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Exploring the Efficiency of Leading and Lagging Indicators in Algorithmic Trading

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Abstract

This paper details a comparison of the overall performance of leading and lagging technical indicators used in algorithmic trading over an extended period. While much of the prior research focuses on index price forecasting and some on statistical arbitrage derived from these predictive techniques, there is a scarcity of studies that assess and evaluate trading strategies. The strategies considered for the study were tested on historical data of the 50 stocks constituting the NIFTYMIDCAP50 index, listed on the National Stock Exchange of India from January 2019 to January 2024. The study examined the Relative Strength Index (RSI), stochastic oscillator, simple moving average (SMA), and exponential moving average (EMA), representing two leading and two lagging indicators, to generate trading signals using fixed parameter sets. Over five years, it was found that strategies based on leading indicators generally underperformed compared to those based on lagging indicators in longer timeframes. The mean percentage returns for strategies using lagging indicators were 37.06, while those using leading indicators were 18.67. The difference in mean returns between leading and lagging indicators across all selected stocks was statistically significant, with a p-value of less than 0.05002.

Keywords: Technical analysis, algorithms, algorithmic trading, Indian stock market, technical indicators, RSI, stochastic oscillator

INTRODUCTION

An algorithm is a set of instructions that is used to accomplish a given task. Trading algorithms are computerized models that incorporate the steps required to trade an order in a specific way [1]. This is called automated trading, also known as black-box trading [2].

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Indicators

Recently, algorithmic trading has become a highly effective method for executing trade quickly and efficiently. Central to the success of algorithmic trading strategies is the use of indicators that provide insights into market trends and potential price movements.

Leading Indicators

The leading indicators were intended to anticipate price fluctuations. The advantages of leading indicators include early signaling for entry and exit, generation of additional signals, and provision of more trading possibilities. They reflect price momentum over a defined look-back period, which is the number of periods used to compute the indicator. Key leading indicators include the Commodity Channel Index (CCI), Momentum, Relative Strength Index (RSI), stochastic oscillator, and Williams%R. When used correctly, leading indicators can predict extreme price movements well in advance but are also vulnerable to false signal generation.

Relative Strength Index

The RSI is a momentum oscillator employed to assess whether the security is overbought or oversold. Figure 1 shows the average RSI construction, which ranges from 0% to 100% [3]. Two horizontal reference lines can be seen: the 30% "oversold" line and the 70% "overbought" line. When the RSI oscillator enters a zone of considerable buying pressure compared with recent history, it is referred to as the overbought region [4]. This frequently indicates that an upward trend will halt. Similarly, the oversold area denotes the bottom portion of the momentum oscillator where a downswing ends, and there is a considerable amount of selling pressure compared with the recent past.

Stochastic Oscillator

A stochastic oscillator value close to zero indicates that today's closing price is near the lowest price that the security has traded over a selected period. Conversely, a value close to 100 suggests that today's closing price is near the highest price that security has reached during the same period. The stochastic indicator, denoted as "%K," is a mathematical ratio representation.

$$\%k = \frac{(Today's\ Close) - (Lowest\ low\ over\ a\ selected\ period)}{(Highest\ over\ a\ selected\ period) - (Lowest\ low\ over\ a\ selected\ period)}$$

A stochastic oscillator produces buy and sell signals in a manner similar to that of an RSI oscillator [4]. A value greater than 80% is considered indicative of the overbought state of the instrument and a value below 20% is considered to indicate an oversold state of the instrument, as shown in Figure 2.

Lagging Indicators

Lagging indicators track trends rather than foresee them. A lagging indicator displays proof of occurrence after the occurrence. These indicators function best when prices follow an extended trend. They do not warn about potential price changes; instead, they reflect on what prices are going on. Moving averages and Moving Average Convergence/Divergence (MACD) are notable examples of lagging indicators. Lagging indicators often reflect price movements with a very observable delay, but they also provide a certain level of robustness to the signals that the leading indicators lack. The comparison and analysis of both indicators under different conditions form the basis of our study.

Simple Moving Average

A simple moving average is determined by averaging the price of security over a specified number of periods, giving equal weight to each price within the chosen timeframe [3]. While moving averages can be calculated using the open, high, and low-price points, the closing price is the most used. For instance, a 5-day simple moving average was calculated by summing the closing prices of the last five days and dividing the total by 5.

Crossover Strategies

Crossover strategies are popularly used for automating trading signals when working with moving averages. This strategy involves using two moving averages with different calculation periods. When the shorter period average crosses the longer-period average from below, the occurrence is considered a bullish indication and generates a buy signal, and vice versa generates a sell signal, as shown in Figure 3. The working logic dictates that the shorter period moving average is more responsive to price movements, and a crossover in any direction indicates a change in the instrument's presiding trend.

Exponential Moving Average

The exponential moving average is determined by assigning more weight to recent values than to previous prices, which eliminates the latency in basic moving averages.

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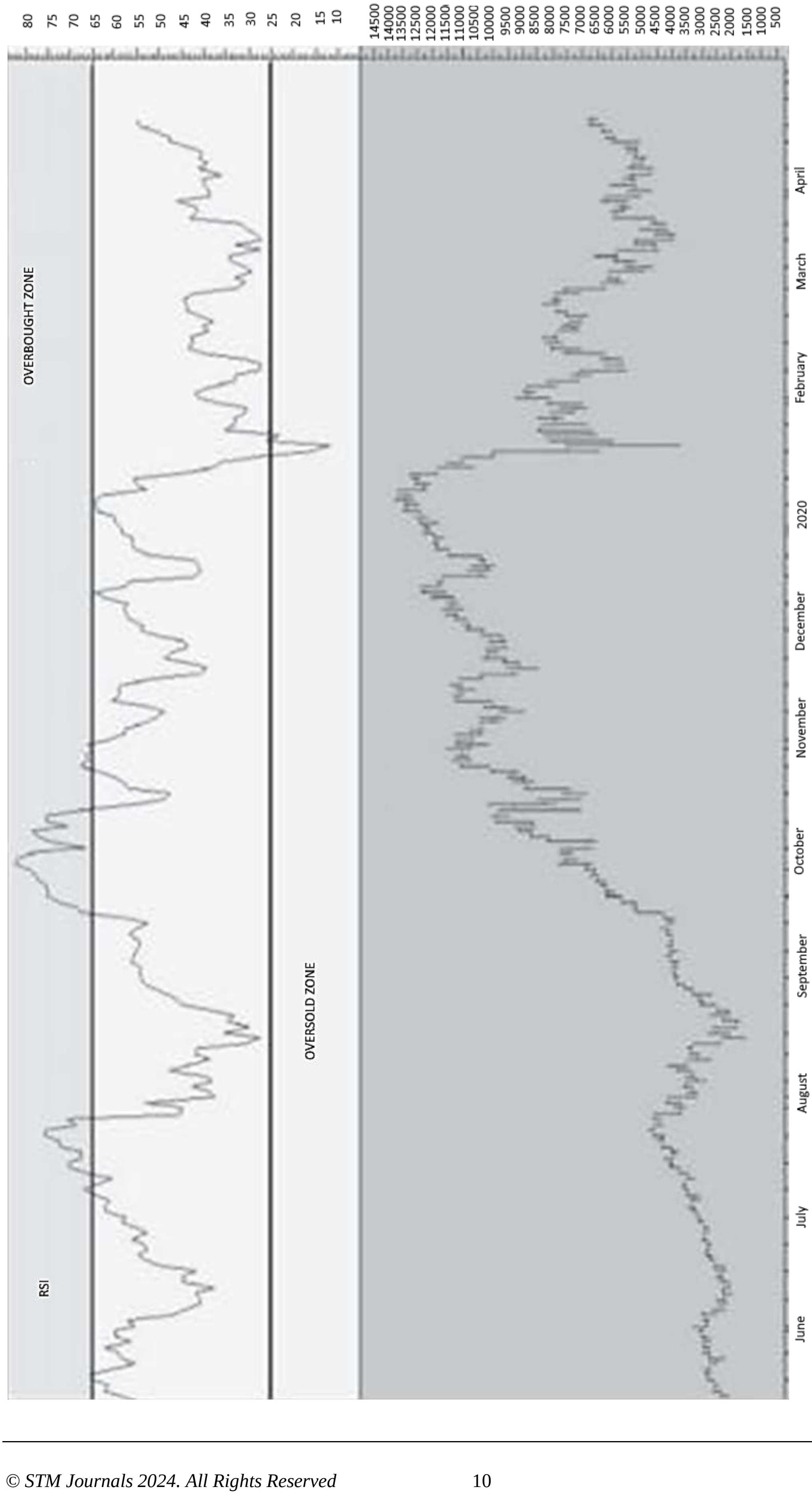

Figure 1. Nifty Chart with RSI [5].

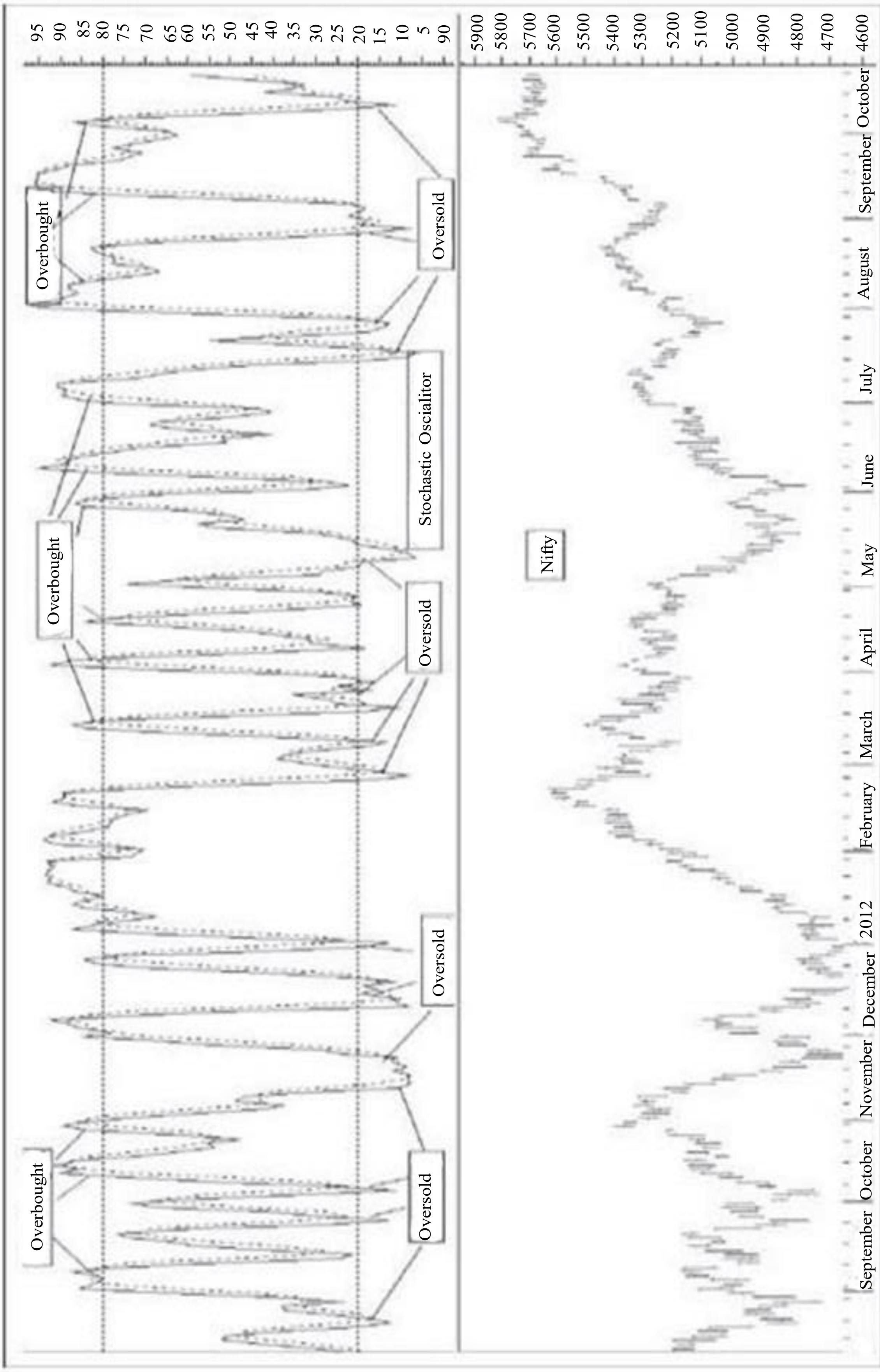

Figure 2. Nifty Chart with Stochastic Indicator [5].

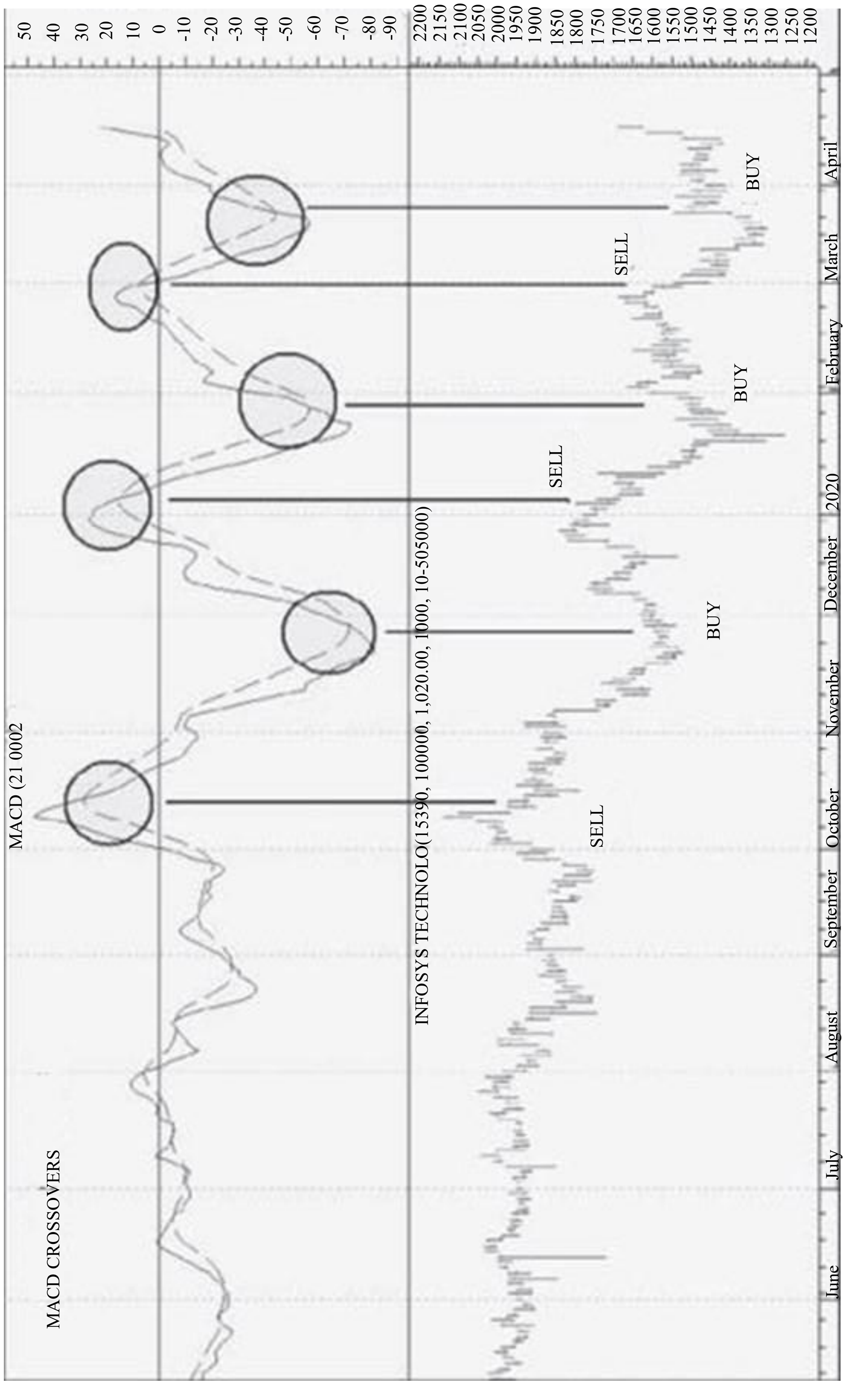

Figure 3. Infosys chart with crossovers [5].

The weighting assigned to the most recent price was defined as the time period of the moving average. The most recent price receives more weight as the EMA's timeframe shortens [6]. EMAs were used in the calculation of the MACD indicator (Moving Average Convergence and Divergence). The use of crossover strategies using EMAs amounts to using the MACD indicator as it uses the same logic to generate buy and sell signals [4].

The strategies are created around these four indicators and the overbought and oversold signals that they generate, very similar to the approach taken by Wu (2021) [7] An overbought indication generates a sell signal, and an oversold indication generates a buy signal.

LITERATURE REVIEW

Statistical Arbitrage

Statistical arbitrage refers to the practice of making decisions regarding a particular instrument based on the predicted value of the stock. The most common utilization of this concept is the creation of algorithmic trading frameworks using technical indicators that generate overbought or oversold signals based on the current state of the oscillators and indicators. Another common approach is to predict future stock values and generate buy and sell signals when the generated value deviates from the current value by over a certain amount. Extensive research has shown that the former approach is well-suited for the intended purpose.

Existing Work

Although many existing studies explore the workings of financial markets, the academic study of algorithmic trading is fairly new. Of the studies that do exist, the overwhelming majority only seek to predict price movements with high accuracy, making use of machine learning techniques, basically treating the price of the security as a time series [8], which enables the prediction of future values as a regression problem, usually via autoregressive methods.

Among the machine learning methods used for time series-based prediction, recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have emerged as leading approaches. Recent studies have demonstrated its effectiveness in various prediction tasks. For example, Troiano and Kumar [9, 10] utilized a novel method by feeding technical indicator values into an LSTM model for stock predictions. This approach is similar to that of Kaur et al. [4], which employed heuristic-based features fed into a grid-search-optimized LSTM model for stock prediction. In contrast, Bouktif et al. [11] focused on volatility prediction using LSTM networks.

In another innovative approach, Patil et al. [12] applied natural language processing-based analysis to predict stock movements for popular companies, such as Microsoft and Tesla. Similarly, Yildirim et al. [13] combined time series analysis with sentiment analysis for trading predictions and strategies. Meanwhile, Kamble [14] used evolutionary optimization to detect support and resistance levels via linear regression and employed a breakout strategy for automated trading.

Other methodologies include, Paik et al. [15] utilized decision trees and ensemble-based bootstrap random forests for stock prediction, and NSE India [16] automated the low-frequency trading strategies using leading indicators and mirroring approaches from our experiment. Additionally, Salkar et al. [17] implemented automated trading based on signal generation from both leading and lagging indicators as well as combined usage for signal generation. Another noteworthy method is presented by Koegelenberg et al. [18], which converts candlestick images into Gramian Angular Fields and then applies convolutional neural networks (CNNs) to predict patterns created by these candlesticks, yielding promising results. Many machine-learning-based prediction approaches do not use the predicted values to automate trading, rendering their results comparable to ours.

Machine learning methods achieve high accuracy in time series-based prediction, but they are not as regularly used in the formulation of automated trading platforms because they are vulnerable to biased performance on historical data, and their computational inefficiency might lead to bottlenecks in high-frequency trading atmospheres. Among the studies using various methods, we compare our findings with all the papers that presented their results in some form of percentage of returns.

PROPOSED METHODOLOGY

Data

All models are evaluated on 50 stocks from the NIFTY Midcap fund [18]. Midcap funds were selected because they are not as susceptible to larger price movements as bigger stocks and are not as vulnerable to market manipulation as smaller stocks. This functions as a clustered sampling method by segregating data according to market share. The data are of a secondary form, sourced from the Yahoo Finance API. AU Small Finance Bank Ltd. (July 31, 2018) was the latest stock listed from the selected instruments. For the experiment, all data used were from January 1, 2019, to January 1, 2024, as shown in Figure 4. We would also like to include data before 2008 to assess the performance of the strategies when the market was in the process of rapid breakdown. This was not possible due to the unavailability of data for all stocks; hence, the next best thing was to include data from 2020 to account for the rushed breakdown caused by the onset of a pandemic.

The opening and closing prices were essential for the calculation of the leading indicators, whereas the lagging indicators operated only on the closing price.

Workflow

The framework used to create the workflow was YFinance, an open-source framework built on publicly available Yahoo APIs. The data are dynamically called into a program using the library. The strategies are built and tested using the Backtrader library in Python, which allows the creation of indicator-based strategies and trading simulation on historical data, which was sourced from YFinance as stated above. The performance metric used was the percentage of returns.

Strategies

Four indicator-based strategies were implemented for comparison using two lagging and two leading indicators. The indicators used were the relative strength index (RSI), stochastic indicators (leading), simple moving averages (SMA), and exponential moving averages (EMA) (lagging). Each strategy was tested to evaluate its performance in predicting market trends and in making trading decisions.

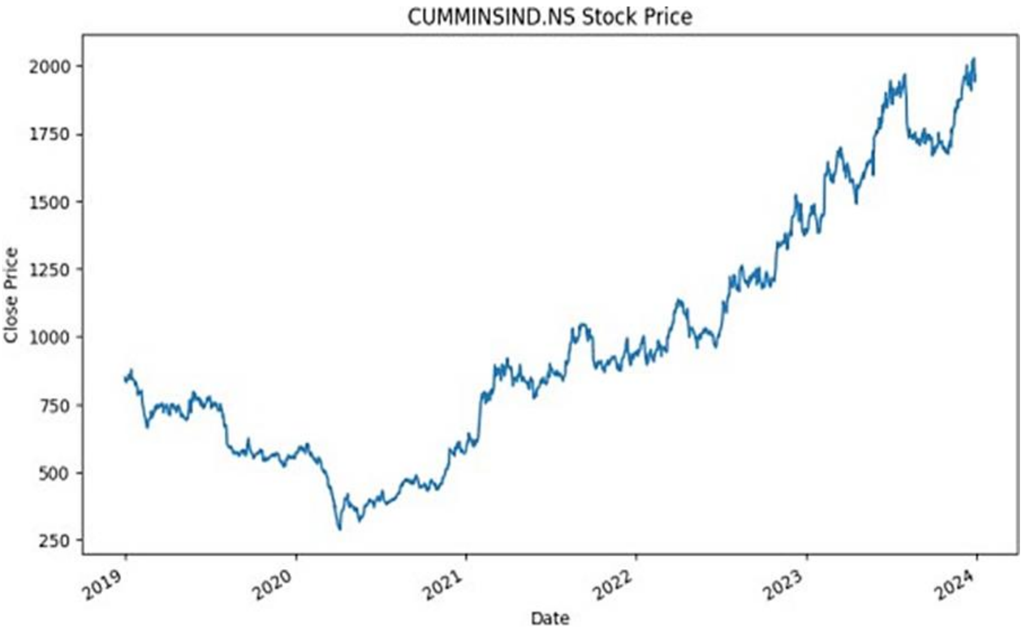

Figure 4. Sample data from the decided time frame featuring the drop of 2020.

The trading decisions were based on the signals produced by the leading indicators. An oversold signal triggered the buying of the stock in a certain predefined amount, and an undersold signal triggered a sell signal in a predefined amount.

The moving averages were used for the implementation of crossover strategies, with averages of two periods being used for the crossovers and subsequent signal generation.

The 'broker' of the back tester was assigned a predefined amount of cash to make trades, namely 10 times the closing price of the first candle.

RESULTS AND DISCUSSION

The average percentage returns over 4 years for the lagging and leading indicators are 37.06 and 18.67, respectively. This difference was statistically significant, with a p-value of less than 0.05. It was also observed that this margin deepened with an increase in the timeframe of consideration, possibly due to the accumulation of false signals by leading indicators. This is substantiated by the fact that Sundareswaran and Sathish [19] whose experiment with a timeframe of 20 days observed average returns of 12% while utilizing a combined approach using both lagging and leading indicators (MACD+RSI) and about 2% while using a resistance breakout-based strategy, which is lagging in nature.

The efficacy of these indicators is directly proportional to the time they are implemented, as substantiated by NSE India [16] which observed returns of up to 47.8% over 12 years. In contrast, Paik et al. [15] employed decision trees to predict stock prices and used these predictions to perform statistical arbitrage, exploiting the discrepancies between predicted and actual market prices for potential gains. They found that, in 66.8% of the cases where trades were made, a profit of over 10% was generated. In comparison, our strategies achieved profits of over 10% in 74.5% of cases. Additionally, Kamble et al. [14] employed evolutionary optimization to predict support and resistance levels, which were then used for trade automation. Their study reported a maximum annualized return of 18.4%, whereas our study achieved an annualized return of 34.14%, as shown in Figure 5 and detailed in the results table.

The difference in mean returns between the leading and lagging indicators across all selected stocks is found to be statistically significant, with a p-value of less than 0.05. In conclusion, the use of indicators to create algorithmic trading strategies proved to be valid.

LIMITATIONS AND FUTURE SCOPE

Another valid metric for the performance of such strategies is the hit ratio, which is defined as the ratio of profitability to total trade. We could not compare our results with some interesting work because of this disparity [20]. Another point of interest that we could not explore in this study was volume-based indicators, such as accumulation and distribution lines and balance volume.

This study focuses on the use of technical indicators in the algorithmic trading of equity stocks. Future work could also be conducted on nonstandard financial instruments, such as cryptocurrency and forex arbitrage.

CONCLUSION

During the 5-year study period, the leading indicators performed worse than the lagging ones. The average percentage returns were 37.06 for lagging indicators and 18.67 for leading indicators. The difference in mean returns between these indicators across all selected stocks is statistically significant, with a p-value of less than 0.05. It is suspected that the leading indicators perform worse because they tend to generate false signals.

1	Stock	Returns			
2		Leading		Lagging	
3		RSI	Stochastic	SMA	EMA
4	ACC	1.964961	36.04069	22.92594	-14.1662
5	AUBANK	37.3603	19.13577	38.77635	64.79553
6	ABBOTINDIA	36.88354	24.03152	41.14633	43.89519
7	ABCAPITAL	13.61178	-9.10458	23.25722	4.717559
8	ALKEM	38.02233	-2.8505	66.11887	65.53069
9	ASHOKLEY	-10.7959	35.36215	-6.27926	21.12364
10	ASTRAL	1.419031	38.16345	49.79387	49.71917
11	AUROPHARMA	1.914209	-26.8681	51.0286	55.8441
12	BALKRISIND	38.41467	21.40703	37.90852	45.06822
13	BANDHANBNK	136.5783	35.9776	24.93786	27.1541
14	BATAINDIA	18.6024	-12.9769	55.83442	49.04324
15	BHARATFORG	11.60819	20.7938	18.66193	16.69157
16	BIOCON	4.846782	-5.38755	8.091321	19.44723
17	COFORGE	10.8353	28.10389	40.63577	47.17663
18	CONCOR	24.05049	36.86849	18.93795	14.56989
19	CUMMINSIND	-1.25258	27.72728	31.60467	38.75863
20	DALBHARAT	20.71686	44.99605	71.35197	75.35601
21	ESCORTS	28.85924	18.98361	62.73676	64.84362
22	FEDERALBNK	29.45885	29.42682	17.00288	23.9193
23	GODREJPROP	-1.20197	18.63064	59.75115	81.48856
24	GUJGASLTD	16.56554	58.41821	83.95449	56.99891
25	HDFCAMC	-21.5367	2.996874	20.40563	59.21842
26	HINDPETRO	52.66984	-2.08072	31.5242	54.52494
27	IDFCFIRSTB	-14.9044	-0.22496	60.46119	58.04276
28	INDHOTEL	34.99359	53.38075	16.82077	17.72117
29	IGL	0.394405	80.74577	12.41786	3.09549
30	INDUSTOWER	19.89449	51.49461	21.90402	22.23059
31	JUBLFOOD	0.063711	32.29628	15.92602	20.49374
32	LTTS	17.62529	-6.48627	58.61045	63.57244
33	LICHSGFIN	-17.4688	19.03563	0.027967	9.354592
34	LUPIN	2.842131	14.09729	10.07974	27.73725
35	MRF	13.14064	1.349482	48.32112	49.19599
36	M&MFIN	-36.3627	7.611585	16.98954	-0.16328
37	MFSL	40.6738	60.34789	16.17942	22.67107
38	MPHASIS	8.369376	4.719417	70.03742	63.96568
39	NMDC	13.93199	-15.2972	56.72575	76.08995
40	OBEROIRLTY	22.15679	53.17837	12.41556	11.74697
41	OFSS	-21.9735	0.026107	-14.8429	23.45588
42	PAGEIND	18.61124	73.74311	26.98991	6.249625
43	PERSISTENT	8.035158	31.51608	74.4059	93.24235
44	PETRONET	36.02065	53.94116	9.072521	6.04087
45	POLYCAB	9.091405	20.3032	48.99405	70.29818
46	PFC	-1.32776	20.5149	58.05281	61.36696
47	RECLTD	3.478863	32.69953	54.01781	56.80332
48	SAIL	6.550744	9.138697	64.53701	34.33078
49	TATACOMM	36.54304	35.72785	51.8582	73.22639
50	UBL	32.87399	50.14705	-21.0935	-19.4325
51	IDEA	-23.75	-35.3125	15.31247	26.56251
52	VOLTAS	18.34721	12.20422	32.36573	23.55497
53	ZEEL	37.64105	13.48742	67.25517	70.93191

Figure 5. Results.

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