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A COMPARATIVE ANALYSIS OF RISK DUE TO ROLLING AVERAGE STRATEGIES USING BAYESIAN CLASSIFIER

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Abstract

Any trading strategy which is a combination of technical indicators will have rolling averages as a natural choice. While it is true that the convergence of short and long rolling average is a widely used concept to analyze the pattern of price changes, the methodology of computing the rolling averages has always been a subject of discussion. In this study, the credibility of simple and weighted rolling averages in predicting the price patterns is analyzed using Bayesian classifier and the accuracy of the strategy which is assessed with back testing is used as a proxy to analyze the risk. The empirical analysis is carried out using the five stocks from NIFTY 50 selected at random. The study proposes two strategies which are:

1. SMA-RSI-ATR which is a combination of MACD computed with simple moving averages along with Relative Strength Index (RSI) and Average True Range (ATR).
2. EMA-RSI-ATR which is a combination of MACD computed with Exponential moving averages along with Relative Strength Index (RSI) and Average True Range (ATR)

Among these two strategies, the study concludes that the strategy SMA-RSI-ATR is associated with larger returns as compared with EMA-RSI-ATR. But the risk associated with SMA-RSI-ATR is higher than that of EMA-RSI-ATR as revealed by the accuracy of the model.

Keywords: Average True Range (ATR), Confusion Matrix, Momentum Indicator, Moving Average Convergence and Divergence (MACD), Naïve Bayes Classifier, Relative Strength Index (RSI), Sensitivity, Specificity, Trend Indicator, Volatility Indicator.

1. Introduction

Predicting the pattern of price changes remains a challenge forever for traders and investors. The technical indicators claim that specific patterns will lead to movement of stock prices in specific directions. But the experience has proved that all those indicators have uncertainty to certain extend. It is also true that in spite of some randomness associated with them, the technical analysis cannot be totally ignored. It is this reason which increases the utility of probabilistic models for stock price prediction. It can be said that the technical analysis tools have enhanced the usage of probabilistic models by throwing more light on the movement of prices. The objective of using a probability model is to assess the performance of a strategy which is combination of technical indicators. The Classical linear regression model can be used to forecast the share prices. But with forecasted prices alone, a trading decision cannot be made. Instead, if there is a model which directly indicates the direction of the movement of the share prices, the result may help the trader to make quick decisions. To enable the same, Classification models are used in this study. Among the various classification models like Bayes classifier, K-nearest neighbour, Decision trees, discrimnant function and Logistic Regression, this study uses the Naïve Bayes Classifier. The best strategy is identified as the one which generates more returns. The risk associated with the returns is analysed using the accuracy of the Bayesian Classifier. The study attempts to identify the more suitable among the two strategies which are SMA-RSI-ATR and EMA-RSI-ATR by analyzing the returns and the risk assessed using the accuracy of the strategy.

2. Review of Literature

The research done on the impact of technical indicators on stock prices is voluminous. Criticism of technical analysis is a topic of concern in academic research supporting the "weak form" efficient market hypothesis as defined by Fama (1970) [6]. The validity of technical analysis is often dismissed due to the belief that stock markets follow a random walk.

The studies by Fama (1965) [5], Fama & Blume (1966) [4] and Jensen & Benington (1970) [8] advocate random walk theory. Brock, Lakonishok & LeBaron (1992) [1] suggested that simple moving average techniques have predictive power when examining the Dow Jones Index between 1897 and 1985. Similar results were established by Bessembinder & Chan (1998) [2] and Craig & Parbery (2005) [3]. However, both the works suggested that the buy-and-hold strategy is superior.

Pring (1991) [10] argued that technical analysis is actually a manifestation of the idea that prices follow trend. He advocates a combination of technical tools as no single indicator has the ability identify the trend reversal. Pruitt et al (1992)[11] and Pruitt & White (1988) [12] evaluated the profitability using a combination of Relative Strength Index, Moving averages and Cumulative volume.

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Murphy (1999) [9] states that the technical analysis is a blend of many approaches and the trader can beat the market using the clues given by the technical tools. He proved that the more the trader uses indicators, the more he may be able to choose the better clues and consequently has more chances to earn abnormal returns.

Kwon & Kish (2002) [8], on the other hand, suggested that technical trading rules had the possibility to be more profitable than a buy-and-hold strategy when examining the NYSE. Lamartine Almeida Teixeira a, Adriano Lorena Inacio de Oliveira (2010) [14] proposed a method with stop loss, stop gain, and RSI filter in the nearest neighbor classification algorithm.

Vasiliou et al. (2006) [17] conducted the study by using Moving average and moving average convergence divergence (MACD) rules and concluded that these strategies produced above average returns as compared to B&H strategy. To investigate the question that whether the tools of Technical analysis outperformed the B&H policy, Lento and Gradojevic (2007) [15] conducted a study employing MACD, Bolinger Bands and filter rules on four different indexes. They established that out of the four rules, the filter and MACD rules performed well. Similarly, BB and filter rules are not profitable after considering the cost of transactions.

Sadegh Bafandeh Imandoust, Mohammed Bolandraftar (2014) [13] developed three models and compared their performances in predicting stock price movement in Tehran Stock Exchange (TSE) Index. They used Decision tree, Random Forest and Naïve Bayesian Classifier classification techniques with ten microeconomic variables and 3 macroeconomic variables as input. The experiment resulted in Decision tree model with 80.08% accuracy, Random Forest with 78.8% accuracy and Naïve Bayesian Classifier with 73.8% accuracy.

Subathra (2020) [16] examined three different types of pivots using discriminant analysis and identified that the pivot point which assigns maximum weight to close price gives better classification.

3. Research Methodology

Smoothing the prices in the time series data help us to understand the tendency of the prices to move in a particular direction. The crossover of short and long moving averages has more predictive ability as it throws more light on the possible uptrend or downtrend. Consequently, the Moving Average Convergence and Divergence (MACD) has become an inevitable technical tool in many trading decisions. Many approaches of computing the moving averages are used in practice. This study considers two strategies based on Simple Moving Average (SMA) and Exponential moving average (EMA). A simple moving average is formed by computing the average price of a security over a specific number of periods. In general, they are computed based on closing prices**.** It is called moving or rolling because the old data is dropped as new data becomes available, causing the average to move along the time scale. It is a lagging indicator as it is based on past prices. The Weighted moving average assign a heavier weighting to recent data points as they carry more relevant information.

The main aim of this work is to identify an appropriate trading strategy. But using a single indicator as a market monitor may not be an effective practice. Hence multiple indicators are used in this work to identify the more competing strategy. A multi-indicator strategy may become redundant when they provide same type of information. Selection of one indicator from each broad category of technical indicators may be an effective way of avoiding this fallacy. With this realization this work considers the following technical indicators to frame the strategies.

The MACD (Moving Average Convergence/Divergence) is a technical analysis tool which shows the relationship between prices and rolling averages. It is the difference between 26 period and 12 period rolling averages. The 9 period rolling averages indicate the trading positions. The divergence in MACD indicates the altering trend. Although the standard setting for the MACD considers the Exponential moving average, any type of moving average can be used. The types used in general are|: The Simple Moving Average (SMA), the Exponential Moving Average (EMA), the Weighted Moving Average (WMA) and the Adaptive Moving Average (AMA). In this study SMA and EMA are compared.

Relative Strength Index (RSI) is a leading indicator that measures the speed and the price movement. RSI which is a momentum oscillator oscillates between zero and 100. The stock is considered overbought when RSI is above 70 and oversold when it is below 30. The Average True Range which measures the intensity of movement of a stock in the past is a volatility measure. With the above technical indicators, the study considers two strategies based on SMA and EMA which are:

1. SMA-RSI-ATR where MACD computed with SMA is used in conjunction with RSI and ATR
2. EMA-RSI-ATR where MACD computed with EMA is used in conjunction with RSI and ATR.

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Classification method

Having decided to use classification algorithms, the next challenge is to pick a dependent variable whose values are the favorable price points. Since the idea is to analyze the relationship between the categorical dependent variable and the selected technical indicators, it is necessary to have a classification algorithm to achieve the objective. Classification is a technique where we categorize data into a given number of classes. The main goal of a classification problem is to identify the category/class to which a new data will fall under. The objective of a trader is to decide whether a stock price will increase or decrease. Since our dependent variable is a random variable, it is decided to utilize probabilistic classifiers which classify the values based on probabilities. The stock market is full of information and if the classification is done by incorporating more information, the process may be successful. Bayes theorem is a concept which revises already existing prior probabilities using additional information. In order to make use of this benefit, Naïve Bayes classifier is used in this study.

The Naïve Bayes Classifier is a supervised learning method. Classification is done in two steps in this study. The first step is a learning step in which the training set is used to construct the model. The second step is a classification step in which the class labels are predicted for the test data based on the constructed model. In this method membership probability for each class is predicted and the class with the highest probability is considered as the most likely class.

Evaluation Measures used for the classification model

In Classification problem a data set of labeled Classification is a common machine learning task. The method utilizes a labeled data set to label the unlabelled data. In general, the performance of the classifier is evaluated based on confusion matrix. Among various evaluation measures furnished by the Confusion matrix, the following measures are used in this study.

i. Accuracy of the fitted model is calculated as the ratio of number of correct predictions divided by total number of predictions.
ii. Sensitivity is the proportion of the positive class correctly predicted.
iii. The proportion of negative class correctly predicted is called Specificity.

4. ANALYSIS

The study uses the Naïve Bayesian Classifier to predict stock price movement. The daily prices of randomly selected NIFTY stocks from 01-01-2020 to 30-04-2021 collected from the official website of National Stock Exchange are used in this study. 75% of the observations are used as training data and the remaining 25% as the testing data for Bayesian classification.

The stocks selected at random from the NIFTY stocks are: PETRONET, GRASIM, BPCL, HDFCBANK and Maruti. The analysis is carried out with the following steps.

Step-1: At the outset, the returns generated are computed using three strategies:

1. Buy and hold strategy
2. SMA-RSI-ATR which is the combination of MACD computed using Simple Moving Average, RSI and ATR.
3. EMA-RSI-ATR which is the combination of MACD computed with Exponential moving average, RSI and ATR.

The comparative movement of buy and hold return and the respective strategic return are represented in Figure 1 to Figure 10. The returns are tabulated to identify the prospective strategy.

Step-2: Having computed the returns, the next step is to apply Bayesian classification, the purpose for which is two-fold:

i. To assess the efficiency of the strategies.
ii. To compute the risk associated with the returns in terms of the accuracy of the fitted models.

The credibility of the fitted model is analyzed using back testing the model by using 75% of the data as training data and the remaining 25% as the testing data.

Among the two strategies SMA-RSI-ATR and EMA-RSI-ATR, the better strategy is the one which satisfies the above criteria. The following figures compare the Buy and Hold return with the returns due to the strategies SMA-RSI-ATR and EMA-RSI-ATR for the randomly selected stocks from NIFTY 50.

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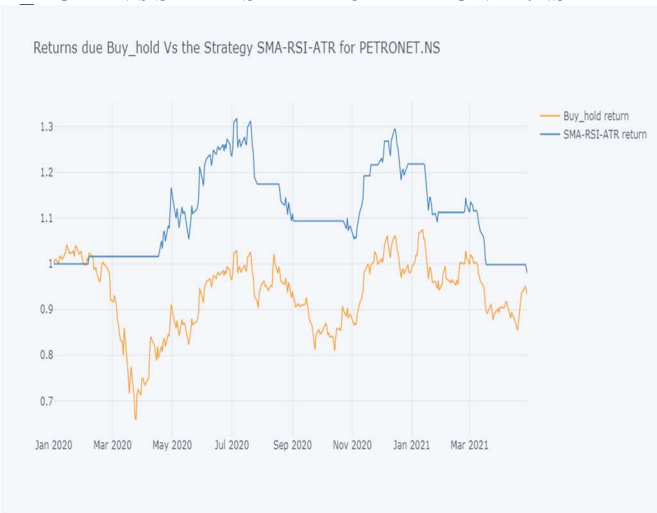
Figure-1: RETURNS DUE TO BUY_HOLD Vs SMA-RSI-ATR for PETRONET.NS



Cumulative return from Buy hold: -6.64 %
Cumulative return from SMA-RSI-ATR Strategy: -2.0 %

Figure-2: RETURNS DUE TO BUY_HOLD Vs EMA-RSI-ATR for PETRONET.NS

Cumulative return from Buy_hold : -6.64 %
Cumulative return from EMA-RSI-ATR Strategy: 7.76 %

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Figure-3: RETURNS DUE TO BUY_HOLD Vs SMA-RSI-ATR for GRASIM.NS

Cumulative return from Buy_hold: 83.0 %
Cumulative return from SMA-RSI-ATR Strategy: 93.31 %

Figure-4: RETURNS DUE TO BUY_HOLD Vs EMA-RSI-ATR for GRASIM.NS

Cumulative return from Buy_hold: 83.0 %
Cumulative return from EMA-RSI-ATR Strategy: 97.76 %

Figure-5: RETURNS DUE TO BUY_HOLD Vs SMA-RSI-ATR for BPCL.NS

Cumulative return from Buy_hold : -5.31 %
Cumulative return from SMA-RSI-ATR Strategy: 8.55 %

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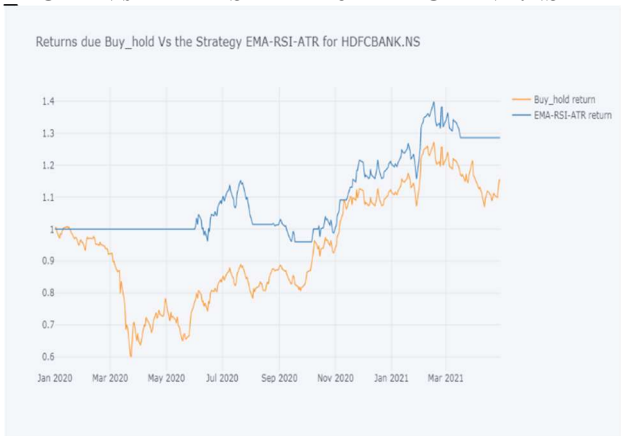
Figure-6: RETURNS DUE TO BUY_HOLD Vs EMA-RSI-ATR for BPCL.NS

Cumulative return from Buy_hold: -5.31 %
Cumulative return from EMA-RSI-ATR Strategy: 14.98 %

Figure-7: RETURNS DUE TO BUY_HOLD Vs SMA-RSI-ATR for HDFCBANK.NS

Cumulative return from Buy_hold: 15.17 %
Cumulative return from SMA-RSI-ATR Strategy: 7.86 %

Figure-8: RETURNS DUE TO BUY_HOLD Vs EMA-RSI-ATR for HDFCBANK.NS



Cumulative return from Buy_hold: 15.17 %
Cumulative return from EMA-RSI-ATR Strategy: 28.6 %

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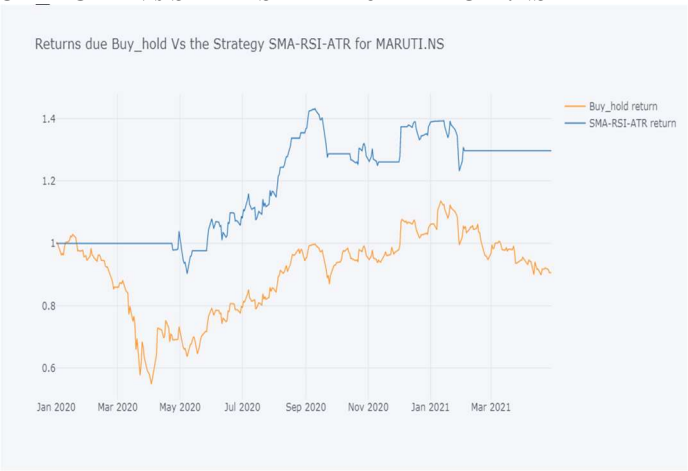
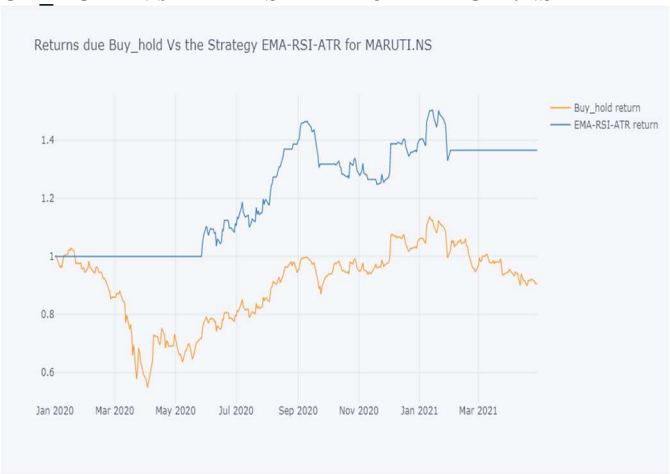
Figure-9: RETURNS DUE TO BUY_HOLD Vs SMA-RSI-ATR for MARUTI.NS



Cumulative return from Buy_hold: -9.4 %
Cumulative return from SMA-RSI-ATR Strategy: 29.73 %

Figure-10: RETURNS DUE TO BUY_HOLD Vs EMA-RSI-ATR for MARUTI.NS



Cumulative return from Buy_hold: -9.4 %
Cumulative return from EMA-RSI-ATR Strategy: 36.56 %

The results generated in the above analysis are summarized in Table-1

Table-1: Cumulative percentage of returns due to Buy and Hold, SMA-RSI-ATR and EMA-RSI-ATR:

Stock	Buy and Hold	SMA-RSI-ATR	EMA-RSI-ATR
PETRONET	-6.64%	-2%	**7.76%**
GRASIM	83%	93.31%	**97.76%**
BPCL	-5.31	8.55%	**14.98%**
HDFCBANK	15.17%	7.86%	**28.6%**
MARUTI	-9.4%	29.73%	**36.56%**

According to Table-1, the cumulative percentage of return due to EMA-RSI-ATR is higher than the respective returns due to buy and hold strategy and SMA-RSI-ATR for all the stocks.

The credibility of the strategies is further tested using back testing for which the trained model fitted with 75% of the data is tested with the remaining 25% of the data. The results are summarized in Table-2.

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Table-2: Confusion Matrix and Accuracy for SMA-RSI-ATR

Stock	SMA-RSI-ATR	
	Confusion Matrix	Accuracy
PETRONET	$\begin{pmatrix} 39 & 23 \\ 6 & 31 \end{pmatrix}$	0.71
GRASIM	$\begin{pmatrix} 32 & 18 \\ 5 & 44 \end{pmatrix}$	0.77
BPCL	$\begin{pmatrix} 32 & 20 \\ 6 & 41 \end{pmatrix}$	0.74
HDFCBANK	$\begin{pmatrix} 37 & 21 \\ 6 & 35 \end{pmatrix}$	0.73
MARUTI	$\begin{pmatrix} 37 & 23 \\ 4 & 35 \end{pmatrix}$	0.73

Table-3: Confusion Matrix and Accuracy for EMA-RSI-ATR

Stock	EMA-RSI-ATR	
	Confusion Matrix	Accuracy
PETRONET	$\begin{pmatrix} 49 & 14 \\ 2 & 34 \end{pmatrix}$	**0.84**
GRASIM	$\begin{pmatrix} 35 & 15 \\ 5 & 44 \end{pmatrix}$	**0.80**
BPCL	$\begin{pmatrix} 31 & 15 \\ 9 & 44 \end{pmatrix}$	**0.76**
HDFCBANK	$\begin{pmatrix} 40 & 11 \\ 6 & 42 \end{pmatrix}$	**0.83**
MARUTI	$\begin{pmatrix} 40 & 19 \\ 3 & 37 \end{pmatrix}$	**0.78**

From Table-2 and Table-3, it is observed that for all the stocks the accuracy is greater for EMA-RSI-ATR, which implies that the risk associated with this strategy is comparatively less.

In general, the performance of the classifier is evaluated based on confusion matrix. Various evaluation measures like Accuracy, No Information Rate, Sensitivity, Specificity, detection rate and Prevalence are used to further justify the credibility of the classification algorithm. Among the above-mentioned measures, the study considers Sensitivity and Specificity.

Sensitivity gives the proportion of the Buy signals which are correctly predicted. Specificity gives the proportion of sell signals which are correctly predicted. Table-3 summarizes the Sensitivity and Specificity values of the two strategies.

Table-4: Sensitivity and Specificity of SMA-RSI-ATR

Stock	SMA-RSI-ATR	
	Sensitivity	Specificity
PETRONET	0.63	0.84
GRASIM	0.64	0.90
BPCL	0.62	**0.87**
HDFCBANK	0.64	0.85
MARUTI	0.62	0.90

Table-5: Sensitivity and Specificity of EMA-RSI-ATR

Stock	EMA-RSI-ATR	
	Sensitivity	Specificity
PETRONET	**0.78**	**0.94**
GRASIM	**0.7**	0.90
BPCL	**0.67**	0.83
HDFCBANK	**0.78**	**0.88**
MARUTI	**0.68**	**0.93**

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The results in Table-4 and Table-5 reveal that the Sensitivity and Specificity values are comparitively higher for the strategy EMA-RSI-ATR.

Hence based on the returns generated (as summarized in Table-1), the Accuracy of the models (as summarized in Table-2) and the Evaluation measures based on Confusion matrix (as summarized in Table-3), the study concludes that EMA-RSI-ATR is better than SMA-RSI-ATR.

5. CONCLUSION

The study considers two strategies SMA-RSI-ATR and EMA-RSI-ATR which are the MACd strategies used in conjunction with RSI and ATR. The two strategies are tested based on the following:

1. The cumulative percentage of returns as compared with Buy and Hold strategy. The EMA-RSI-ATR resulted in greater returns than Buy and Hold strategy and SMA-RSI-ATR for all the stocks considered in this study.
2. The credibility of the generated trading signals are tested using Bayesian classifier models fitted with trading signals as dependent variable and RSI and ATR as explanatory variables. The suitability of the fitted models is tested with accuracy of the results generated which is computed by back testing. By considering the Accuracy of the fitted model as a proxy for the risk associated with the strategies, it is found that the risk associated with EMA-RSI-ATR is less since the accuracy is comparatively high.
3. The suitability of the findings is further analyzed using two evaluation measures based on the confusion matrix. The proportion of the Buy signals which are correctly predicted as given by Sensitivity are comparatively higher for EMA-RSI-ATR. Also, the proportion of Sell signals which are correctly predicted as given by Specificity values are comparatively higher for EMA-RSI-ATR for all the stocks except BPCL.

Hence based on the above findings it is concluded that EMA-RSI-ATR generates more returns than SMA-RSI-ATR. The confusion matrices reveal that the false trading signals generated by EMA-RSI-ATR are comparatively less than that of SMA-RSI-ATR. The accuracy of the fitted model is considered as a proxy for the risk of a trading strategy. Hence EMA-RSI-ATR generates more returns with less risk.

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