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Machine Learning Based Evaluation of Moving average, Super trend and RSI Indicators for Crafting Profitable Trading Strategies in Nifty 50 Indices

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Abstract: Investors and traders consistently explore innovative methods to achieve success in stock market trading. Leveraging technical analysis tools, particularly for Nifty, is crucial in anticipating market trends and price fluctuations. A combination of leading and lagging indicators provides valuable insights, aiding decision-making in trading and investments. This study focuses on prominent technical indicators such as Machine Learning Moving average, the Super trend and Relative Strength Index (RSI), analyzing their parameters and evaluating their potential to create reliable and profitable trading strategies for Nifty.

***Index Terms* -** Machine Learning Moving Average, Super Trend, Relative Strength Index, Nifty 50, Technical Analysis, Back Testing.

I. INTRODUCTION

The stock market offers numerous strategies for trading options, aimed at assisting traders in pinpointing precise entry and exit opportunities. Predicting strike rates with accuracy poses a persistent challenge for market participants. The movement in option prices is influenced by a combination of economic conditions, social trends, political occurrences, and psychological factors. Some widely employed techniques of option price estimation are time series forecasting, technical analysis and fundamental analysis each having strengths & weaknesses of its own.

A technical trading approach involves establishing a framework of rules that produce actionable trading signals. Basic trading models often incorporate one or two key parameters to fine-tune the timing of these signals. These parameters collectively define the operational rules of the system. The foundation of technical analysis lies in the assumption that price movements exhibit recurring patterns shaped by the dynamic sentiments and behaviors of investors responding to various influences. It emphasizes the notion that historical price trends provide valuable insights into anticipating future market behaviors.

II. REVIEW OF LITERATURE

Technical analysis, a widely employed methodology for forecasting future price movements based on historical price and volume data, has garnered significant attention from researchers and practitioners alike, particularly within the dynamic context of emerging markets such as India. This review synthesizes findings from selected studies, examining the application, effectiveness, and evolving strategies related to technical analysis in the Indian stock market and beyond. Several empirical studies have explored the efficacy of technical analysis in the Indian equity landscape. Sudheer (2015) conducted an empirical investigation into trading through technical analysis in the Indian stock market, assessing its utility as a decision-making tool [1]. Similarly, Pushpa BV, Sumithra C.G., and Madhuri Hegde (2017) focused on how technical analysis aids investment decision-making, specifically studying select stocks in the Indian market. Their work collectively contributes to understanding the practical applicability of technical indicators for investors operating within the Indian financial ecosystem [2].

Further, Talwar, Shah, and Shah (2019) offered a practitioner's perspective on identifying buy-sell signals using key technical indicators for selected Indian firms, bridging the gap between theoretical models and real-world trading practices [3]. These studies underscore the relevance and continued interest in validating technical analysis frameworks in a local context. Beyond general application, specific trading strategies and their profitability have been a subject of interest. Ranjit Singh and Reshampal Kaur (2014) delved into developing effective and profitable stock trading strategies, providing insights into methodologies aimed at maximizing returns [6]. The domain of options trading, a more complex derivative instrument, also leverages technical insights. The International School of Financial Markets (undated) has outlined various options trading strategies, highlighting the structured approaches used in this segment [5].

More recently, Patil and Gala (2022) conducted a study specifically on key technical indicators for effective and profitable strategies in options trading of Nifty, an important Indian index. This research indicates a growing specialization in applying technical analysis to derivative markets within India [8]. The academic inquiry into technical analysis also extends to more advanced predictive methodologies. Kadida Ramadhani Shagilla Mashaushi (2006) provided a comprehensive analysis of various technical trading strategies, laying foundational understanding for the broader spectrum of approaches [7].

Moreover, the integration of computational techniques has opened new avenues. Jan Ivar Larsen (2010) explored predicting stock prices by combining traditional technical analysis with machine learning algorithms [4]. This interdisciplinary approach suggests a future trajectory where advanced computational power could enhance the accuracy and robustness of technical predictions, moving beyond conventional charting patterns.

III. IMPORTANT TECHNICAL INDICATORS FOR DEVELOPING SUCCESSFUL AND LUCRATIVE STRATEGIES

A technical indicator represents a set of data points calculated by applying specific mathematical formulas to stock price data. These indicators provide insights into the strength and direction of price trends, particularly in relation to option strike prices. Their primary roles are to alert traders, validate market movements, and predict potential price actions. Among the numerous technical indicators available, this study emphasizes the application of the Machine Learning Moving average, Super trend Indicator and the Relative Strength Index (RSI) to NIFTY indices, assessing their efficiency in designing strategies aimed at maximizing profitability.

3.1 Moving Average using Machine Learning

Using the weighting function derived from the Gaussian Process Regression technique, the Machine Learning Moving Average (MLMA) is a responsive moving average. The user can modify characteristics like responsiveness and smoothness through the settings. Bands are another feature of the moving average that are used to indicate potential reversals. By eliminating noisy price fluctuations, the Machine Learning Moving Average estimates the price's underlying trend [10].

A longer-term moving average will be returned by a higher “Window” setting, while the responsiveness and smoothness of the moving average will be impacted by a higher “Forecast” setting; higher positive values will yield a more responsive moving average, while negative values will yield a smoother but less responsive one. Please take note that overshoots will occur when the “Forecast” setting is set too high, since the moving average will not fit the price well.

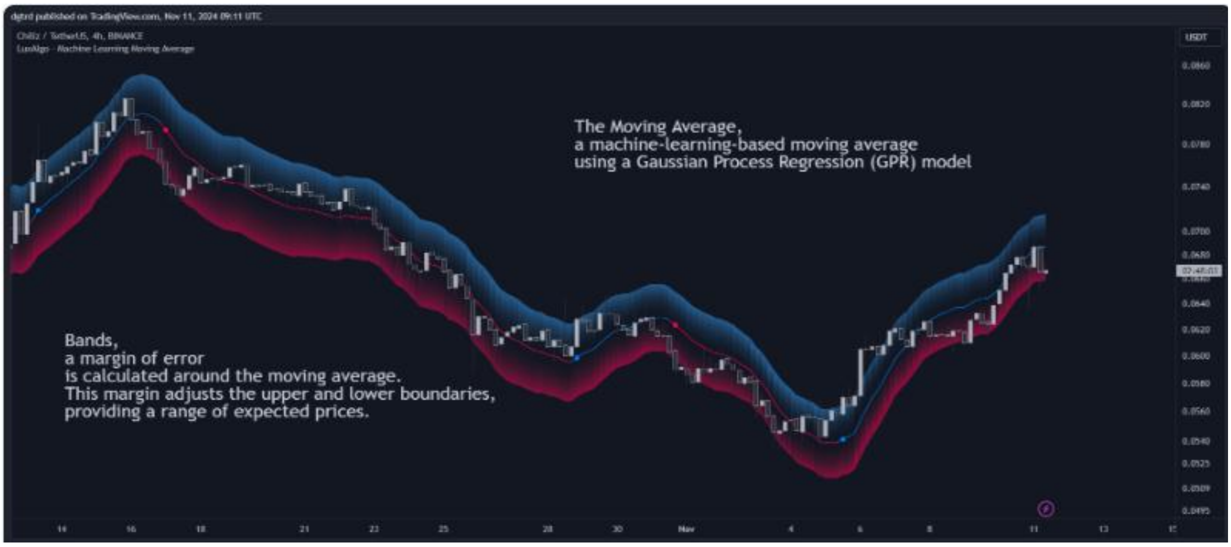

Figure 3.1.1-The Machine Learning Moving average using GPR Model

The color of the moving average changes to blue (default) in an uptrend and fushia (default) in a downtrend based on the predicted trend direction based on the bands explained below. The range that price movements most likely fluctuate within is shown by the top and lower extremities. When the price moves above or below the band extremities, signals are produced; colored circles on the chart indicate turning moments.

Window: The time frame is used to calculate the moving average. A smoother average is produced by higher values, which highlight long-term patterns and eliminate short-term oscillations.

Forecast: Establishes the Gaussian Process Regression projection horizon. Greater values produce a moving average that is more sensitive, but they will also cause more overshoots, which could make the fit with the price weaker. A moving average with negative values will be smoother.

Sigma: Affects the weight distribution via regulating the Gaussian kernel's standard deviation. A longer-term moving average is produced by higher Sigma values.

Multiplicative Factor: Modifies the upper and lower extremity bounds; greater values result in wider bands and fewer turning points that are returned.

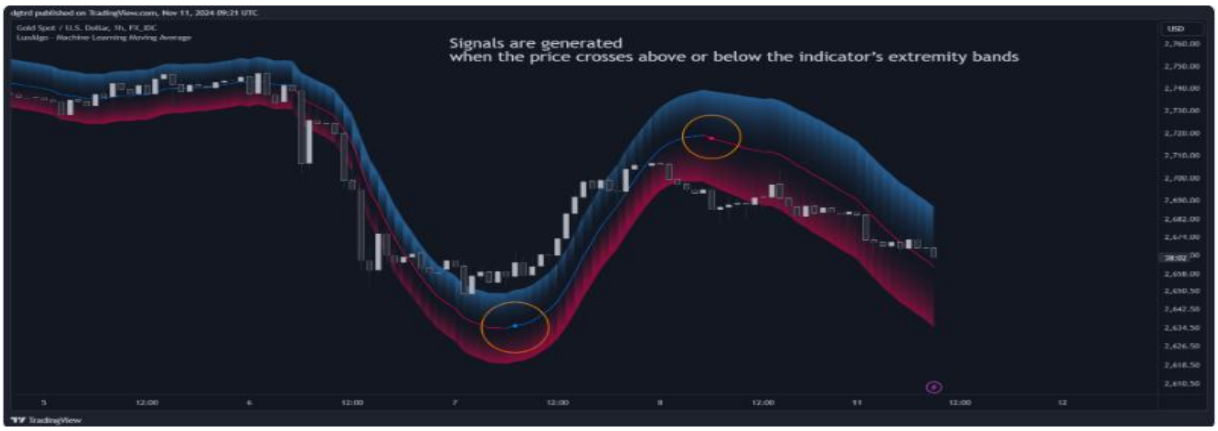

Figure 3.1.2-The MLMA with Signals Generated

3.2 Super Trend Indicator

The super trend indicator is a trend-based tool that helps evaluate price direction in the market. It is user-friendly and offers dependable information about ongoing trends. The indicator is based on two main parameters: the period and the multiplier. The default values of these parameters are 10 for the Average True Range (ATR) or trading period and 3 for the multiplier. The ATR is a crucial component of the Super trend indicator because it computes market volatility and helps in calculating its value. It determines the direction of price movement in a trending market. When displayed on stock price charts, the super trend indicator visually depicts the current market trend: a green signal represents rising prices, while a red signal indicates falling prices. This simple visual representation helps traders easily understand and track market movements.

3.2.1 How the Super Trend Indicator Functions

The period and the multiplier are the two basic parameters used to generate the super trend indicator. However, before exploring its specifics, it is crucial to grasp the concept of the Average True Range (ATR). The ATR serves as a volatility indicator by evaluating the price range of a security over a defined period.

The computation of ATR starts with the calculation of the True Range (TR) for every period, which is the highest value among the following: a) The difference between the current high and the current low, b) The true difference between the current high and the last close, and c) The absolute difference between the present low and the last close.

After calculating the TR values for all periods, the ATR is obtained by computing the moving average of these TR values over the chosen number of periods (n). This results in a smoothed indicator of market volatility, providing a clearer perspective on price fluctuations.

3.2.2 Signals to Buy and Sell

The ST indicator is a dynamic tool positioned either above or below an asset's closing price to identify buying or selling signals. It adjusts its colour to reflect market conditions: green for buy signals and red for sell signals.

When the indicator drops below the closing price, it changes to green, suggesting a buying opportunity. In contrast, when it moves above the closing price, it turns red, indicating a selling signal. The point of crossover, where the buy or sell signal is initiated, represents a shift in trend. For example, the indicator turns green when a purchase signal is present, and the closing price is above the indicator value. The indicator turns red and the closing price drops below the indicator value when a sell signal is given. To achieve particular trading goals, the super trend indicator's settings change over time.

Table 3.2.1: Configurations of the Super Trend indicator for different time frames

No.	Trading Type	Periods	Multiplier	Chart Time Frame
1	Intraday / Positional / Long-term	9	9	5 min / 15 min / Daily
2	Intraday / Positional / Long-term	14	3	5 min / 15 min / Daily
3	Intraday / Positional / Long-term	10	3	5 min / 15 min / Daily

Figure 3.2.1- In Daily Time Frame Super Trend is applied

From the above Figure 3.2.1- In Daily Time Frame Super Trend is applied - It has been noted that when we use several Super trend indicators with various parameters to NIFTY charts for daily time frame, there are multiple buying and selling signal are generated for Super trend (14,1) & Super trend (10,3) but there is no difference between buying and selling signal. In case of Super trend (10,7) buying and selling signal are generated less.

3.3 Relative Strength Index (RSI)

The Relative Strength Index (RSI) is a commonly used momentum indicator in technical analysis. It measures the extent of recent price changes to determine whether an asset is in an overbought or oversold state. By comparing the magnitude of upward price movements to downward movements, the RSI generates a value normalized on a scale of 0 to 100.

This indicator aids traders by providing insights into bullish or bearish momentum and is typically displayed below an asset's price chart. Additionally, the RSI helps assess market trends: values above 50 signify an upward trend, while values below 50 indicate a downward trend.

The RSI also identifies specific market conditions:

a. Overbought: When the RSI reaches 70 or higher, it suggests that prices may have increased beyond market expectations.
b. Oversold: When the RSI drops to 30 or below, it signals that prices may have fallen excessively relative to market conditions.
c. This makes the RSI an essential tool for identifying trends and potential reversals in price movements.

3.3.1 How this Indicator Works

The Relative Strength Index (RSI) can form unique chart patterns, such as double tops, double bottoms, and trend lines, which may not appear on the price chart itself. Traders can also identify support and resistance levels directly on the RSI. In bullish markets or upward trends, the RSI often fluctuates between 40 and 90, with the 40-50 range commonly serving as a support zone. In bearish markets or downward trends, the RSI generally ranges from 10 to 60, where the 50-60 range typically acts as a resistance zone. These thresholds can shift depending on the selected RSI settings and the strength of the underlying trend.

Price divergence occurs when the RSI fails to confirm new highs or lows in the underlying asset, signalling a potential reversal. Furthermore, a Top Swing Failure is identified when the RSI creates a lower high and subsequently drops below a prior low. Similarly, a Bottom Swing Failure takes place when the RSI forms a higher low followed by a rise above a previous high. Such patterns and divergences offer valuable insights for predicting price movements and reversals.

Table 3.3.1 illustrates the configurations for different time frames and their respective purposes.

No.	Goal	Period	Over Bought	Over Sold	Time Frame of Chart
1	Intraday Trading	9 to 11	70	30	5 Min
2	Positional Trading	14	70	30	15 Min
3	Long Term Trading	20 to 30	70	30	Daily

Figure 3.3.1- In Daily Time Frame RSI(14) & RSI (20) are applied

From the above **Figure 3.3.1 - In daily time frame**, With RSI (14), it is observed that when Periods is set to 14, there are fewer overbought and oversold signals during the time frame. With RSI (20) on the 1-day time frame, it is observed that when Periods is set to 20, very few overbought and oversold signals appear during the time frame. But with RSI (9), it has been noted that when Periods is set to 9 as a parameter to the RSI indicator for NIFTY charts, multiple overbought and oversold signals appear during the time frame.

IV. Nifty and Back Testing

The Nifty 50 is a comprehensive index representing 50 companies that capture the overall market trends. It is derived using the free-float market capitalization approach. This index serves diverse functions, including as a reference for fund portfolio benchmarks and the creation of financial products like index funds, ETFs, and structured instruments [9]. The top ten constituents of the Nifty index by weightage are as follows: HDFC Bank Ltd. holds the highest weight at 12.58%, followed by ICICI Bank Ltd. at 8.46% and Reliance Industries Ltd. at 8.09%. Infosys Ltd. and ITC Ltd. occupy the next positions with 6.17% and 4.10% respectively. Larsen & Toubro Ltd. and Tata Consultancy Services Ltd. hold 4.05% and 4.03% weightage. Rounding out the top ten are Bharti Airtel Ltd. at 4.03%, Axis Bank Ltd. at 2.99%, and State Bank of India at 2.98%. This data highlights the concentration of the Nifty index's performance on a select few stocks, with the top three constituents alone accounting for over 29% of the total weight.

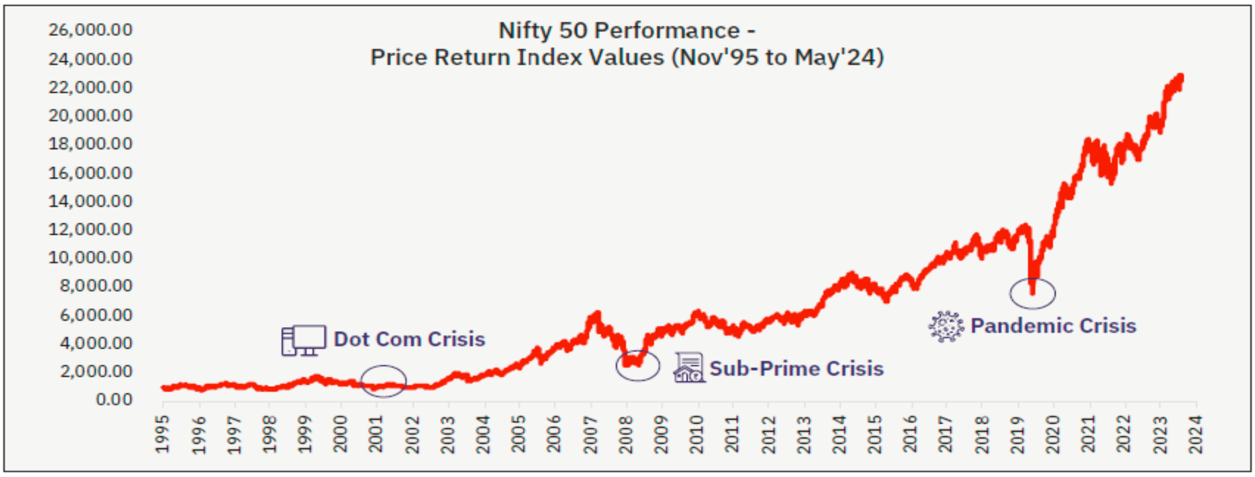

Figure 4.1 Nifty 50 Performance (Nov'95 to May'24)

4.1 MLMA Back Testing Jun'24 to Dec'24 (31% Profit in 7 Months)

Figure 4.1.1- MLMA Back Testing Jun'24 to Dec'24

The chart shows a series of bullish and bearish trends, with notable price movements captured by the buy and sell signals. The highlighted areas indicate both profitable upswings (buy signals) and downswings (sell signals). Signals appear to capture significant swings. For instance: An 8.03% return over 59 days in one trade. Another four trade with 5.40%, 7.34%, 5.01%, 5.27% gains, total around 31% gain in 7 Months periods.

4.2 Super Trend Back Testing Jun'24 to Dec'24 (31% Profit in 7 Months)

Figure 4.2.1- Super Trend Back Testing Jun'24 to Dec'24

The chart shows a series of bullish and bearish trends, with notable price movements captured by the buy and sell signals. The highlighted areas indicate both profitable upswings (buy signals) and downswings (sell signals). Signals appear to capture significant swings. Three trade with 11.60%, 7.13%, 10.86% gains, total around 30% gain in 7 Months periods.

4.3 RSI Back Testing Jun'24 to Dec'24 (25.5% Profit in 7 Months)

Figure 4.3.1- RSI Back Testing Jun'24 to Dec'24

The chart shows a series of bullish and bearish trends, with notable price movements captured by the buy and sell signals. The highlighted areas indicate both profitable upswings (buy signals) and downswings (sell signals). Signals appear to capture significant swings. Three trade with 11.85%, 7.52%, 6.16% gains, total around 25.5% gain in 7 Months periods.

V. CONCLUSION

These three indicators can be used by a trader to pinpoint the exact entrance moment and suitable departure from a market deal. Effective use of these indicators facilitates precise technical analysis, which aids traders in identifying the best times to join or exit the market. Indicators like Supertrend and Relative Strength Index (RSI), which forecast based on historical data, are dependable and efficient tools for making informed judgments in call and put options, especially when dealing with NIFTY trading. Their data-driven approach increases the legitimacy of decision-making procedures

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