Technical Analysis Indicators in Stock Market Using Machine Learning: A Comparative Analysis

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Abstract- Stock price forecasting is a very interesting topic in financial studies. Technical analysis indicators are mathematical models/calculations that help us predict stock price direction. The share market is not an ideal place for prediction as the share market is very volatile and share prices keep on fluctuating based on multiple factors. According to business reports, more than 90-95% of traders lose their money in the share market. The main objective of this work is to apply understanding of technical analysis indicators like RSI, exponential moving averages, Heiken Ashi candlesticks, price-volume analysis, MACD, decision tree, random forest analysis, Naïve Bayes classifier, neural network and KNN. The work in this research paper compares and analyses short-term profit considering 5-year data (2015-2019) for high-traded stocks based on accuracy.

Keywords- Stock market, Technical analysis, Technical indicators, RSI, Exponential moving average, Heiken Ashi candle sticks, Price volume analysis, MACD, Decision tree, Random Forest analysis, Naïve Bayes classifier, Neural network, KNN.

I. Introduction

Stock market trading is area of interest of many people of different age groups as people can earn money from trading in stock market. But it is impossible for person to predict stock direction with surety because stock price fluctuates every second. There are number of factors that keep affecting stock prices which are not under one's control.

According to business reports, in India less than 4% of entire population invest in stock market. This means that, most of people have predefined misconceptions about stock market. Most of people do trading without sufficient knowledge of why are they buying or selling a particular stock. This is not called as trading. This can be called as gambling. Hence most of traders lose money in stock market. But if we use technical analysis indicators to predict stock prices then it can lead to minimizing our losses and making some profit.

Many people over decades have tried various strategies to predict stock prices and have proposed many technical indicators for the same. This research paper aims to use technical indicators like RSI, exponential moving averages, Heiken Ashi candlesticks, price-volume analysis, MACD, decision tree, random forest analysis, Naïve Bayes classifier, neural network and KNN and thereby make the comparison based on accuracy of indicators for short term profit. In this research paper, indicators are back tested on highly traded stocks like Hdfcback, Reliance, Wipro, Britannia, Bajajfinsv, Hindunilvr, Nestleind, Maruti, Tatamotors, Titan and such 25 stocks considering time period of 5-year data from 2015 to 2019. All abbreviations used throughout the paper are mentioned in table 1.

Table 1: Abbreviations used.

NSE	National Stock Exchange.
BSE	Bombay Stock Exchange.
FOREX	Foreign Exchange.
SZZS	Shanghai Composite Index.
SH	Shanghai Stock Index.
SZ	Shenzhen Stock Index.
MA	Moving Average.
WMA	Weighted Moving Average.
EMA	Exponential Moving Average.
RSI	Relative Strength Indicator.
MACD	Moving Average Convergence Divergence.
SVM	Support Vector Machine.
MLP	Multilayer Perceptron.
RNN	Recurrent Neural Network.
LSTM	Long Short-Term Memory.
KNN	K-Nearest Neighbor.
BTST	Buy Today Sell Tomorrow.
STBT	Sell Today Buy Tomorrow.

This research paper can contribute to increase people's knowledge about technical analysis indicators and remove their misconception about stock market. With help of this research paper, reliability of technical analysis indicators for high volume stocks can be tested.

II. Literature Review

Correct prediction of stock market trends is of great importance as it helps in gaining profit or minimizing loss. Many methods have been deployed for the same.

The use of MACD, RSI and KDJ indicators was proposed by [2] for short term gain and 8-year data of Shanghai (SH) stock index and Shenzhen (SZ) stock index was considered and conclusion was the combination of the three oscillators can have a relatively higher possibility to predict the short-term stock changes. Results given by [2] also show that the oscillators cannot accurately predict the increasing and decreasing price of stock irrespective of bull or bear market.

The use of RSI for short term profit was considered by [15] and Nifty fifty selected stocks like Reliance, ICICI Bank, HDFC Bank, Axis Bank, TCS were taken for analysis over 7-year period and conclusion was RSI shows a significant presence in case of a long strategy at 10% and 5% level of significance.

The use of MACD, RSI and combination of both was considered by [1] and data considered was S&P 500 index over 10 years of data and conclusion was combination of MACD and RSI together can give much better results than individual indicator.

The use of MA, WMA and EMA for short term profit was proposed by [7] and Forex (foreign exchange) market data was considered over 1.5-year and conclusion was EMA is always better than WMA and WMA is always better than MA for any dataset.

The use of decision tree and neural network was proposed by [8] and Australian stock market data was considered. Their conclusion was the decision tree models are more accurate than neural network model, for smaller dataset whereas neural network performs better as for larger dataset.

The use of moving averages and for short term profit was considered by [4] and Shanghai composite index (SZZS) data was considered for analysis over 12-year period and conclusion was the short-term (5-10 Dual MAs) can generate higher profits in market before 2000 and the long-term (10-60 Dual MAs) is better since 2000.

The use of Support Vector Machine (SVM), Multilayer perceptron (MLP), Naive Bayes, Recurrent neural network (RNN), Decision Tree and Long Short-Term Memory (LSTM) was proposed by [13] and data of listed company was considered over 8-year data and their conclusion was MLP has higher accuracy than Decision Tree, Decision Tree is having higher accuracy than others under f-measure, and Decision Tree is more accurate than Naive Bayes. Performance f decision tree and RNN is better than other indicators.

The use of Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest, Softmax models and Naive Bayes was proposed by [14] and 5-to-10-year data was considered for Amazon, Cipla, Eicher, Bata and Bosch and conclusion was, Random Forest algorithm has most accurate predictions for large datasets and Naive Bayesian Classifier has most accurate predictions for small datasets. Results of [14] also reveal that reduction in the number of technical indicators reduces the accuracies of each algorithm.

The use of statistical and machine learning techniques is proposed by [16] and conclusion was hybrid approach which use combination of both statistical and machine learning approach will be more useful for prediction.

The use of nine machine learning models using Decision Tree, Random Forest, Adaboost, XGBoost, SVC, Naïve Bayes, KNN, Logistic Regression and ANN and two deep learning methods using RNN and LSTM was proposed by [17] and two types of data was employed continuous and binary data. Their conclusion was results show significant improvement if binary data is used instead of continuous data.

The use of candlestick model, regression along with machine learning models was proposed by [18] and prediction accuracy was analyzed and improved to 85%.

The use of Decision Trees, Random Forests, ensemble learning, XGBoost, Relative Strength Index (RSI) and Stochastic Oscillator was proposed by [19] and conclusion was Random Forests and XGBoost classifier had give good results. Parameters considered were accuracy, precision, recall, specificity, and F-score.

Effect of news sentiments on stock market is discussed by [20] and conclusion was with 70.59% accuracy direction of stock market can be predicted in short term.

Significance of investment in top performing stocks in index was proposed by [21] and conclusion was investing in top performing stocks increases profit as they are less prone to market volatility.

From the above literature survey, it is observed that there is scope to gain insights in the stock market through analysis of traditional indicators and machine learning to make better trading decisions and maximize profit.

With help of this research paper, reliability of technical analysis indicators for high volume stocks can be tested.

III. Proposed Methodology

This research paper applies technical analysis indicators and backtests on 5-year data to find out efficiency of all indicators.

Data source for this research has been taken from NSE India website. Data is taken for highly traded stocks like Hdfcback, Reliance, Wipro, Britannia, Bajajfinsv, Hindunilvr, Nestleind, Maruti, Tatamotors, Titan and such 25 stocks. Data is taken on daily time frame.

A. Exponential Moving Average 5-8-13:

According to [4] and [9], dual moving average are more effective than single moving average and exponential moving average are more effective than normal moving average. So, this research paper uses 5 EMA, 8 EMA and 13 EMA. 5-8-13 is considered as best combination of moving average for prediction of stocks direction as numbers 5, 8 and 13 are Fibonacci numbers.

Formula for EMA is:

$$EMA_t = P_t * (smoothing/(1+days)) + EMA_{t-1} * (1-(smoothing/(1+days)))$$

where, EMA_t means exponential moving average at time t. P_t means price at time t and smoothing means smoothing factor. This research paper assumes smoothing factor as 2.

If 5 days EMA > 8 days EMA > 13 days EMA then it is buy signal. If 5 days EMA < 8 days EMA < 13 days EMA then it is considered as selling signal. If above 2 conditions are not satisfied then there is hold signal until clear signal satisfying any of above 2 conditions are met.

EMA 5-8-13 gives us both buying and selling indications.

B. Price volume analysis:

Price volume strategy is an important strategy while trading. This research paper assumes if volume of D_i day is more than average volume of previous 5 days then it as buy signal.

Price volume analysis gives us only buying signals.

C. Heiken Ashi candlestick patterns:

Heiken Ashi candlestick pattern are better deciphered than traditional candlestick chart and hence its easier to identify market trends and movements.

$$HAopen_t = (HAopen_{t-1} + HAclose_{t-1})/2$$

$HAclose_t$ = (open + high + low + close)/4

$HAhigh_t$ = MAX (high, $HAopen_t$, $HAclose_t$)

$HAlow_t$ = MIN (low, $HAopen_t$, $HAclose_t$)

This research paper assumes that if difference between open and close price of Heiken Ashi candlestick is more than 0.5% then close is more than open price then it is buy signal. If difference between open and close price of Heiken Ashi candlestick is more than 0.5% then open is more than close price then it is sell signal.

Heiken Ashi candlestick patterns gives us both buying and selling indications.

D. Relative Strength Indicator:

RSI is used to check momentum of stock.

RSI = 100 – (100/(1+RS))

where, RS is relative strength i.e., average of 14 days gain divided by average of 14 days loss.

Usually, it is considered that if RSI value goes below 20 then stock is undervalued and it is buy signal and if RSI value goes above 80 then stock is overvalued and it is sell signal. This research paper assumes same 20-80 pair for buying and selling decisions.

RSI gives us both buying and selling indications.

E. Moving Average Convergence Divergence:

MACD is trend following momentum indicator. MACD is lagging indicator.

MACD line = 12 days EMA – 26 days EMA.

MACD signal line = 9 days EMA of MACD line.

MACD histogram = MACD line – MACD signal line.

This research paper assumes standard values of 12 days EMA and 26 days EMA for calculation. If MACD line > MACD signal line and MACD histogram is greater than 0 then it is buy signal. If MACD line < MACD signal line and MACD histogram is less than 0 then it is sell signal.

MACD gives us both buying and selling indications.

F. Moving Average Convergence Divergence crossover:

This research paper assumes MACD crossover as special case of MACD where MACD line and MACD signal line crossover each other and considering buy or sell decision same as MACD decision.

MACD crossover gives us both buying and selling indications.

G. Decision tree:

Decision tree are tree like structure which helps us to make us decision whether to buy or sell stock based on column values. Dataset input columns are gap up or gap down open, volatility and all above mentioned parameters like EMA, price volume analysis, Heiken Ashi candlesticks, RSI and MACD. This research paper uses used python inbuilt libraries for implementation and has considered 70% training data and 30% testing data for prediction.

Decision tree gives us both buying and selling indications.

H. Random forest:

Random forest is collection of decision tree for improved accuracy. Dataset input columns are gap up or gap down open, volatility and all above mentioned parameters like EMA, price volume analysis, Heiken Ashi candlesticks, RSI and MACD. This research paper uses used python inbuilt libraries for implementation and has considered 70% training data and 30% testing data for prediction.

Random forest gives us both buying and selling indications.

I. Naïve Bayes classifier:

Naïve Bayes classifier is another method for supervised learning for classification. Dataset input columns are gap up or gap down open, volatility and all above mentioned parameters like EMA, price volume analysis, Heiken Ashi candlesticks, RSI and MACD. This research paper uses used python inbuilt libraries for implementation and has considered 70% training data and 30% testing data for prediction.

Naïve Bayes classifier gives us both buying and selling indications.

J. Neural network:

MLP is another method for supervised learning for classification. Dataset input columns are gap up or gap down open, volatility and all above mentioned parameters like EMA, price volume analysis, Heiken Ashi candlesticks, RSI and MACD. This research paper uses used python inbuilt libraries for implementation and has considered 70% training data and 30% testing data for prediction.

K. K-Nearest Neighbor:

KNN algorithm is one more supervised learning model which was used in this research paper. This research paper has taken k as 10 for calculation. Dataset input columns are gap up or gap down open, volatility and all above mentioned parameters like EMA, price volume analysis, Heiken Ashi candlesticks, RSI and MACD. This research paper uses used python inbuilt libraries for implementation and has considered 70% training data and 30% testing data for prediction.

L. Entering and exiting positions:

This research paper assumes that, stock will be bought or sold whenever indicated by technical analysis indicator and exit from stock anytime when profit is achieved within 5 days and if even after 5 days profit is not achieved then accept loss and exit on 5^{th} day's closing price.

Loss can be minimised by placing stop loss order based on risk appetite.

IV. Experimental Results

This research paper finds out accuracy of various technical indicators on 25 high volume stocks from different sectors. These technical analysis indicators are tested on stocks like Hdfcback, Reliance, Wipro, Britannia, Bajajfinsv, Hindunilvr, Nestleind, Maruti, Tatamotors, Titan and such 25 stocks. After applying these technical analysis indictors, there wasn't much difference between results. So, irrespective of sector in which stock lies, technical analysis indicators give almost same accuracy. But high accuracy doesn’t always mean profit. There are chances that there are multiple small profits and one big loss can wipe out all previously achieved profits. Anyways, this can be avoided by putting a stop-loss order as per risk appetite.

Accuracy of a particular indicator is calculated as the sum of all correctly given predictions to the sum of all given predictions by that indicator. In table 2, table 3 and table 4 accuracy for indicators is shown for 1, 2, 3 and 5 days. In figure 1, figure 2 and figure 3 graphical representation for accuracy is shown.

Table 2: HDFCBANK analysis from 1st Jan 2015 to 31st Dec 2019.

Result (Accuracy):	Profit after 1 day	Profit within 2 days	Profit within 3 days	Profit within 5 days
EMA 5-8-13:	52.007 46965	64.239 02894	70.308 12325	76.097 10551
Price volume analysis:	55.4	68.8	74.2	80.6
Heiken Ashi candlestick analysis:	50.069 73501	62.622 03626	69.456 06695	75.732 21757
RSI analysis:	53.125	68.75	75	78.125
MACD analysis:	49.791 84013	61.865 11241	68.359 70025	74.104 91257
MACD crossover analysis:	53.846 15385	69.230 76923	73.626 37363	75.824 17582
Decision tree analysis:	49.722 222	58.611 111	65.555 555	68.888 888
Random forest analysis:	51.388 888	61.111 111	70.833 333	78.333 333
Naïve Bayes classifier analysis:	55.833 333	58.611 111	65.277 777	75
Neural network analysis:	53.333 333	58.055 555	60.555 555	68.611 111
K nearest neighbours analysis:	49.722 222	58.888 888	66.944 444	76.944 444

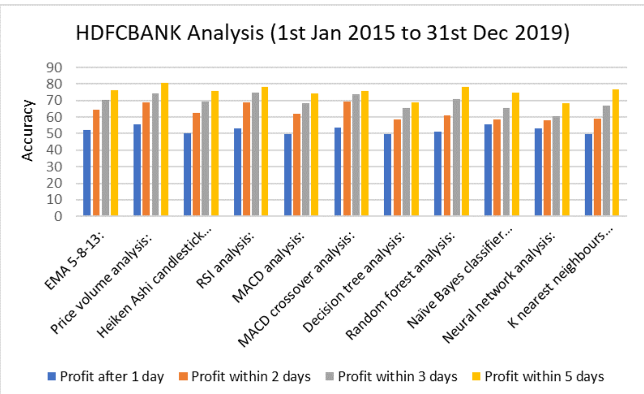

Figure 1: HDFCBANK analysis from 1st Jan 2015 to 31st Dec 2019.

Table 3: RELIANCE analysis from 1st Jan 2015 to 31st Jan 2019.

Result (Accuracy):	Profit after 1 day	Profit within 2 days	Profit within 3 days	Profit within 5 days
EMA 5-8-13:	50.046 94836	62.065 7277	67.605 6338	73.802 8169
Price volume analysis:	53.801 16959	68.421 05263	74.269 00585	79.532 16374
Heiken Ashi candlestick analysis:	51.925 19252	63.036 30363	67.986 79868	73.377 33773
RSI analysis:	54.166 66667	66.666 66667	70.833 33333	75
MACD analysis:	50.957 53539	63.030 80766	68.526 22814	74.521 23231
MACD crossover analysis:	55.660 37736	64.150 9434	68.867 92453	71.698 11321
Decision tree analysis:	52.5	57.222 222	57.499 999	65.277 777
Random forest analysis:	51.666 666	63.611 111	70.833 333	77.222 222
Naïve Bayes classifier analysis:	55.555 555	61.666 666	66.666 666	69.444 444
Neural network analysis:	46.666 666	58.888 888	67.222 222	68.666 666
K nearest neighbours analysis:	49.444 444	61.944 444	70.277 777	76.944 444

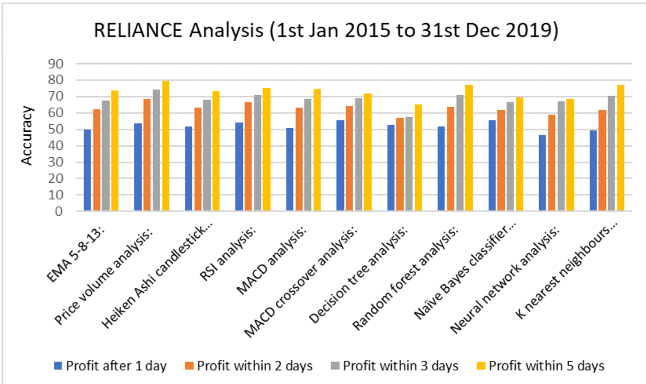

Figure 2: RELIANCE analysis from 1st Jan 2015 to 31st Dec 2019.

Table 4: WIPRO analysis from 1st Jan 2015 to 31st Dec 2019.

Result (Accuracy):	Profit after 1 day	Profit within 2 days	Profit within 3 days	Profit within 5 days
EMA 5-8-13:	51.267 60563	64.037 55869	71.549 29577	77.558 68545
Price volume analysis:	53.174 60317	65.079 36508	70.436 50794	77.777 77778
Heiken Ashi candlestick analysis:	50.961 53846	64.062 5	70.913 46154	77.644 23077
RSI analysis:	42.105 26316	63.157 89474	71.052 63158	78.947 36842
MACD analysis:	51.623 64696	64.945 87843	72.273 10575	77.768 52623
MACD crossover analysis:	44.705 88235	60	70.588 23529	76.470 58824

Decision tree analysis:	46.944 444	49.722 222	61.666 666	70.833 333
Random forest analysis:	55	57.777 777	66.666 666	73.888 888
Naïve Bayes classifier analysis:	49.166 666	60.833 333	62.5	74.166 666
Neural network analysis:	50.277 777	54.722 222	61.111 111	68.333 333
K nearest neighbours analysis:	48.333 333	53.055 555	61.111 111	72.777 777

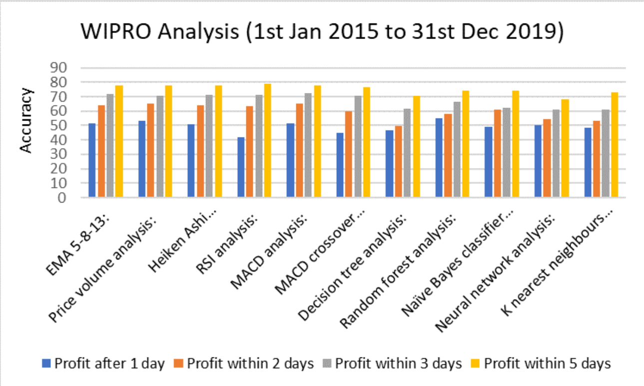

Figure 3: WIPRO analysis from 1st Jan 2015 to 31st Dec 2019.

Except for price-volume analysis, all technical analysis indicators used in this research paper can give both buying and selling indications. So, the time frame of the data was changed to the time period when the coronavirus impacted India and the market crashed to check if the accuracy of indicators changes. These indicators were still able to give predictions with the almost same accuracy.

V. Conclusion

As number of days increases, accuracy of indicators increases and chances of getting profit from stock market also increases. On an average for any high-volume stock, if BTST or STBT trade is taken based on any technical analysis indicator then probability of making profit is 50%, if trade is taken for time period of 2 days, then probability of making profit is 60%, if trade is taken for time period of 3 days, then probability of making profit is 70%, if trade is taken for time period of 5 days, then probability of making profit is 75% and it goes on increasing. There is no remarkable difference between traditional prediction methods like moving averages, RSI, MACD etc. and python-based models like decision tree, random forest, KNN, MLP, etc. but both traditional and python-based models are using statistics as base. In general, all moving average give prediction with same accuracy with difference of $\pm$2%. RSI gives very less indications as compared to other indicators. Various stocks follow various indicators and there is no universal indicator that each stock must follow. Higher accuracy doesn't mean that trade is always profitable as there are chances where there can be multiple small profit trades and if even a few trades make big losses, then all previous profits can be lost. Anyways, this can be avoided by putting a stop-loss order.

VI. Future work

This research paper assumes that people use technical indicators for trading but there is trading based on other factors as well like fundamental analysis, insider trading, etc. So, further technical analysis indicators can be combined with news sentiment analysis to further increase accuracy of prediction. This research paper takes into consideration only high-volume stocks so low volume can be taken into consideration. But low volume stocks can be manipulated by promoters. This research paper doesn't distinguish between growth stock and dividend yielding stocks. This research paper doesn't take into considerations events like stock split, dividend bonus, company merge, etc. Due to this external events price may go up or down based on how people perceive these events. This research paper doesn't take into considerations brokerage fees, GST, SEBI charges, stamp duty charges, etc charges that are needed for trading irrespective of profit or loss from trade.

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