:00:00....
Profit Factor                           0.958302
Expectancy [%]                         -0.004712
SQN                                    -1.249524
_strategy                                 Signal
_equity_curve                                ...
_trades                               Size  Ent...
dtype: object
```

Based on the backtesting results, it is evident that certain strategies such as MACD, Supertrend, RSI, TEMA, and ADX Strategies showed promising performance, generating positive results. On the other hand, strategies like DEMA, Heikin-Ashi, and Williams %R yielded negative results, indicating areas for further optimization or caution when implementing these strategies in live trading scenarios. It is crucial to continuously monitor and refine strategies based on changing market conditions and risk tolerance.

MODEL BUILDING

For technical trading to generate buy and sell signals, Advanced techniques and machine learning models can be used like neural networks, random forests, and support vector machines can be used to develop predictive models for generating buy and sell signals. It's important to note that no single technical analysis model is foolproof, and it's often best to use a combination of different indicators and strategies to generate more reliable buy and sell signals. Additionally, it's crucial to back test and validate any trading strategies before implementing them in a live market environment.

Random forests, an ensemble learning method that combines multiple decision trees, each trained on a slightly different subset of the data to improve the accuracy and robustness of the predictions. Powerful machine learning technique that can be very effective for generating trading signals. They can be used to identify the most important features driving market movements and generate trading signals. Ability to capture complex, non-linear patterns in financial data that may be difficult to identify using traditional technical analysis techniques using random forest by learning directly from historical data, this model can potentially uncover new trading strategies and signals that human analysts may miss. The random forest algorithm will automatically identify the most relevant features that are driving market movements and use those to make buy/sell predictions. One of the major advantages of random forests is their ability to handle nonlinear relationships and complex interactions between variables. This is particularly useful in financial markets, where there are often intricate dependencies between different factors.

When applied to financial markets, the random forest model can be trained on a variety of technical and fundamental features, such as technical indicators (moving averages, oscillators, etc.), price and volume data. Random Forest abilities is useful in financial markets, where there are often intricate dependencies between different factors. Which can be eventually valuable for developing trading strategies and refining technical analysis approaches and this made Random Forest applicable.

With package of RandomForestClassifier performed a model building, turns out Accuracy (0.97) and F1- score as 0.96. Now as we know our final_y has shown us returns of 91% (from backtesting), so now if my model precision decreases, in turn my returns too decrease in the same proportion. Having a model F1-score of 0.96 suggests that 96% of the times my model takes right decision i.e decision according to my strategy of taking decision to buy or sell based on the max indicator signals.

ANALYSIS

Automation:

So now that we have our indicators, we also have them back-tested, the next step is to automate them. Now you might ask what the need for automation is. Basically, as a human, it is not at all feasible to keep watch on all the 11 indicators some of which are not just single indicators but a combination of indicators. Now you might say we could keep a watch at the final Y but we as humans are bound to make errors and we might lose sight at a point in time so that when automation comes into the picture. In the above paragraph, I will draw a picture to explain the whole process of automating the technical as well as the sentiments.

So let's start with the indicators, to start with firstly we have to create a loop that would run every 3minute i.e. after every 180 seconds for that we need a condition that is always true that's when while loop comes into the picture, so we would start our framework by **" while true: "** loop which would run for the whole time and in this now we want the loop to freeze that's when we use the **"time. sleep(180)"** command to freeze the working of our loop for 180 seconds and then run again. This was our basic structure of the loop. Next comes getting the real-time data for that we have used a Python package called tvdatafeed which stands for trading view data feed, which we will call after every three minutes and would ask it to provide us data of open high low close volume of the present as well as previous candles with almost 1000 candles after every three minutes where with every 3 minutes a new entry comes with it.

Now within this we will start to insert my indicators all those strategies which we have developed earlier. These indicators were enclosed inside a function so that they could be called anywhere. Within that structure we started calling the indicator functions but first we must call our support and resistance i.e our pivot points and central pivot range as all our indicators are based on entry and exit defined based on support and resistance. Now that we have our support and resistances we will start calling our indicator functions. As I've told earlier, we have in total created 11 indicators and 1 chart pattern, here over the course of code we will call every indicator function.

Next comes the Sentiments we in our automation process we have also automated the sentiments prediction. What my loop will do, it will create a Web-driver using the selenium package, this package is used when we want to scrap news when the data which we need is inside a javascript code. So, this web-driver will create a synthetic copy of the grow website and it will go inside the news page and fetch the topmost news i.e the first top headline and then using a transformer model (gemini-pro) it will give us the sentiment of that specific news headline.

Now as we want to combine this news sentiment into our dataset, we want that it should correspond to our technical analysis data-frame we should have the sentiment score after every 3 minutes so what we have done we have printed that same sentiment

1000 times (since at each 3minute my tvdatafeed library fetches 1000 rows of data). Later, we have concatenated the sentiment data-frame with the technical indices dataframe.

So, to conclude my process of automation after every 3 minutes, my while loop will start by first fetching the data later it will start applying all the technical indicators on the fetched data and after that we will also generate the sentiment data and then concatenate the sentiment data with our technical data. After this comes the main step i.e integrating the random forest model this random forest model it will run on the data. This current model which I'll be using is the model which I have tested on my past data, that same model will consider this present data as its test data and give me the final_y predicted values (also every three minute) based on which I will decide whether to buy(1) sell(-1) or stay still(0).

VISUALIZATION:

Now even in that Automation process as I've told earlier that it not at all feasible to keep a watch on all those 11 to 12 indicators so for that purpose, we did the process of automation. Now even in that it is not possible to keep looking at the numbers that's when visualization comes into picture. In our further Study we have visualized the whole automation process to conclude our whole project into one simple chart which would basically just tell us when to buy when sell and when to stay still.

We have used the plotly package for this purpose where we have first started by integrating the following things

1. Candlesticks which would help us to understand the price position, the open high low close
2. Volume bar chart (Histogram) which would indicate the current volume in that specific timeframe
3. Pivot points i.e our support and resistances
4. Central pivot range which would help us to understand the price behaviour and locate the centre of gravity
5. An indicator which would indicate whether to buy or to sell or to stay still.
6. A separate sentiment analysis visual treat which will give signals as red, green and yellow for downtrend uptrend and no signal respectively.
7. Finally, an indicator which would indicate whether an ascending triangle pattern was observed or not.

From this process we have concluded almost all our previous steps, we started with sentiment analysis which we have used to generate the sentiments every three minute with that we have also developed our own indicator which would indicate buy sell in the chart. This indicator in its back testing has given us wonderful returns of 91% which is on and all very good.

CONCLUSION

We aimed to develop such a trading set-up which would be beneficial and generate profits. All the indicators that we have designed are made in such a way that it satisfies the 3-minute timeframe.
Another motive of this study was to understand the reason behind building a machine learning model. The condition on the basis on which we have made our final_y was considering the final y based on what maximum number of indicators are trying to say.
The model f1-score for that turned out to be 95% where the returns for y_actual was 91% and when back tested the y_predict based on the predictions given by the random forest model, it gave us returns of 93% which is greater than ours. This acts as proof to show that there are times when my condition of taking a trade based on what maximum no. Of indicators are trying to say might be wrong but the predictions given by my model won't be wrong.
This insight that we have gained acts as a very important factor behind the reason why algorithmic trading is the future.

Future Scope

- Faster execution.
- Access to global or multiple stocks.
- Maximize profit: reducing misleading candles
- Equal or nearly same importance to sentiment and technical analysis.

REFERENCES

1. Yechan Han, Jaeyun Kim, and David Enke. A machine learning trading system for the stock market based on n-period min-max labeling using Random Forest. Expert Systems with Applications, 211, 1 2023. ISSN 09574174. doi: 10.1016/j.eswa.2022.118581
2. Lo, A. W., Mamaysky, H., & Wang, J. (2000). Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *Journal of Finance*, 55(4),1705-1765.
3. Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance*, 47(5), 1731-1764.
4. Lee, C. M., & Swaminathan, B. (2000). Price momentum and trading volume. *Journal of Finance*, 55(5), 2017-2069.
5. Zhang, X., Fuehres, H., & Gloor, P. A. (2011). Predicting stock market indicators through Twitter “I hope it is not as bad as I fear”. *Procedia-Social and Behavioral Sciences*, 26, 55-62.
6. Sprenger, T. O., Tumasjan, A., Sandner, P. G., & Welpe, I. M. (2014). Tweets and trades: The information content of stock microblogs. *European Financial Management*, 20(5), 926-957
7. Menkveld, A. J. (2013). High frequency trading and the new-market makers. *Journal of Financial Markets*, 16(4), 712-740.
8. Hasbrouck, J. (2013). High-frequency trading: Background, concerns, and regulatory developments. *Journal of Economic Perspectives*, 27(2), 51-72.
9. Kirilenko, A., Kyle, A. S., Samadi, M., & Tuzun, T. (2017). The Flash Crash: High-frequency trading in an electronic market. *Journal of Finance*, 72(3), 967-998.

APPENDIX:

All codes are available in below link:

https://drive.google.com/drive/folders/1TasnYI_NiH-5xE_xh7PHddEh0lTUyDxv?usp=sharing