Prediction of Trends in Stock Market using Moving Averages and Machine Learning

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Nithin R Rao
M. S. Ramaiah University of Applied Sciences

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Shoban Dinesh
Department of Computer Science and Engineering
MS Ramaiah University of Applied Sciences
Bengaluru, India
shbndns@gmail.com

Nithin Rao R
Assistant Professor, Department of Computer Science and Engineering
M S Ramaiah University of Applied Sciences
Bengaluru, India
nithin.cs.et@msruas.ac.in
https://orcid.org/0000-0002-3308-8251

S P Anusha
Department of Computer Science and Engineering
MS Ramaiah University of Applied Sciences
Bengaluru, India
anushasp109@gmail.com

Samhitha R
Department of Computer Science and Engineering
MS Ramaiah University of Applied Sciences
Bengaluru, India
samhitharsam@gmail.com

Abstract*— Forecasting the direction of price movement of the stock market could yield in significant profits. Traders use technical analysis, which is the study of price by scrutinizing the past prices, to forecast the future price of the stock. Moving average is a technical analysis tool that helps the trader see the trend and identify key price points for trading the stock. While being a trend indicator, the moving average is also a lagging indicator. Lagging indicator is a financial signal that is given only after a large shift in price has taken place. This paper aims at using Machine Learning techniques on a Technical indicator. The proposed model will apply Regression on Moving averages to reduce the latency of the trading signal given and thus overcome its drawback. The model can predict the reversal of trend by predicting the trading signal given by the moving averages.

***Keywords*— Moving average, Moving average Crossover, Trend prediction, Regression, Machine Learning, Stock Market**

I. INTRODUCTION

Stock market refers to the collection of markets and exchanges where regular activities of buying, selling and issuance of shares of publicly-held companies take place. A stock, also known as shares, in general represents the ownership claims of a business.

"Buy low, sell high" is a strategy where the trader buys the stock a low price and sells it a high price to complete a profitable transaction. Unfortunately, it not easy to determine if a stock price is low enough or high enough and hence, it is challenging to implement this strategy consistently. For this reason, traders consider other factors like moving averages, the business cycle and consumer sentiment.

Technical analysis is the study of past market data, mainly price and volume in pursuit of forecast of the future direction of the prices [3]. Technical indicator is a calculation of technical analysis which supports the trend of information of price movement. Technical analysis contradicts the long held Efficient Market Hypothesis (EMH). EMH states that market prices follow a random walk and cannot be predicted based on their past behaviour [9].

The moving average is simple technical indicator that smoothens the price data by creating a constantly updated average price. The moving average is used to identify trends and when one moving average crosses over another, it generates trading signals.

Trading strategy is a fixed plan designed to achieve a profitable return by going long or short in the market. Traders use the moving average crossover as a trading strategy, wherein they buy the stock when the short term moving average crosses over the long term moving and sell the stock when it crosses under.

While moving average is a trend indicator, it is calculated based on the past data and is also called a lagging indicator. A lagging indicator gives the trading signal only when a large shift in price has taken place. Lag is latency from the point of actual trend reversal to when the trading signal is given. Since the signal is given when a large shift in the price takes place, lag is a disadvantage of the moving averages and it reduces the potential profit that the trader makes.

To overcome the disadvantage of the moving average strategy, use of machine learning technique is proposed in this paper. Through regression, the moving average crossover can be predicted ahead of time thereby not only reducing the lag but also predicting the point of trend reversal.

The paper is organized as follows: Section 2 presents the Related Work; Moving Average Crossover is discussed in section 3; In section 4 the proposed model is explained; Methodology used in the paper is mentioned in section 5; the results of the proposed model is discussed in section 6. Finally, section 7 is devoted to conclude the paper.

II. RELATED WORK

Authors in [1] compare the profitability of the different types of Moving Average and find that the simple moving average outperforms all other types of moving averages. Murphey comments "moving averages are a totally customizable indicator which means that the user can freely choose whatever time frame they want to choose. There is no right time frame when setting up the Moving Average. The best way to figure out the appropriate one is to experiment with a number of different time periods and until you find which one fits your strategy". However, few analysts disagree and work on finding the optimum time frame for the moving average [3].

The use of data mining techniques on stock market is based on the theory that historical data holds essential memory for predicting the future direction [4]. The authors in [5] propose to use decision tree on historical data that includes previous, open, minimum and maximum, last data to predict the action the trader needs to take. The accuracy of the model is not very high because the company's performance depends on internal factors, financial reports, and performance of the company in the market. The authors in [4] combine the five methods namely, Typical Price, Bollinger Bands, Relative Strength Index (RSI), Chaikin Money Flow (CMI) and Moving Averages to predict if the following day's close will increase or decrease. A decision tree is used to select the relevant technical indicators from the extracted feature set which is then applied to a rough set-based system for predicting one-day-ahead trends in the stock market in [6]. The model developed in [7] uses a wide range of technical indicators like volume based, price based and overlays. These are given as features to a decision tree in order to select the important features and the prediction is made by the adaptive neuro fuzzy system.

Artificial Neural Networks (ANN) is the most commonly used technique for stock market prediction, in most cases, they suffer from over-fitting [17], and in order to address this problem authors in [8] introduce a machine learning model that integrates Particle Swarm Optimization (PSO) and Least Square Support Vector (LSSVM). The model takes 5 technical indicators are input features, which includes RSI, Money Flow Index (MFI), Exponential Moving Average (EMA), Stochastic Oscillator, Moving Average Convergence/Divergence (MACD), along with price, compares the actual price values with the PSO-LSSVM, LSSVM and ANN results. Model developed in [9] uses variety of technical indicators as input features. Correlation between stock prices of different companies is found and Genetic Algorithm (GA) is used to select the most informative input features among technical indicators. The proposed GA-SVM model outperforms the standalone Support Vector Machine (SVM). The authors in [10] propose a two-stage prediction scheme. Support Vector Regressor (SVR) is used in first stage and ANN, Random Forest (RF) and SVR is used in the second. The model uses Simple Moving Average (SMA), EMA, Momentum (MOM), Stochastic K% (STCK), Stochastic D% (STCD), MACD, RSI, Larry William's R% (WR), Accumulation/Distribution (ADO), Commodity Channel Index (CCI) as features for the first stage prediction and second stage. It is observed that the error values increase as the prediction is made much more in advance. The aim in [11] was to predict stock market trend using macroeconomic variables and technical indicators jointly and separately, Granger causality tests are performed to identify inputs (macroeconomic information and technical indicators) that statistically cause changes in stock returns.

In order to classify the one day ahead trend as uptrend, downtrend or no trend, [12] uses Genetic Algorithm to minimize the trend prediction error by optimizing the decision tree-based feature and the SVM based prediction. Attributes such as Oil rates, Gold & Silver rates, Interest rate, Foreign Exchange (FEX) rate, news and social media feed is taken as input along with SMA and Autoregressive Integrated Moving Average (ARIMA) values to predict the day's closing price. It is found that Multi-Layer Perceptron (MLP) outperforms Single Layer Perceptron (SLP), Radial Basis Function (RBF) and SVM in [13]. In [14], a deep learning model is developed, the financial news data is trained as event embedding. A Recurrent Neural Network (RNN) with 7 hidden layers is trained with features that are extracted from ARIMA analysis in [15]. In [16] four deep learning models are trained on stocks from NSE and NYSE. Convolutional Neural Network (CNN) based model outperforms MLP, RNN, Long Short-Term Memory (LSTM) based model and is capable of capturing the abrupt changes in the system.

From the Literature Survey, it is evident that most of the work in stock prediction using machine learning with technical indicators involve training the model using technical indicators in the input features to either predict the stock market price or predict the stock market trend. This is done to model the patterns in the price and the technical indicators. There is clear gap in literature to identify the drawbacks of the technical indicator-based trading strategy and apply machine learning to defeat the disadvantage. This paper considers the latency in the moving average crossover strategy as a drawback of the strategy and aims at overcoming the disadvantage by using machine learning.

III. MOVING AVERAGE CROSSOVER

The Moving Average (MA) crossover strategy is one of the popular technical analysis tools used by investors in financial markets. When the short-term MA crosses above the long-term MA, this means that average prices over the short period are relatively higher than those over the longer period and the prices have an upper momentum [3].

A bullish crossover occurs when the shorter moving average crosses above the longer moving average. This is also known as a golden cross. A bearish crossover occurs when the shorter moving average crosses below the longer moving average. This is known as a dead cross [2]. The bullish crossover is the indication that the stock price will increase in the upcoming days, the trader considers this as a signal to buy the stock. The bearish crossover is the indication that the stock price will decrease in the upcoming days, and the trader should sell the stock. In this paper, the shorter moving average is 10-days long (MA10) and the longer moving average is 20 days long (MA20). When MA10 crosses over MA20, a buy call is generated and when MA10 crosses below MA20, a sell call is generated.

Fig 1, shows the moving average crossover in IBM stock. The first set of buy and sell calls are profitable as the buy call is given when the price is low and the sell call is given when the price is high. But the sell call is given when the downtrend had already begun, which means that the profit would potentially be higher, as the price was higher before the sell call was given. The second set of buy and sell calls are not profitable as the buy call is given when the price is higher than when the sell call is given. This is because of the latency.

Fig 2 shows the moving average crossover in GOOGL stock. The buy call is given when the uptrend had already begun which means the stock prices were lower before buy call was given. The profits made by the trader would have been higher if the buy call was given earlier.

Fig 3 shows the moving average crossover in AAPL stock. The sell calls are given when the stock prices are low. Due to latency, the sell calls are given at the end of the downtrend. Despite the prices being higher before the calls are given, the trader will not be able to capitalize on it following the moving average strategy. The profits made would be increase if the sell calls were given before, when the stock prices are higher.

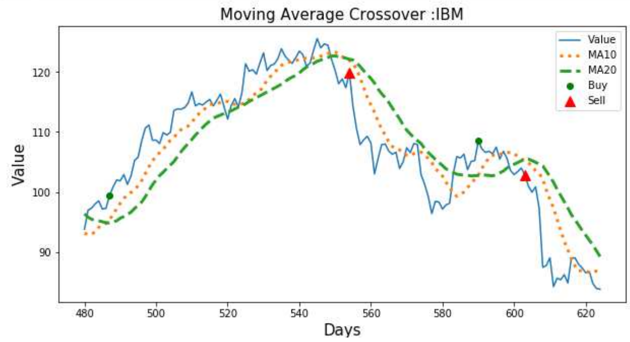

Figure 1: Moving Average Crossover: IBM

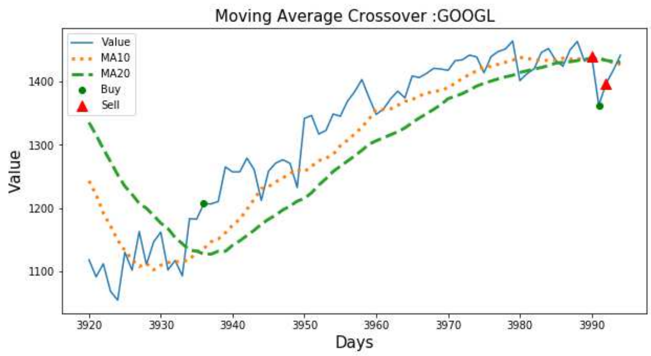

Figure 2: Moving Average Crossover: GOOGL

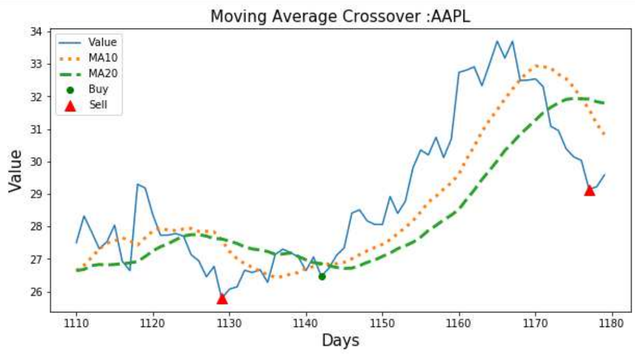

Figure 3: Moving Average Crossover: AAPL

IV. Proposed Model

This paper proposes the use of Machine Learning on Technical Indicators. The proposed model apply regression on the moving average to predict the moving average crossover ahead in time.

Stock market data of International Business Machines Corporation (IBM), Alphabet Inc (GOOGL) and Apple Inc. (AAPL) of New York Stock Exchange (NYSE) are collected. IBM dataset has 5288 rows, GOOGL has 4083 rows and AAPL has 5288 rows. Each row represents a day's Date and the closing Price. The process of data pre-processing includes the calculation of the 2 moving averages, after which the dataset has 4 columns, Date, Price, MA10 and MA20.

After pre-processing, Regression algorithm is trained on the short-term and long-term moving average. The moving averages are then predicted for the upcoming days, if the predicted short-term moving averages crosses over the predicted long-term moving average, the model returns 1. If the predicted short-term moving average crosses below the predicted long-term moving average, the model returns -1. If there is no crossover between the predicted moving averages, the model returns 0.

The output of the proposed model are three classes. The output -1 means that the model predicts a bearish crossover, it predicts a Sell call. A bullish crossover is said to predicted if the model gives 1 as the output, a Buy call is predicted. No action needs to be taken when the output is 0. The calls given by the moving average crossover will be the "actual" values, against which the proposed model will be evaluated. Since the output of model is one of 3 classes, the evaluation of the model will be done using classification performance metrics.

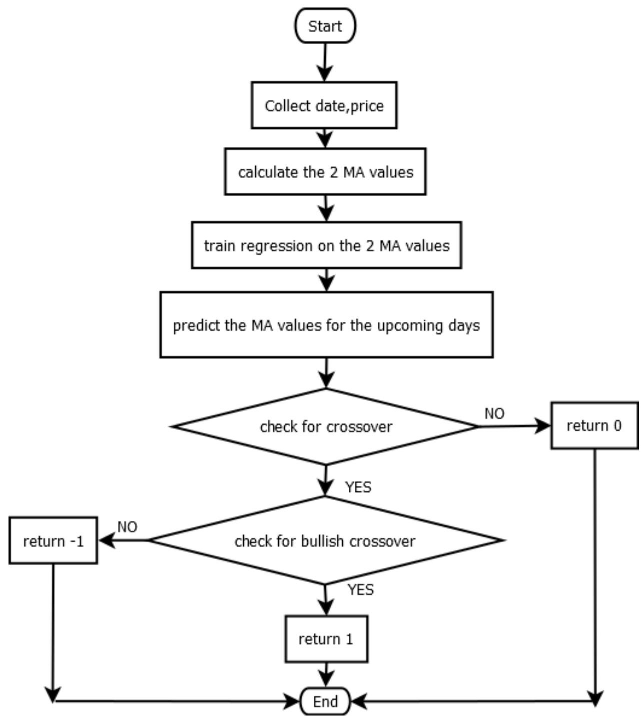

Figure 4: Flowchart of the proposed model

V. Methodology

1. Moving average

Moving average of a given day is the average of the previous 'n' days' price.

$$MA = \frac{A_1 + A_2 + \ldots + A_n}{n}$$

Where, $A_1, A_{2,...} A_n$ are the stock price in a previous 'n' day
n = number of time periods

2. Confusion Matrix:

Confusion matrix is used to evaluate the performance of a classifier. Each row in the confusion matrix represents the actual class. While each column represents the class predicted by the classifier. The intersection of the actual and the predicted class is the number of corrected classified outputs of the models. Therefore, the diagonal of the matrix represents all the True Positives.

3. Accuracy:

Accuracy is metric of evaluating classification models. It is ratio of number of correct predictions to the total number of predictions.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{n}}$$

n= Total number of samples
TN is the number of True Negatives

4. Precision:

Precision is the accuracy of the positive predictions of the classifier.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

TP is the number of True positives,
FP is the number of False Positives

5. Recall:

Recall is also known as sensitivity or true positive rate. Recall is the ratio of positive instances that are correctly detected by the classifier.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

FN is the number of False Negatives

6. F1 score:

F1 score is the combination of precision and recall in a single metric. It is the harmonic mean of precision and recall.

$$\text{F1} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

7. Regression

Regression is used to train on the 2 moving averages and to predict if the moving averages are going to crossover

$$\widehat{y_t} = \widehat{\beta_0} + \widehat{\beta_1}\, x_{1,t} + \widehat{\beta_2}\, x_{2,t} + \cdots + \widehat{\beta_k} x_{k,t}$$

y is the variable to be forecast
$x_{1,t}$ ... $x_{k,t}$ are the k predictor variables for time t
β_1 ... β_k measure the effect of each predictor after taking into account the effects of all the other predictors in the model

VI. RESULTS

Table 1 shows the confusion matrix of the model on the IBM stock. The accuracy of the model is 79.7%. The precision is 77.3%. The recall is 79.7% and F1 score is 77.9%. Table 2 shows the confusion matrix of the model on the GOOGL stock. The proposed is developed with 80.4% accuracy, 78.6% precision, 81.4% recall and 79% F1 score. Table 3 shows the confusion matrix of the model on the AAPL stock. The accuracy, precision, recall and F1 score are 80.5%, 78%, 80.5% and 78.5% respectively. Table 4 shows the overall performance of the proposed model on IBM, GOOGL and AAPL.

Figure 5 shows the model results on the IBM stock. The predicted sell calls are given before the actual sell calls, not only when the stock prices are higher but also at the end of the uptrend, when the price is highest in the range. Hence maximizing the profits made. While the second sets of actual calls are not profitable, the buy and sell calls given by the model are profitable. By predicting the actual buy call ahead in time and when the stock prices are low, the model converted the second set of calls, which would previously incur loss, profitable.

Figure 6 shows the model results on the GOOGL stock. The predicted buy call was given not only when the stock prices are lower compared to the actual buy, but also at the start of the uptrend, which is the point where the stock prices are the lowest in the range. Previous to the predicted buy calls, the price was in a downtrend. The predicted buy calls are given at the point of trend reversal which is the point of highest profits.

Figure 7 shows the model results on the AAPL stock. While the actual sell calls are given when the stock prices are lowest points in the range, the predicted sell calls are given when the stock prices are higher. Thereby increasing the profits made.

Figure 5: Model Results: IBM

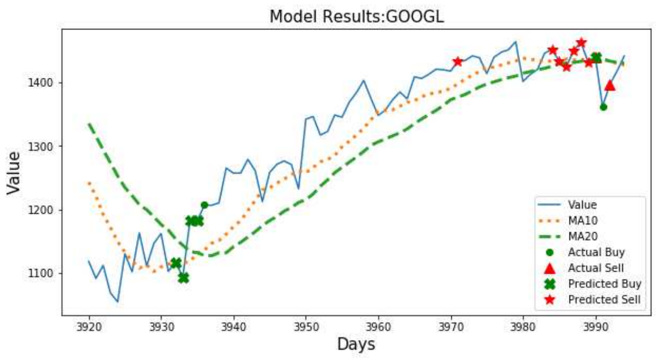

Figure 6: Model Results: GOOGL

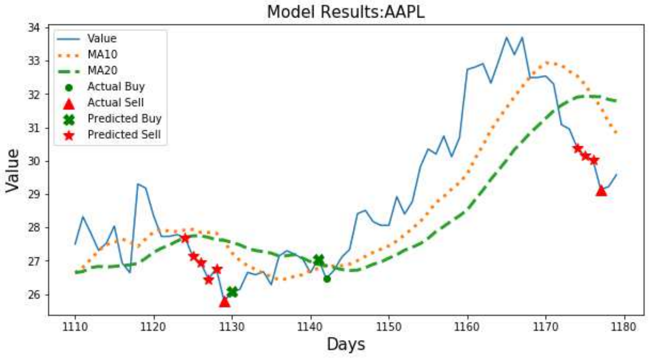

Figure 7: Model Results: AAPL

TABLE 1: Confusion matrix for IBM stock

	Actual SELL	Actual NO ACTION	Actual BUY
Predicted SELL	169	354	5
Predicted NO ACTION	194	3854	140
Predicted BUY	8	364	170

TABLE 2: Confusion matrix for GOOGL stock

	Actual SELL	Actual NO ACTION	Actual BUY
Predicted SELL	145	235	3
Predicted NO ACTION	179	2992	97
Predicted BUY	9	292	124

TABLE 3: Confusion matrix for AAPL stock

	Actual SELL	Actual NO ACTION	Actual BUY
Predicted SELL	159	355	6
Predicted NO ACTION	201	3916	104
Predicted BUY	7	352	158

TABLE 4: Overall performance of the proposed model

	Accuracy	Precision	Recall	F1 score
IBM	0.797	0.773	0.797	0.779
GOOGL	0.804	0.786	0.804	0.790
AAPL	0.805	0.780	0.805	0.785

VII. CONCLUSION

This paper proposes the use of Machine learning on technical indicators in order to overcome the disadvantages of the indicator-based trading strategy. This method identifies the latency of moving averages as a disadvantage and proposes an algorithm to overcome the drawback.

The proposed model was developed with 79.7% accuracy on the IBM stock, 80.4% accuracy on the GOOGL stock and 80.5% accuracy on the AAPL stock. The model predicts the bearish and bullish crossover ahead in time in order to reduce the latency and to predict the reversal of trend. From the results obtained, it is evident that the proposed model not only overcomes the disadvantage of the moving average but also assists the trader to increase the profits.

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