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ANALYSING TRADING STRATEGIES AND FORECASTING STOCK PRICES USING LSTM

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ABSTRACT

Algorithmic Stock Trading has been legalized in India since 2008, with SEBI (Securities and Exchange Board of India) regulating the norms governing the same. Earlier, regulations restricted third-party algorithms to be used in circulation with APIs (Application Programming Interface), as these were unregulated by registered brokerages. Owing to the COVID19 pandemic, SEBI relaxed these underlying norms, easing up both algorithm usage for an end-user, as well as the number of trade orders that can be placed per second (which went up from 20 to 120). This article aims to analyze optimal trading strategies for various stocks using both classic mathematical techniques and Recurrent Neural Networks (RNN). Stock prices will be forecasted using data analytics implementing indicators like supertrend and VWAP and machine learning models like LSTM. Upon fine-tuning parameters in both approaches, trend directions and triggers will be plotted (in the case of existing indicators and strategies) and predictions with trade triggers (in the case of LSTM). Furthermore, stocks will be categorized by trading techniques - growth, momentum, and value and further the best strategy with the expected profit percentage in each case will be identified.
Keywords*: Stock Trading, LSTM, Indicators, Trading Strategies, Forecasting.*

1. INTRODUCTION

Stock trading has steadily taken over a significant chunk of a consumer's personal finance portfolio, with a good deal of financial knowledge, capacity, and purchasing power increasing over the years. Stock trading today, even algorithmic, depends upon the user/trader manually identifying all potential trades. This creates a host of problems, from manual errors even if one follows the strategy by the book, to lag/delay in calculating. On a sidetrack, amateurs entering the market are often confused with scores of trading strategies and stocks & hence are disincentivized from entering trading. Paired up with relaxed SEBI norms, algorithmic trading is speculated to be the future of stock trading, with users from all experience levels - amateurs to professionals - delving into the same.

This research is majorly divided into three sections. First, identify optimum indicators and stocks for each category. Second, implementing these on a day-chart in TradingView and tabulating profit percentage and drawdown for each stock-indicator combination. Third, building an LSTM agent to forecast prices as well as give trade triggers, while tabulating profit percentages.

Paper is organized as follows. The related works are presented in section II. Section III and IV discusses the research gap and objectives. Section V proposes the methodology. Section VI converses the results and observations. The research work is concluded in section VII.

2. RELATED WORK

Significant amount of work has been done in the fields of statistical analysis of trade triggers [1] and using machine learning to automate trading [2] individually. However, in the reviewed literature one method is found linking both fields [3] within which only one trading methodology could be seen. Comparisons for both long and short trades have been added whenever feasible, to gauge an idea of how that affects a trader's portfolio. Forecasting and predicting using pre-existing strategies have been extensively researched and optimized [4]. LSTM models have been used to perform sentiment analysis in financial markets [5, 8,9]. However, the present research will be focused on executing the long trades. Furthermore, there has been a comparative analysis of past and future stock returns. [6,10] Stock trading has often been categorized into three major categories, amongst others - growth, momentum, and value. Indicators are of utmost importance in trading algorithms, as they're the key to building strategies. Extensive amounts of work has been found on these strategies [7] but there exists a limited elaboration on functioning with the above-mentioned trading categories.

This present work aims to link these individual fields into a single study, to provide easy-to-interpret comparative results, as well as categorize them by major trading methodologies.

3. RESEARCH GAP

As already highlighted, the primary gap in research is the interlinkage of all fields. Hence, this project mainly works on bridging this gap.

Furthermore, the authors aim to include all three major trading methodologies and perform a comparative study on them. This is the primary reason why so many previous attempts to build strategies have not yielded good results - appropriate indicators and methods have not been applied to each methodology.

Forecasting models have been built using various machine learning algorithms [11,12]. However, seldom been put up on a comparative scale against classical algorithms, let alone categorized by trade type. The aim is to build an agent that can predict prices in real-time, tick-by-tick, to be deployed on either an existing trading platform or our own.

Furthermore, previous research done has been driven towards theoretical review of trading strategies using machine learning [3], while not providing quantitative results as proof to supplement that work. This project aims to provide numerical comparisons for the same.

Research around stocks often focusses solely on return percentages, while not keeping drawdown ratios in mind. As a trader, drawdown is essential to consider while evaluating a strategy, as that is the maximum sum of money lost at one point. It is not financially feasible for a trader to incur losses above 20-30% in an algorithmic trading strategy.

4. OBJECTIVES OF THE RESEARCH

The main objective of the research is to analyse optimal trading strategies for various stocks using both classic mathematical techniques and recurrent neural networks (LSTM) Identified problem is addressed as follows:

1. Study different indicators and use them in real-time simulations to test optimal indicators.
2. Build strategies using appropriate identifiers and test them on value, momentum, and growth stocks.
3. Train Machine Learning models to forecast stock prices and back test using optimal strategies.
4. Compare all the strategies against value, growth and momentum stocks.

5. METHODOLOGY

5.1 Tools and Techniques Used:

Tools and techniques used for analysing and back testing trading strategies and machine learning models:

1. Trading View Platform
2. Pine Script language
3. Python Programming Language
4. Jupyter Notebook
5. GitHub Version Control
6. Google Workspace

5.1.1 Trading View Platform:

A charting platform and social network used by 30M+ traders and investors worldwide to spot opportunities across global markets. In this research, this category is primarily used to back test strategies and indicators on stock data.

5.1.2 Pine Script:

Pine script is a programming language created by TradingView to back test trading strategies and create custom indicators. Pine script was designed to be lightweight, and in most cases, you can achieve your objectives with fewer lines of code compared to other programming languages.

5.1.3 Python:

Python is an interpreted high-level general-purpose programming language. Its design philosophy emphasizes code readability with its use of significant indentation. Its language constructs as well as its object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects.

5.1.4 Jupyter Notebook:

The Jupyter Notebook is a web application for creating and sharing documents that contain code, visualizations, and text. It can be used for data science, statistical modelling, machine learning, and much more.

5.1.5 Github:

GitHub is a code hosting platform for version control and collaboration. It lets you and others work together on projects from anywhere. This tutorial teaches you GitHub essentials like repositories, branches, commits, and pull requests.

5.1.6 Google Workspace:

Google Workspace is a collection of cloud computing, productivity and collaboration tools, software and products developed and marketed by Google. We primarily used Google Docs, Presentation and Excel to collaborate for work.

5.2 Implementation:

For the proposed research, strategies and indicators as well as the LSTM model need to be tested against all types of stocks - Value, Momentum & Growth. From this, one can conclude and summarize the result.

The research implementation will be divided into 4 sections.

1. Segregating different types of stocks (Value, Momentum and Growth).
2. Creating and analysing strategies (moving averages and SuperTrend) on the TradingView platform using Pine Script.
3. Implementing machine learning model (LSTM) on Jupyter Notebook using Python.

5.2.1 Classifying Stocks:

a) **Value Stocks**: By definition, value stocks refers to those stocks which are currently trading at a lower value than their intrinsic value. Generally, the Nifty Stocks (Top 50 Large Cap Indian Stocks) fall into this category. We take a few of the stocks from this bucket.
b) **Growth Stocks**: Growth stocks are those stocks that might trade at a higher price in the future owing to their potential. Long trades on these types of stocks are generally profitable. These stocks are not fixed and change very frequently. Therefore, we used projections from platforms like Groww and Zerodha to shortlist this bucket of stocks.
c) **Momentum Stocks**: Momentum stocks are those stocks that are gaining momentum and show an uptrend on the candlestick chart. Short trades on these types of stocks are generally profitable but run a high risk of a sudden dropdown. These stocks are not fixed and change very frequently too. Therefore, we used projections from platforms like Groww and Zerodha to shortlist this bucket of stocks.

5.2.2 Strategy Analysis

While keeping a baseline investment of ₹1,00,000 common throughout all analysis, we switch commissions on the basis of the platform being traded upon. Some platforms charge a per-trade fee, and hence it would not be feasible for strategies that involve multiple trade entries and exits in a short period of time (as shown below in Fig. 3 and Fig. 12. Hence, we proceed with a platform (TradingView) that provides a fee based on the volume of trade. The slight change (0.004%) observed in classical strategies and LSTM is due to the platform's surcharge for user-run code as an algorithm, as opposed to using pre-existing indicators.

However, slippage has not been observed or assigned in this study for ease of analysis. Slippage refers to the difference between the expected price of a trade and actual trading price. Usually, traders accept slippages of <5% to evaluate good strategies. Lower the slippage, lower is the volatility that the strategy works against.

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We have used SMA (Simple Moving Average) as it has proven to give good results [5] [6] [9] in the past. It takes into account the average closing prices of a stock for 20 (SMA20) and 50 (SMA50) days. A common strategy is to identify trades based on these two lines (SMA20 and SMA50) intersecting.

Upon researching indicators and strategies that traders use nowadays, Supertrend, ATR (Average True Range), and Pivot Points were picked, either as stand-alone or in combination. Next, the aim was to build optimum combinations into strategies, and identify which strategy works best for a stock. Pine Script was used on the TradingView platform for the same. Here's a detailed analysis of the strategies -

a. Supertrend Stand-alone

Supertrend plots two lines, or bands, to show an overall expected buy or sell trend.

Mathematically,

*Upper Line=(High+Low)/2+Multiplier*ATR* *(1)*

*Lower Line=(High+Low)/2-Multiplier*ATR* *(2)*

Fig. 1.Supertrend Stand-Alone Graph

b. Supertrend with Pivot Points

Fig. 2. Supertrend With Pivot Points

Here, we used pivot points to identify potential market movements. Trades are assigned to buy/sell signals according to their position above/below the pivot point, respectively.

Mathematically,

P = (High+Low+Close)/3 *(3)*

c. Supertrend with explicit ATR

Here, we used ATR (Average True Range) explicitly to get a better understanding of stock volatility.

Mathematically,

$$ATR = (1/n) \sum_{(i=1)}^{(n)} TR_i \quad (4)$$

where TR is the true range of one instance.

$$TR = Max[(H-L), Abs(H-C_p), Abs(L-C_p)] \quad (5)$$

Fig. 3. Supertrend With Explicit ATR

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IDENTIFYING TRADES USING LSTM:

While referring to previous research, LSTM has given the best performance and accuracy as compared to other models like ARIMA (Siami-Namini and Namin, 2018). Optimal layer density has also been worked on, as referred previously. Next, a trading agent was built to plot trade signals and calculate profit percentages.

SMA (Simple Moving Average) was used as the baseline indicator for the agent, with a conditional buy when the 20-day SMA went above the 50-day SMA and sell in the opposite scenario. A 0.9384 : 0.0616 train-validation split was used. As each day's prediction requires data from a fixed sequence of days before it, 60 had been set as the training period. E.g., if the model is to predict tomorrow's prices, it would need data from the past 60 days.

This model was again run on all stocks, keeping the same initial input but an added 0.004% commission (for brokerage fee).

Table I. Strategy Inputs and Formulae

Strategy	Formula/Split	Input	Commission
Supertrend	Upper Line = (High+Low) / 2+Multiplier*ATR Lower Line = (High+Low) / 2-Multiplier*ATR	1,00,000	0.1 + taxes
Supertrend + Pivot Points	Pivot Point = (High+Low+Close)/3	1,00,000	0.1 + taxes
Supertrend + ATR	$ATR = (1/n) \sum_{(i=1)}^{(n)} TR_i$	1,00,000	0.1 + taxes
LSTM	0.9384 : 0.0616 (training data : validation data)	1,00,000	0.104% + taxes

6. RESULT AND OBSERVATIONS

Following are some results from TradingView's strategy tester tool:

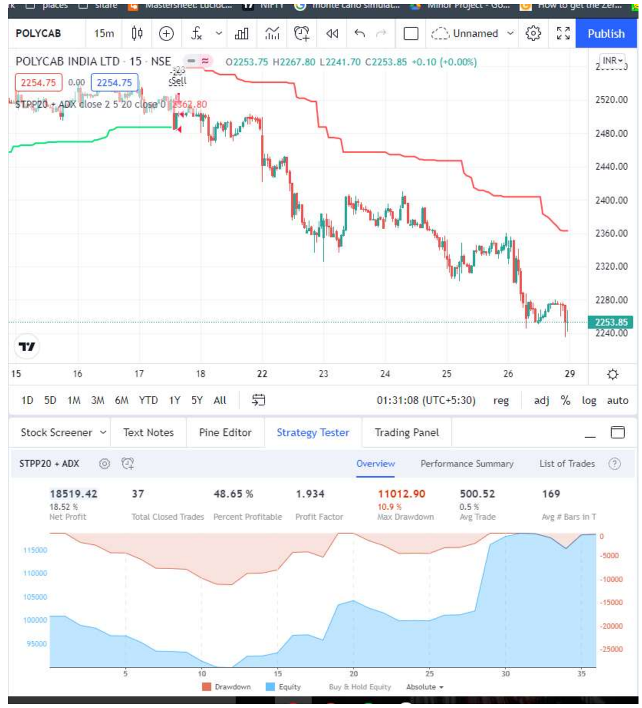
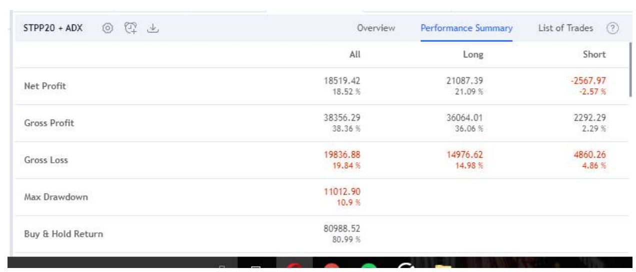


FIg. 4. Supertrend + Pivot Points-Tested On POLYCAB Stock. The Profit Percentage Is At 18.52%, With A Maximum Drawdown Of 10.9%.



STPP20 + ADX	All	Long	Short
Net Profit	18519.42 18.52 %	21087.39 21.09 %	-2567.97 -2.57 %
Gross Profit	38356.29 38.36 %	36064.01 36.06 %	2292.29 2.29 %
Gross Loss	19836.88 19.84 %	14976.62 14.98 %	4860.26 4.86 %
Max Drawdown	11012.90 10.9 %		
Buy & Hold Return	80988.52 80.99 %		

Fig. 5. Detailed Performance Summary Showing Profitable Long Trades But Short Ones Going Into Losses.

As seen in the above example, strategy 2 (Supertrend + Pivot Points) was tested on POLYCAB, which is a momentum stock. As the maximum drawdown is 10.9% and profits are reasonably high, it is a good result. Drawdown refers to the maximum per cent of initial investment lost in the given time period. Values above 15-20% are rejected as those wouldn't be profitable to the trader.

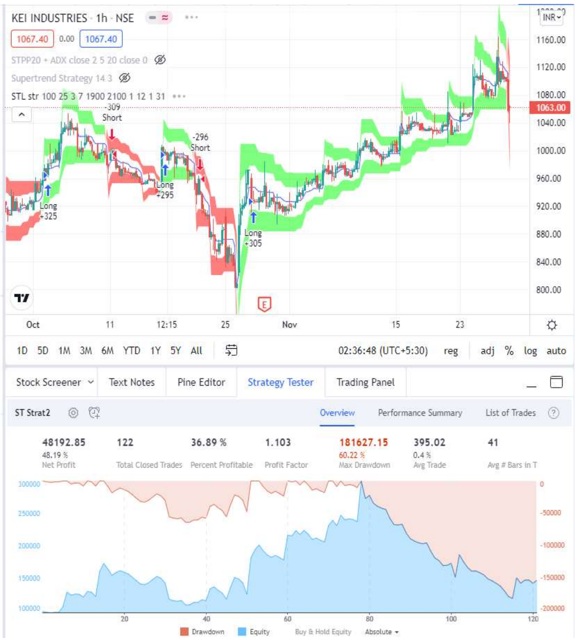


Fig. 6. Supertrend + ATR Tested On KEI INDUSTRIES.

Fig. 8. Supertrend + ATR On HINDUSTAN UNILEVER

Here, even though the profit percentage is very high (48.19%), this case will be rejected owing to maximum drawdown being 60.22%. It isn't feasible for a trader to lose more than half their money just to expect eventual profits.

In the previous two scenarios, it is clear that the strategy is going into losses. Hence, the general trend indicates strategy 3 is not feasible for value stocks like Kotak, Reliance, etc.

Fig. 7. Supertrend + ATR On KOTAK MAHINDRA BANK

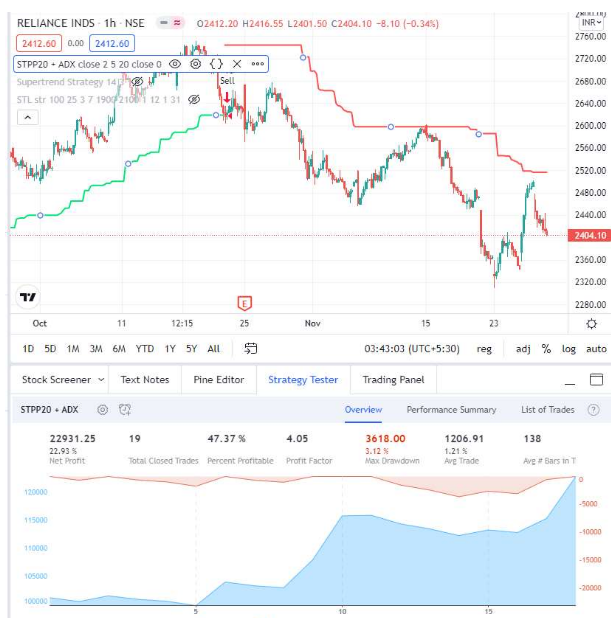


Fig. 9. Supertrend + Pivot Points On RELIANCE INDUSTRIES.

In the above scenario, strategy 2 (Supertrend + Pivot Points) was tested on Reliance Industries. A profit of 22.93% with a maximum drawdown of 3.12% and

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47.37% per cent profitability were seen. These conditions signal a successful strategy.

This was also tested on other value stocks, obtaining high-performing results (tabulated in table 2). Reasonably well-performing results are obtained for all three categories using strategies and analytical methods. The results found will be further used as a benchmark against the LSTM model.

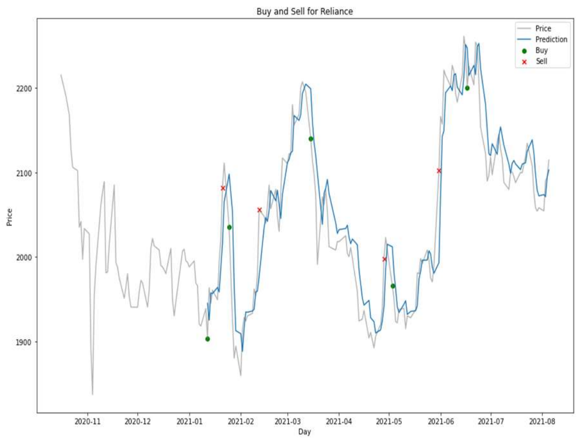

Fig. 10. LSTM Agent On RELIANCE.

Trade indicators on the grey (actual price) line are based on movement patterns in the blue (predictions) line. Notice that the initial period has no prediction, as that data is being used as a prerequisite to be training the model (As mentioned before, a day's prediction requires 60 prior days' data).

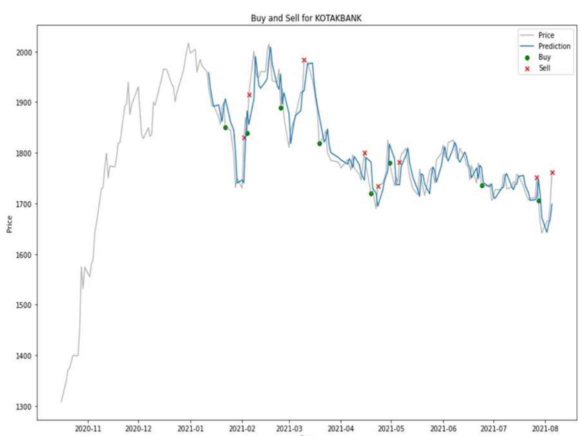

Fig. 11. LSTM Agent on KOTAKBANK.

Notice how overfitting is prevented to a large extent by training on multiple epochs (we used 3 - where the model went through the entire dataset thrice to determine trends). More could be used, but computational time increases manifold in that scenario, which isn't feasible in case one wanted to implement this in real-time.

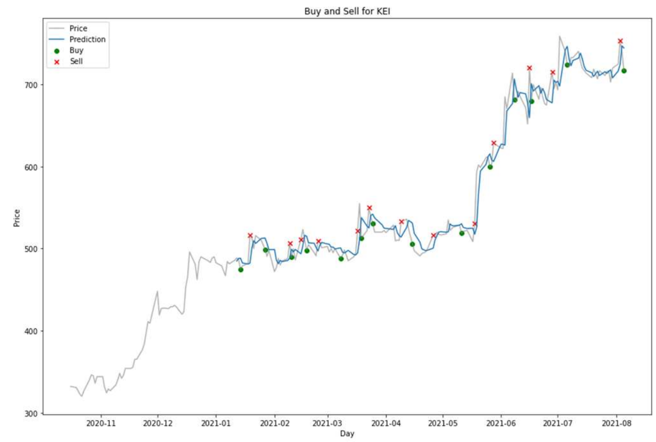

Fig. 12. LSTM Agent On KEI INDUSTRIES.

The red crosses indicate sell signals and green circles indicate buy ones. Number of trades can be identified in this stock. However, hold on all the trend for all momentum stocks, cannot be attained.

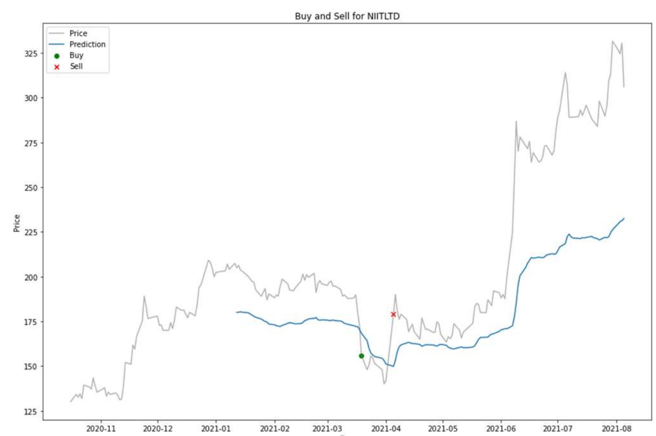

Fig. 13. LSTM Agent On NIITLTD

For the same time and parameters as Kei Industries, the agent fails to perform well on NIIT Ltd., even though both are momentum stocks. One reason could be high volatility in the NIIT stock's opening prices, which leads to lower accuracy in the model.

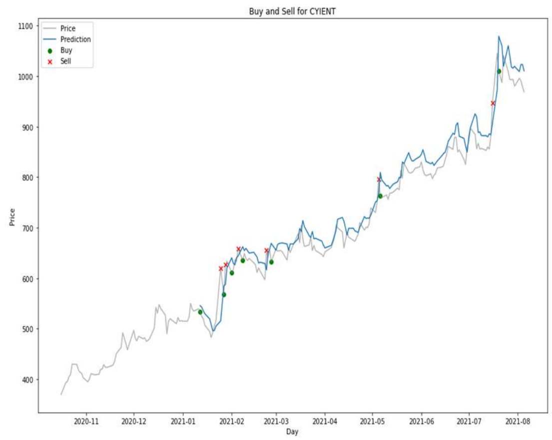

Fig. 14. LSTM Agent On CYIENT.

The agent performs extremely well on CYIENT, giving returns of 112.26%. This, along with poor performance in all other strategies as well, strengthens our belief that NIITLTD has volatility, and the fault doesn't lie with strategies for momentum trading.

Now, we have tabulated results for both LSTM and strategies to see the optimum techniques.

Table II. Profit Percentage Comparison

	Stock	LSTM Profit %	ST Profit %	ST+PP Profit %	ST + ATR Profit %
VALUE	RELIANCE	5.93	26.79	22.93	3.25
VALUE	AXISBANK	61.89	-5.67	0.58	-69.18
VALUE	HDFCBANK	24.33	0.73	-3.53	-17.05
VALUE	ICICIBANK	22.46	8.68	0.86	13.81
VALUE	BAJFINANCE	17.29	32.77	36.9	-53.57
VALUE	INFY	1.8	4.23	8.69	5.05
VALUE	LT	17.9	-3.45	5.83	-25.76
VALUE	HINDUNILVR	11.23	-7.11	8.94	-16.98
VALUE	KOTAKBANK	12.53	-0.95	-1.82	-18.43
MOMENTUM	KEI	71.3	6.94	8.46	48.19
MOMENTUM	POLYCAB		45.27	13.64	186.17
MOMENTUM	CHAMBLFERT	18.63	-2.23	2.05	29.28
MOMENTUM	NIITLTD	14.743	-1.01	2.23	-37.12
MOMENTUM	CYIENT	112.26	9.57	4.16	311.06
GROWTH	GILLETTE	10.63	44.32	-0.51	70.5
GROWTH	MGL		-10.01	4.17	-46.19
GROWTH	HDFCAMC		72.46	6.39	170.17
GROWTH	COLPAL	1.94	-10.76	1.58	5.44
GROWTH	PGHL	7.77	35.35	-2.92	3.17

Higher values are better. Shades go from white towards green on a row-wise basis, where the darkest shade indicates best within the row. Some stocks (POLYCAB, MGL, HDFCAMC) haven't been tested with the LSTM Agent as sufficient training data was unavailable.

Table III. Drawdown Percent Comparison

	Stock	ST Max DD	ST+PP Max DD	ST+ATR Max DD
VALUE	RELIANCE	9.4	3.12	32.78
VALUE	AXISBANK	9.02	3.09	72.57
VALUE	HDFCBANK	8.47	5.64	43.83
VALUE	ICICIBANK	4.2	1.86	39.67
VALUE	BAJFINANCE	27.7	13.2	62.52
VALUE	INFY	4.44	2	27.24
VALUE	LT	15.83	7.24	40.09
VALUE	HINDUNILVR	25.49	2.63	41.72
VALUE	KOTAKBANK	23.15	9.34	40.24

MOMENTUM	KEI	12.84	0.71	60.22
MOMENTUM	POLYCAB	4.07	2.52	27.11
MOMENTUM	CHAMBLFERT	5.03	0.46	34.15
MOMENTUM	NIITLTD	4.11	0.35	61.78
MOMENTUM	CYIENT	7.45	1.37	31.99
GROWTH	GILLETTE	31.81	12.54	13.5
GROWTH	MGL	14.85	2.89	58.42
GROWTH	HDFCAMC	16.12	9.86	30.23
GROWTH	COLPAL	19.69	3.95	25.73
GROWTH	PGHL	39.42	18.86	51.24

Higher values indicate higher drawdown percentages, which signals poor accuracy and performance.

7. CONCLUSION

In the present research, it can be concluded that strategy III i.e. Supertrend along with ATR is inefficient in trading due to unacceptable drawdown values for all stocks. The same can be verified through table II. Hence, the scope of comparison limits to the two previous traditional strategies and the LSTM model.

It can be seen from Table I that the LSTM agent can outperform strategies in most scenarios for value and momentum stocks. For growth stocks, data (albeit limited) suggests strategy 1 (supertrend only) outperforms the agent and strategy 2.

The LSTM model was an overall success and the primary objective of the research have been achieved. Upon analysing stocks used, it is discovered that a single algorithm can't perform well on all types of stocks. Furthermore, in an algorithm, one indicator isn't enough to give a strong indication for a trade. The combination results of at least two indicators per algorithm is required to attain the results.

Drawdown is a sanity-check of algorithms, as it isn't practically feasible for a trader to invest using an algorithm that has 50% returns but 75% drawdown, as it results in the trader losing 3/4th of their money at one point in time.

Overall, the proposed algorithms give better results than buy-and-hold, and even most conventional trading algorithms (that give returns of 15-20% on an average). The future scope of the research may be: -

1. Test on foreign markets like the NYSE and FTSE.
2. Practically test strategies on real trades.
3. Automate the whole process end-to-end.
4. Provide UI for the end-user.
5. Provide a profitable algorithm for short-term trading.

This study is not devoid of weaknesses -

1. Simple Moving Average considers historical data, and even though it's accurate eventually, is unable to reflect changes and identify trades quickly. This is one reason why a gap is observed in trade identification by LSTM.
2. As the model has to run all epochs for each individual stock, it's time-consuming to switch from trading on one stock to another.

This leaves more scope for future research, which can either deal with these problems or address the following:

1. Slippage analysis for trading
2. Using NLP (Natural Language Processing) to identify qualitative factors towards stock trading (e.g. news) [21] [22].
3. Hyperparameter tuning, in order to identify optimal trading conditions while using LSTM.

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