Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

Backtesting Brilliance: Leveraging Analytics for Comparing Buy & Hold Vs. Trading Strategies based on Technical Indicators

[1]Dr. Anjali Bhute
[1]NMIMS School of Commerce NMIMS, Navi Mumbai, India

[2]Mukund Madhav Tripathi*
[2]NMIMS School of Commerce Navi Mumbai, India (*Corresponding Author)

[3]Divyang Jadav
[3]NMIMS School of Technology Management & Engineering, Navi Mumbai, India

[4]Aditya Kasar
[4]NMIMS School of Technology Management & Engineering, Navi Mumbai, India

[5]Amit Bathia,
[5]NMIMS Anil Surendra Modi School of Commerce, Mumbai, India

ABSTRACT

Purpose

This study performs backtesting of the technical trading strategies on MAANG stocks using the analytics platform. In addition, specific ML models are used on Sensex prices to understand whether stock movements are well explained by the trading signals. The ability to forecast stock market movements has the potential to attract investors to invest in the financial rewards attached to them.

Methodology

We have used the quantmod and PerformanceAnalytics packages of R to test the trading strategies of technical indicators. The stock prediction model is tested using TA-Lib which is again an open-source library in Python.

Findings

We have found the backtesting results of trading strategies consisting of technical indicators and compared them with the risk-return tradeoff of the buy-hold strategy. In addition, the ML models for stock price predictions provided some interesting results.

Practical implications

This study contributes to the literature on the application of analytics to trading strategies. The past performance of stocks based on these strategies is beneficial for traders and investors to investigate different strategies and technical signals.

Originality and Future Scope

The combination of indicators used in the study to backtest and model building was novel and unique compared to most similar studies. For further improvement, this study can be extended to include more technical indicators and stocks to build a robust prediction model for stock prices.

Keywords: technical indicators, backtesting, ML algorithm, technical analysis, analytics

Declaration: This research received no specific grant from any public, private, or nonprofit organization.

JEL Classification: G1, G17

1. INTRODUCTION

The arrival of big data has significantly accelerated the field of analytics, which entails identifying significant trends and conveying them via a methodical approach. Analytics is the practice of applying computer programming, statistics, and operations research to quantify data and determine their value. It is particularly useful in areas where a large amount of data or information is stored.

When it comes to maximizing the potential of big data analytics in the financial industry, business and procedural factors such as the level of collaboration and big data analytics governance of the organization are more important than technical details such as the hardware and software produced by technology companies. (Lawler and Joseph, 2017). The following are the main ways in which big data affect financial markets: excess trading volumes, portfolio management, idiosyncratic volatility, risk analysis, return predictions, volatility forecasts, market valuations, comovement, and option pricing. (Hasan et al., 2020) The public prefers programmatic quantitative trading over traditional investment approaches because it is immune to human emotions, can overcome human limitations, eliminate subjective judgment, and, with the correct plan, significantly improve the likelihood of profit. (Liu., 2023)

Backtesting lays the foundation for the successful development of trading systems. Backtesting is the process of restructuring trade using given trading strategies based on historical data to test the effectiveness of the strategies. It is done by rebuilding the trading that has happened in the past by applying rules of a strategy on the past data. The results offer statistics for gauging the efficacy of this strategy. This is based on the principle that any trading strategy that has shown successful results in the past is more likely to be successful in the future and the trading strategies that had been proved unsuccessful in the past will continue to be unsuccessful in the future as well.

Backtesting is a crucial technique in the field of financial analysis that uses stock market data to achieve explainability and increase the possibility that research will be applied in the real world. (Arnott et al., 2018) According to Prado (2018), this is the process of evaluating a model's viability in the past to give one the confidence to use it going forward. This is based on the common-sense idea that tactics that have been effective or ineffective in the past will probably continue to be effective and ineffective in the future as well.

The subject of the present study is to backtest selected trading strategies using analytics. The purpose is to test a model based on trading signals for stock price prediction using an ML program.

2. RELATED WORK

2.1 Analytics in Financial Issues

The three primary advantages of implementing data analytics and business intelligence in accounting systems are improved decision-making processes, increased accuracy, and increased efficiency. Accounting professionals' decision-making capacities have increased while using real-time data through data analytics. Generally, business intelligence and big data analytics have a favorable impact on accounting systems until they conflict with corporate policies and procedures. (Aziz, 2023)

Large datasets found in banking and finance organizations were addressed by creating a few Monte Carlo trials using well-known methods and algorithms. Furthermore, as an additional incremental contribution to determining the credit risk of financial organizations, a linear mixed model (LMM) has been implemented. Better judgments can be made without the runtime component by utilizing big data to extract value from the data. Financial organizations would be less at risk when forecasting which clients will successfully make their payments and more of the credit can be disbursed to eligible firms. (Pérez-Martín et al., 2018)

In Chinese firms, venture capital plays an important role in promoting innovation performance, as assessed by the quantity and quality of patent applications. Regression research on panel data using analytics demonstrated the interdependence of sectors with high technological intensity and a greater reliance on outside funding. (Sun et al., 2020)

Studies on bankruptcy prediction have developed over time, showcasing various approaches, a wide range of criteria, and particular model applications. In terms of analytical accuracy, neural networks and multivariate discriminant analysis appear to be the most favorable approaches for predicting bank frauds. The number of factors included in the model did not ensure its accuracy. As long as bankruptcy prediction models are properly exposed to auditors, managers, lenders, and analysts, they may prove highly helpful in real-world scenarios. (Bellovary et al., 2007)

The relative quantity of explanatory factors, rarity of fraud data, and definition of fraud present obstacles for models designed to detect financial statement fraud. Improving audit companies' client portfolio decisions and identifying fraudulent filings are two of the significant advantages of improvised fraud detection. Regulators have to focus their investigations on a limited number of companies, but they can identify possible fraudulent firms more affordably by utilizing advancements in financial statement fraud prediction models. (Perols et al., 2015)

Money laundering and retail banking fraud are two financial crimes that pose a significant threat to stakeholders in the financial system. A record of statistical techniques was invented to be used to forecast money laundering. Usually, a money laundering case is contrasted with an acceptable activity case. The two sets are combined to create a single numerical number that represents possible money laundering, for which a statistic linked to the Bayes ratio is used. (Sudjianto et al., 2010)

Analytics are now extensively used to understand the interconnection between stock market performance and macroeconomics variables. Market behavior after a financial crisis can be of immense utility in strengthening the theory behind it. In addition, many of the challenges are overcome by using analytics platforms to test interrelationships. (Bhute. 2022)

Analytics in the portfolio management process involves issues such as asset screening, portfolio allocation, and trading, and the focus is on the data analytics methodologies to be applied. Portfolio managers using analytics consider not only the technical indicators that identify short- to medium-term movements in share prices and valuation indicators but also the financial data of the companies' future prospects when choosing stocks. The Markowitz mean-variance (MV) criterion served as the foundation for many additions that covered more intricate and realistic scenarios. Similarly, machine learning approaches for trading help analyze vast amounts of unstructured data in an algorithmic, dynamic, and real-time setting, with little need for a portfolio manager's interaction. (Andriosopoulos et al., 2019)

Stock market predictions are very challenging because of non-stationary, obvious and chaotic data, which creates a lot of difficulty for the investors to use their funds to maximize their stock market earnings. Artificial Neural Networks (ANN) are the most used technique for stock market prediction which is a complex task involving the analysis of many related factors. (Gandhmal and Kumar, 2019)

2.2 Backtesting Technical Indicators

The historical simulation of the performance of an algorithmic strategy is called a backtest. Because they enable researchers to assess the risk/reward profile of an investment strategy prior to committing, backtests are important tools. (Bailey et al., 2015) To find out the profitability of trading strategies, brokers and investors have been using backtesting as a tool to determine the profitability of trading strategies. This also helps them understand how trade is going to occur in the market. We have moved on from applying simple trading strategies to using more complex algorithms with more information and high frequency data. A simple trading strategy can be backtested using parallel algorithms to evaluate its effectiveness. (Ni and Zhang., 2005)

Much literature is available on the backtesting of technical indicators. Indicators such as EMA, MACD, ROC, and RSI, were used to study the technical analysis of Indian IT firms. (Pandya., 2013) Moving averages were found to give different results in the Bursa Malaysia pre and post global financial crisis. (Mohd. Nor et al., 2017) MACD, RSI and Stochastic Oscillator failed to provide any reliable trading signals on the basis of some predetermined rules. (Vikneswaran., 2016) MACD and RSI trading rules were found to be profitable in London Stock Exchange. (Chong and Ng., 2008) To generate some buy and sell recommendations for small-time investors RSI, MACD, momentum and stochastic rules were tested on the price data of Spanish companies. (Rosillo et al., 2013)

It is difficult to select indicators from the available list, even for experienced traders. Guppy multiple moving average and average directional index are found to be effective but give late signals compared to the moving average convergence divergence and relative strength index, which generates a large number of false signals. (Talwar et al., 2018) There are technical trading strategies that are effective in analyzing Indian stocks like SMA, EMA, RSI and BB. As per the Sharpe and Sortino ratios for THE sample of stocks considered, Bollinger bands and RSI gave the best results. (Tada et al., 2023)

Backtesting of trading strategies published in scholarly or professional journals rarely includes the number of trials they have undertaken to obtain the results. Since the number of trials was probably not considered, it is very likely that the researchers' findings were false positives. Academic and investment institution researchers are not motivated to publicize these results for learning purposes. (Bailey et al., 2014).

The idea of simulating historical performance extends beyond systematic strategies. A model can easily be built based on the trading history of an active trader. We can also replicate the financial results of a newspaper's investment advice and test its prior forecasts. However, tracking newspaper recommendations and implementing a systematic approach based on historical data are not the same, as the former was done in real time without any performance monitoring and the latter did not. (Schumann., 2018)

2.3 Analytics for Trading

A trial was conducted to understand the effectiveness of the technical analysis used in BRICS Member States' capital markets. Additionally, it was found that, in particular markets, technical research and straightforward analysis may be complementary. To meet the demands of each BRICS member conducting these investigations, it was established that a wide range of assets were transferred. New data and South Africa's membership in the BRICS have updated the results of earlier investigations. Action classes outperformed both the buy and maintain strategy' returns and the average portfolio for each nation. India and Russia have high sample-portfolios. (Souza et a., 2018) Machine learning models were able to analyze long-term price movements using technical indicators, such as moving average, moving average convergence/divergence, relative strength index, stochastic oscillator, and on-balance volume. An indicator called the sentiment ratio can be developed using text mining for related stocks. Some technical indicators have positive effects on trading strategies compared to others. (Lin et al., 2023)

There is a tedious approach to neural networks for improving predictions in stock markets. (Pang et al., 2020). The efficacy of four Deep Learning architectures—RNN, CNN, MLP, and LSTM—for predicting the day-by-day stock price of the Banking, IT, and Automobile sectors from NSE was also presented. (Hiransha et al., 2018) It has been demonstrated that CNN performed noticeably better and could estimate NYSE when trained on NSE data. Linear and nonlinear models were compared by the authors. The ARIMA model, which is like the linear model, was selected for comparison.

An algorithmic stock trading model was proposed that combines the signals from various technical indicators, such as the moving average convergence divergence MCDM, price rate of change and stochastic oscillator, to generate more reliable trading signals. (Darie et al., 2011) Further an artificial market was simulated with different stock market entities that would trade as per the pre-initiated rules of the market. (Daniel et al., 2008) Technical analysis was combined with KNN classification. Indicators, such as MS, RSI, and BB, were used in the analysis. For this machine-learning process, the parameters are taken from the prices and volumes of stock trades. Based on the output, buy/sell recommendations are made. (Lamartine et al., 2010)

This study focused on building machine learning models using technical indicators. We will examine the process of collection, classification, and cleaning of data using tools and frameworks that are not frequently used in the available literature.

3. EMPIRICAL FRAMEWORK

3.1 Problem Statement: *To backtest the various trading strategies using the various analytics platforms and find out if stock movements are well explained by the trading signals.*

Trading rules have always fascinated the tribe of investors who believe in making money quickly. Analytics is a game changer in the field of investments and trades. The purpose is to propose a two-stage stock return prediction model by generating and using technical analysis trading indicators in the first stage and in the subsequent stage a machine learning algorithm is implemented.

3.2 Hypothesis to be tested:

H1: Buy & Hold strategy is outperformed by a trading strategy for the liquid stocks.

H2: Stock prices are explained well by trading signals

3.3 Data: The study covers last ten years data of MAANG (Microsoft, Amazon, Apple, Netflix, Google) stocks and Sensex prices to backtest using the Exponential Moving Average (EMA), Average True Range (ATR), Simple Moving Average (SMA) Crossover strategy, Bollinger Bands (BB), Relative Strength Index (RSI), Doji Patterns, Engulfing Patterns and test the prediction model.

3.4 Techniques: Trading strategies were tested using the quantmod and PerformanceAnalytics packages of R. The trading strategies that were tested in particular were Simple Moving Average Crossover, Bollinger Bands Crossover and Relative Strength Index. The stock price prediction model was tested using TA-Lib, which is a free library in Python. We have taken the Sensex closing prices as the explained variable to be explained by variables as Volume, MA20, MA30, RSI, ATR, UBAND, LBAND, DOJI and Engulfing.

3.5 Methodology for Data Processing:

3.5.1 Backtesting Simple Moving Average Crossover Strategy

The SMA crossover strategy takes inputs for stock symbol, time range and the moving average periods. The SMA periods are taken as 50 and 200 days. Historical prices for the MAANG (Microsoft, Amazon, Apple, Netflix, Google) stocks are extracted. We have calculated the 50-day and 200-day SMAs and buy and sell signals are generated based on their crossovers.

In a simple moving average crossover strategy, a buy signal is generated when the 50-day SMA crosses above the 200-day SMA, and a sell signal occurs when it crosses below. The signals are used to update the daily trading position of buy, sell, or hold. Daily stock returns are generated and the buy and hold strategy (stocks are held) is compared with the SMA based strategy (signals) on the basis of annualized performance metrics.

3.5.2 Backtesting Bollinger Band Crossover Strategy

For Bollinger Bands strategy, we have used a 20-day moving average with a 2-standard deviation to generate buy and sell signals for the MAANG stocks. Historical prices of these stocks are extracted and adjusted for missing values. In Bollinger

Bands, the upper, lower and middle bands are calculated to generate the buy/sell signals. When the price crosses above the lower band, a buy signal is generated, and a sell signal is generated when it crosses below the upper band. The signals update the trading positions and in case of no new signal, the previous positions are maintained. Daily stock returns are generated and the buy and hold strategy (stocks are held) is compared with the BB-based trading strategy (signals) on the basis of annualized performance metrics.

3.5.3 Backtesting Relative Strength Index Strategy

We have retrieved the historical adjusted closing prices for the MAANG stocks. The missing values are filled forward. 14-Day Relative Strength Index is calculated and trading signals are generated based on RSI crossing key thresholds. A bullish or bearish signal is generated when RSI moves above 30 or drops below 70. Based on the generated signals, a position tracking vector determines whether to hold, exit or maintain the prior position. Daily returns are calculated and the buy and hold strategy (stocks are held) is compared with the RSI-based strategy's returns on the basis of annualized performance metrics. We could assess the effectiveness of an RSI driven trading strategy versus a passive investment strategy.

3.5.4 Testing of Price Prediction Model based on Trading Signals

To test a price prediction model based on signals generated by technical indicators, we have downloaded Sensex price data from Yahoo Finance and calculated the following technical indicators-

1. 20-Day Moving Average
2. 30-Day Moving Average
3. 14-Day Relative Strength Index
4. Average True Range
5. Bollinger Bands (Upper and Lower)
6. Doji Pattern
7. Engulfing Pattern
8. Stock Volumes

We then have prepared features and target by creating specific columns for technical indicators as features and closing prices of Sensex as target. The data is then split into training (up to 2022) and testing (2023 onwards) dataset. We have trained two machine learning models, Random Forest Regressor with 500 trees and K-Nearest Neighbors (KNN) regressor (after scaling features) to predict closing prices using training data. The model's performance is evaluated on both training and testing datasets.

4. EMPIRICAL RESULTS AND DISCUSSION

In Table 4.1, the Simple Moving Average Crossover strategy is tested for short and long moving averages taking past prices for 50 and 200 days. For the same period the SMA strategy risk-return trade-off was compared with a buy-hold strategy. The strategy outperforms the buy-hold strategy for Microsoft, Amazon and Netflix stocks. The backtesting of the Simple Moving Average Crossover Strategy (SMA50-200) shows that the Buy & Hold strategy works for Apple and Google stocks which rejects the hypothesis that the Buy & Hold strategy is outperformed by the trading strategy for these two stocks.

STOCKS	MICROSOFT		AMAZON		APPLE		NETFLIX		GOOGLE	
	SMA 50-200	B&H	SMA 50-200	B&H	SMA 50-200	B&H	SMA 50-200	B&H	SMA 50-200	B&H
Annualized Return	**0.2726**	**0.2828**	**0.2278**	**0.2258**	**0.2077**	**0.2728**	**0.2067**	**0.2515**	**0.1331**	**0.1769**
Annualized Std Dev	**0.2457**	**0.2706**	**0.2623**	**0.3317**	**0.2514**	**0.2837**	**0.3597**	**0.4464**	**0.2236**	**0.2794**
Annualized Sharpe (Rf=0%)	**1.1096**	**1.0449**	**0.8686**	**0.6809**	**0.8263**	**0.9615**	**0.5746**	**0.5635**	**0.5953**	**0.6331**

Table 4.1 Simple Moving Average Crossover Strategy
(Source: Author's Output)

In Table 4.2, the Bollinger Band Crossover strategy was tested for the past 20 days with a permissible deviation of 2. For the same period, the BB strategy risk-return trade-off was compared with a buy-hold strategy. The strategy fails to outperform the buy-hold strategy for all selected stocks. The backtesting of Bollinger Bands Crossover Strategy (20,2) shows that the Buy & Hold strategy has a greater Sharpe ratio for all stocks which rejects the hypothesis that the Buy & Hold strategy is outperformed by the trading strategy for liquid stocks.

Table 4.2 Bollinger Band Crossover Strategy

STOCKS	MICROSOFT	AMAZON	APPLE	NETFLIX	GOOGLE	MICROSOFT	AMAZON	APPLE	NETFLIX	GOOGLE
	BB (20,2)	B&H	BB (20,2)	B&H	BB (20,2)	B&H	BB (20,2)	B&H	BB (20,2)	B&H
Annualized Return	0.1216	0.2828	0.0757	0.2258	0.1005	0.2728	0.0298	0.2515	0.0688	0.1769
Annualized Std Dev	0.2080	0.2706	0.2422	0.3317	0.1982	0.2837	0.3100	0.4464	0.1974	0.2794
Annualized Sharpe (Rf=0%)	0.5847	1.0449	0.3125	0.6809	0.5146	0.9615	0.0962	0.5635	0.3484	0.6331

(Source: Author's Output)

In Table 4.3, the Relative Strength Index strategy is tested for the past 14 days prices to determine the trading moves for an overbought and oversold situation. For the same period, the RSI strategy risk return trade-off is compared with a buy-hold strategy. The strategy fails to repudiate the buy-hold strategy for all selected stocks. Backtesting of Relative Strength Index Crossover Strategy (14) shows that the Buy & Hold strategy has a greater Sharpe ratio for all the stocks which rejects the hypothesis that trading strategy outperforms Buy & Hold strategy for liquid stocks.

Table 4.3 Relative Strength Index Strategy

STOCKS	MICROSOFT	AMAZON	APPLE	NETFLIX	GOOGLE	STOCKS	MICROSOFT	AMAZON	APPLE	NETFLIX
	RSI (14)	B&H	RSI (14)	B&H	RSI (14)	B&H	RSI (14)	B&H	RSI (14)	B&H
Annualized Return	0.0572	0.2828	0.0677	0.2258	0.0857	0.2728	0.0636	0.2515	0.0488	0.1769
Annualized Std Dev	0.1421	0.2706	0.2238	0.3317	0.1847	0.2837	0.2697	0.4464	0.1939	0.2794
Annualized Sharpe (Rf=0%)	0.4028	1.0449	0.3027	0.6809	0.4638	0.9615	0.2359	0.5635	0.2518	0.6331

(Source: Author's Output)

In Table 4.4, a stock price prediction model is tested by taking the dependent (target) variables as Sensex Closing Prices and the independent (features) variables as Volume, MA20, MA30, RSI, ATR, UBAND, LBAND, DOJI and Engulfing. The Random Forest Regressor score is better than the KNeighborsRegressor for the test data, with the given technical indicators used as features for both models. The KNN model rejects the hypothesis that trading signals explain stock prices well.

Table 4.4 Model for Stock Price Prediction

Models	RandomForestRegressor	KNeighborsRegressor
Scores		
Training Dataset (Up to 2022)	0.9989490013712847	0.9991895780333269
Test Dataset (From 2023)	0.7502597855139406	0.5030787860160577

(Source: Author's Output)

A prediction score was obtained for the two ML algorithms for the Sensex data. The fitting of the ML models was tested for Sensex returns based on the prediction score. Random Forest Regressor scored better than the other algorithms did. This approach is new because of its simplicity, efficacy, and potential for use with other technical indicators. The results demonstrate that trading signals and their competitiveness are enhanced by the incorporation of machine learning techniques into technical analysis procedures.

5. CONCLUSION AND FUTURE SCOPE

The combination of indicators used in the study to backtest and model building was novel and unique compared to most similar studies. The indicators are executed separately on each stock database, predicting stock price directional changes and generating trade signals. The strategy returns based on the signals generated by the technical indicators are compared with the buy & hold returns. The buy-hold strategy outperformed the Bollinger-band crossover and relative strength index strategies for all five MAANG stocks. Mix results were noticed in the case of a simple moving average crossover strategy for all the five stocks.

We have combined technical indicators and ML models to create a price prediction model. The machine learning models used (Random Forest and K-Nearest Neighbors) allow for evaluating feature importance and prediction accuracy. We have demonstrated the potential of integrating technical analysis and machine learning for stock market forecasting. To enhance predictive accuracy, the model also calls for more refinement such as feature engineering or model tuning.

Backtesting was performed without considering the drawdown risk. In addition, the transaction cost and impact cost of a trade were not considered in the return calculations. MAANG stocks are selected because they are large cap stocks with high liquidity. The trading strategies can be backtested for different sets of stocks, for different time periods and parameters. The prediction model can be improved by incorporating better features (i.e., technical indicators). In addition, hyperparameter tuning of technical indicators may provide better results. For further improvement, this study can be extended to include more technical indicators and stocks to construct a robust stock price prediction model.

REFERENCES

1. Andriosopoulos, Dimitris & Doumpos, Michalis & Pardalos, Panos & Zopounidis, Constantin. (2019). Computational approaches and data analytics in financial services: A literature review. Journal of the Operational Research Society. 70. 1-19. 10.1080/01605682.2019.1595193.
2. Arnott, Robert D. and Harvey, Campbell R. and Markowitz, Harry, A Backtesting Protocol in the Era of Machine Learning (November 21, 2018), http://dx.doi.org/10.2139/ssrn.3275654
3. Bailey, D., J. Borwein, M. L´opez de Prado and J. Zhu, "Pseudo-mathematics and financial charlatanism: The effects of backtest overfitting on out-of-sample performance," Notices of the AMS, 61 May (2014), 458–471.
4. Bailey, David H. and Borwein, Jonathan and Borwein, Jonathan and López de Prado, Marcos and López de Prado, Marcos and Zhu, Qiji Jim, The Probability of Backtest Overfitting (February 27, 2015). Journal of Computational Finance (Risk Journals), 2015, http://dx.doi.org/10.2139/ssrn.2326253
5. Bellovary, J. L., Giacomino, D. E., & Akers, M. D. (2007). A review of bankruptcy prediction studies: 1930 to present. Journal of Financial education, 1-42.

6. Bhute, Anjali. (2022). Financial Analytics for Interlinking Stock Market and Macroeconomic Performance- Post Financial Crisis 2008. Model Assisted Statistics and Applications, 239 – 245.
7. Chong, T.T.L, Ng, W. K., (2008), Technical analysis and the London stock exchange: Testing the MACD and RSI rules using the FT30, Applied Economics Letters, Vol. 1, no. 15, pp. 1111– 1114
8. Darie MOLDOVAN, Mircea MOCA, Ştefan NIŢCHI. "A Stock Trading Algorithm Model Proposal, based on Technical Indicators Signals". Informatica Economică vol. 15, no. 1/2011.
9. Dattatray P. Gandhmal, K. Kumar, Systematic analysis and review of stock market prediction techniques, Computer Science Review, Volume 34, 2019, 100190, ISSN 1574-0137, https://doi.org/10.1016/j.cosrev.2019.08.001.
10. de Prado ML (2018) Advances in financial machine learning, 1st edn. Wiley, New York
11. Daniel Paraschiv, Srinivas Raghavendra, and Laurentiu Vasiliu. "Algorithmic Trading on an Artificial Stock Market". C. Badica et al. (Eds.): Intel. Distributed Comput., Systems & Appl., SCI 162, pp. 281–286, 2008. springerlink.com.
12. Farooq Aziz (2023). Data analytics impacts in the field of accounting, World Journal of Advanced Research and Reviews, 18(02), 946–951, https://doi.org/10.30574/wjarr.2023.18.2.0863
13. Hasan, M.M., Popp, J. & Oláh, J. Current landscape and influence of big data on finance. J Big Data 7, 21 (2020). https://doi.org/10.1186/s40537-020-00291-z
14. Lamartine Almeida Teixeir, Adriano Lorena Inácio de Oliveira. "A method for automatic stock trading combining technical analysis and nearest neighbor classification". Expert Systems with Applications 37 (2010) 6885–6890.
15. Lawler, J., Joseph, A. (2017). Big Data Analytics Methodology in the Financial Industry. Information Systems Education Journal, 15(4) pp 38-51. http://isedj.org/2017-15/ ISSN: 1545-679X
16. Lin, T., Yu, J., Chen, J., & Huang, C. 2023. Application of Machine Learning with News Sentiment in Stock Trading Strategies.International Journal of Financial Research, 14(3), 1
17. Liu, J. 2023. Research on Quantitative Trading Strategies Based on the Turtle Trading Rule.Highlights in Business, Economics and Management, 10, 72-80
18. M. Hiransha, E. A. Gopalakrishnan, V. K. Menon and K. P. Soman, "NSE stock market prediction using deep-learning models," in Procedia Computer Science, vol. 132, pp. 1351–1362, 2018.
19. M. J. S. de Souza, D. G. F. Ramos, M. G. Pena, V. A. Sobreiro and H. Kimura, "Examination of the profitability of technical analysis based on moving average strategies in BRICS," Financial Innovation, vol. 4, no. 1, pp. 3, 2018
20. Mohanty, P. (2023). Financial Analytics. Wiley India
21. Mohd. Nor, S., Wickremasinghe, G., (2017), Market efficiency and technical analysis during different market phases: Further evidence from Malaysia, Investment Management and Financial Innovations, Vol.14, no.2,pp. 359-366. 10.21511/imfi.14(2-2).2017.07
22. Ni, Jiarui & Zhang, Chengqi. (2005). An Efficient Implementation of the Backtesting of Trading Strategies. 3758. 126-131. 10.1007/11576235_17.
23. Pandya, H., (2013), Technical analysis for selected companies of Indian IT sector, International Journal of Advanced Research, Vol.1, no.4, pp. 430-446
24. Perols, Johan and Bowen, Robert M. and Zimmermann, Carsten and Samba, Basamba, Finding Needles in a Haystack: Using Data Analytics to Improve Fraud Prediction, April 6, 2015, http://dx.doi.org/10.2139/ssrn.2590588
25. Pérez-Martín, A., Pérez-Torregrosa, A., & Vaca, M. Big Data techniques to measure credit banking risk in home equity loans, Journal of Business Research, Volume 89, 2018, Pages 448-454, ISSN 0148-2963, https://doi.org/10.1016/j.jbusres.2018.02.008.
26. Rosillo, R., de la Fuente, D., Brugos, J. L., (2013), Technical analysis and the Spanish stock exchange: Testing the RSI, MACD, momentum and stochastic rules using Spanish market Companies, Applied Economics, Vol. 45, no. 12, pp. 1541-1550
27. Schumann, Enrico, Backtesting (December 31, 2018). Forthcoming in "Numerical Methods and Optimization in Finance (2nd ed)," by M. Gilli, D. Maringer and E. Schumann, http://dx.doi.org/10.2139/ssrn.3374195
28. Sudjianto, A., Yuan, M., Kern, D., Nair, S., Zhang, A., & Cela-Díaz, F. (2010). Statistical methods for fighting financial crimes. Technometrics, 5-19.
29. Subramaniam, P., Vikneswaran, M., (2016), A study of financial indicators' reliability in technical analysis, European Academic Research, Vol.4, no.8, pp. 6805-6834

30. Tadas, Harikrishna & Nagarkar, Jeevan & Malik, Sushant & Mishra, Dharmesh & Paul, Dipen. (2023). The effectiveness of technical trading strategies: Evidence from Indian equity markets. Investment Management and Financial Innovations. 20. 26-40. 10.21511/imfi.20(2).2023.03.
31. Talwar, Shalini & Pranav, Shah & Utkarsh, Shah. (2019). Picking Buy-Sell Signals: A Practitioner's Perspective on Key Technical Indicators for Selected Indian Firms. Studies in Business and Economics. 14. 205-219. 10.2478/sbe-2019-0054.
32. Wenqi Sun, Yuanjun Zhao, Lu Sun, Big Data Analytics for Venture Capital Application：Towards Innovation Performance Improvement, International Journal of Information Management, Volume 50, 2020, Pages 557-565, ISSN 0268-4012, https://doi.org/10.1016/j.ijinfomgt.2018.11.017.