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Deployment of a Smart Trading System for Intelligent Stock Trading

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ABSTRACT

In this article we evaluate the deployment of a smart trading system that exploits the features of different technical indicators for intelligent stock trading. Depending on their behaviors, these indicators help in trading under various market conditions. Our smart trading system uses a unified trading strategy that selects five indicators from three well-known categories referred as leading, lagging, and volatility indicators. The trading system looks for common trend signals from at least three indicators within a certain period of time. Collectively generated signals from the technical indicators are used to train a neural network model. The trained neural network model is then used to produce buy and sell signals for trading in stocks. The system is efficient and convenient to use for both individual traders and fund managers. We tested the model on actual data collected from Saudi Stock Exchange and New York Stock Exchange. The performance of the model was checked in terms of percentage returns. The results of the proposed trading model were compared with the benchmark trading strategy. The deployed smart trading system is efficient to produce significant returns over the longer and shorter timeframes.

Keywords: *Stock market forecasting, Time series data, Smart trading, Trend indicators, Artificial neural network*

1. Introduction

Trading stocks is very intricate profession that requires an efficient trading system and careful planning with persistent hard work and reliable strategy [1]. Many traders seek help of the professionals to get guidance which is normally costly. Others use different software without any prior experience and knowledge. Furthermore, there are investors who are unfamiliar with the use of technology, and they often fell into vicious market cycles [2, 3]. Before investing, a trader must acquire the knowledge of the company, its business operations and financial statements [2]. Moreover, the purpose of a trading model is to help traders to make right decisions at the right time and to avoid any trading decision which is based on emotions or random news. Professional trading models aim to setup rules of taking trades, and they wait for the good opportunities to invest the capital [4].

The use of Technical Indicators (TIs) for stock trading helps in chart analysis and to look for new patterns available in data values. Based on the nature of a technical indicator, it may be a leading, lagging, or volatile indicator. Leading TIs like Relative Strength Index (RSI) and Triple Exponential Average (TRIX) predict trends based on rate of change of stock prices and they are also called momentum-based indicators [5, 6]. To measure volatility level of stock prices, we use volatile technical indicators. One of the examples of volatile TIs is the Average Directional Index (ADX) [7]. The lagging technical indicators are used to quantify the strength of a trend. Exponential Moving Averages (EMA) and Moving Average Convergence Divergence (MACD) are among some well-known lagging indicators [5, 8]. They are called lagging indicators because of their delayed feedback after a large shift has occured.

The traditional algorithms used to implement technical indicators are slow and computationally costly. Artificial Intelligence (AI) with its application in various fields serves as compact and efficient solution for the real world problems. The field of Artificial Neural Network (ANN) as an extension of AI is quite advanced now. Neural networks mimic the working of the human brain, and they provide solutions for the AI and machine learning related problems. Since last few decades, automated trading based on neural networks and technical indicators is used for forecasting in financial markets [9, 10].

Recurrent Neural Network (RNN) is normally considered to deal with the sequential data problems. Long Short-Term Memory (LSTM) as a variant of RNN is capable of learning from historical time-series data and predicts the future values. Stock market data is an example of time-series data, and it is very suitable to train an LSTM neural network for predictions. Many studies show the effectiveness of LSTM neural network for predicting the future prices after they are trained on historic stock prices [11]. These models are limited and may not provide information about the consistent changes of the price values [12]. Our proposed trading system model is designed differently, and it is capable to learn the behavior of technical indicators. Instead of predicting the future price values, it predicts trends, and generates buy/sell signals accordingly.

Our smart trading model can efficiently respond to a set of data values for predicting new up or down trends and it helps in profitable trading by generating buy and sell signals. We compare the performance of this model with the performance of a benchmark trading strategy called Buy & Hold (B&H) and the results show that the proposed smart trading model is efficient, and it produces significant returns over the longer

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and shorter timeframes.

2. Literature Review

Several types of trading strategies are developed to analyze the market conditions and the future price levels. Trading strategies systemize the process of taking trades and they help to set the rules for productive trading. Trading systems implement predictive models to help the traders. In all the models, the basic goal is to construct a strategy based on price movement or the market volatility and to give recommendations for taking trades [13]. Some well-known strategies are used to develop new trading models [14]. A smart trading model helps to automate the trading process by employing some probabilistic reasoning on price values and volume information [15, 16].

Researcher have used Open, High, Low, Close (OHLC) values of stock data along with the business news, social media, and market sentiment analysis to predict future prices [17, 18]. Widely available trading systems use various technical indicators, such as ADX, TRIX, RSI, MACD etc., and the performance of the system is optimized by using smart techniques, like swarm optimization method or artificial neural networks [19-21]. In most cases, the aim is to find patterns in the past prices of a stock and then use statistical and analytical methods to predict future price values [22, 23].

Unified Trading Strategy benefits from the features of multiple indicators and it helps to automate stock trading by providing potential opportunities of buying and selling shares in stock market [24]. Five different technical indicators, including EMA, ADX, MACD, RSI, and TRIX are simultaneously applied on the stock data and if three or more technical indicators are able to mark a potential trend, UTS generate buy/sell signals accordingly. The marked up/down trends and corresponding buy/sell signals are generated under the combined influence of collaborated technical indicators [24].

Machine learning helps to solve the problems of algorithmic trading. With the help of forecasting by machine learning methods, we can avail particular opportunities for useful trading [25]. LSTM works effectively with time series data like stock price values. It has been used extensively to investigate prediction for stocks, econometrics, and financial markets [26-28]. The features of LSTM are added with other methods for better predictions [29].

Our smart trading system do not train an LSTM model on regular stock price values. We adopt the data values which are marked by UTS as a part of up/down trend. The expected result of trained model is to efficiently predict the future movements of market by establishing a correlation of data patterns and market trends. In this supervised machine learning process, the trend data is considered as input and the output is a binary signal of value zero or one. The output is zero, if the set of input price values form a down-trend, and it is one, if these values are a part of up-trend. Such kind of trained neural network models are able to replace the traditional trading by searching for potential buy/sell opportunities. This solution provides reusability with effective and efficient operation.

3. Methodology

UTS generates highly accurate buy and sell signals to enter and exit a trade. Some popular technical indicators like MACD, ADX, EMA, RSI, and TRIX form the base of UTS. The selection of these technical indicators is from three broad categories such as leading, lagging and volatility indicators. The technical indicators are applied on the historical data of stock prices and the corresponding trends are marked and stored. To mark a valid trend, it must be commonly declared by at least three of total five indicators (Fig. 1). Later, the data from these confirmed trends is used to train a neural network. In the following subsection, we briefly describe these indicators and their usage.

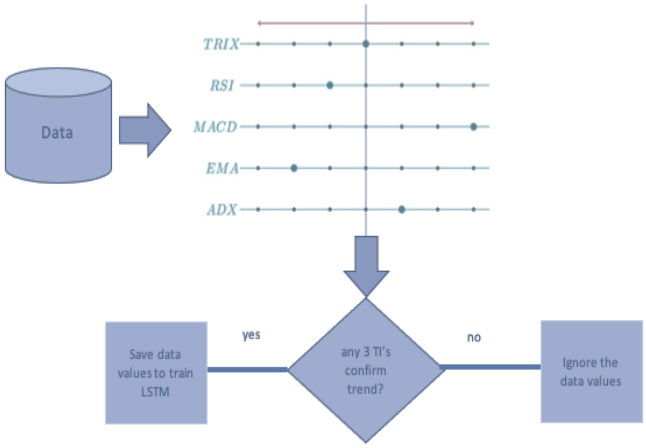

Fig. 1: Searching and saving common trends data marked by different indicators

3.1. *Technical Indicators and their Interpretation*

In this section, we provide definitions of technical indicators that are used by the trading model along with their interpretations.

Let C_t represent the closing price of a stock on a particular trading day, where the subscript t stands for time and it starts from 1 and ends at some value T, i.e., $1 \leq t \leq T$. Similarly, H_t, L_t, and O_t denote the high, low, and open prices of a stock.

Define an index set for a period of p number of trading days as follows, $I_{t,p} = \{i: t - (p-1) \leq i \leq t\}$, where $p \leq t \leq T$. For example, if $p = 10$ and $t = 10$ then $I_{10,10} = \{i: 1 \leq i \leq 10\}$.

3.1.1 *Simple Moving Average (SMA)*

Given a sequence of closing prices $\{C_t\}_{t=1}^{N}$ for N days, simple moving average (SMA) for the period p is defined by taking the arithmetic mean of subsequences of p terms, that is,

$$s_t = \frac{1}{p}\sum C_i \tag{1}$$

Here, simple moving average is represented by s. It yields a new sequence $S_p = \{s_t\}_{t=p}^{N}$. The simple moving averages are used to measure the direction of the trend whether it is upward or downward.

3.1.2 Exponential Moving Average (EMA)

Exponential Moving Average (EMA) works like a filter that applies weights to older values in a time series that keep decreasing exponentially. Given a sequence of closing prices $\{C_t\}_{t=1}^{N}$, EWMA for the period *p* is defined as follows:

$$E_t = wC_t + (1-w)E_{t-1} \qquad t \geqslant 2 \tag{2}$$

where *E* represents the exponentially weighted moving average, *w* is a smoothing constant and it is calculated by the formula $w = \frac{2}{p+1}$. The values of *w* lie between 0 and 1. The first EWMA E_1 is set in different ways, for example, $E_1 = C_1$, or E_1= mean of the first *p* values. It yields a new sequence $\{E_t\}_{t=1}^{T}$. Some authors prefer to take $\{E_t\}_{t=p}^{T}$ .The exponential weighted moving averages are used to measure the direction of the trend whether it is upward or downward. The difference between SMA and EMA is that EMA gives higher weights to the recent prices of a stock.

3.1.3 Triple Exponential Moving Average (TRIX)

It is considered as a momentum indicator that follows the trend. It shows the percentage change in the EMA of closing prices that has been smoothed three times. It is given as:

$$E_t^1 = E_t(C_t)$$
$$E_t^2 = E_t(E_t^1)$$
$$E_t^3 = E_t(E_t^2)$$
$$TRIX_t = \frac{E_t^3 - E_{t-1}^3}{E_{t-1}^3} \tag{3}$$

TRIX is plotted against time *t* on the *xy*-plane. The TRIX-curve keep oscillating around a zero-line.

Rule: A buy signal is generated whenever the TRIX-curve crosses the 0-line from bottom and a sell signal vice versa. But most of the time, the use of TRIX is augmented with other indicators or the candlestick chart.

3.1.4 Moving Average Convergence Divergence (MACD)

It is a difference of short EMA and long EMA, given as follows:

$$\mathrm{M_t} = \mathrm{E^{short}} - \mathrm{E_t^{long}} \tag{4}$$

This yields a sequence of MACD, $\{M_t\}_{t=1}^{N}$.The most used short and long EMAs are 12-day and 26-day EMAs. MACD is used in diverse ways, we will describe the two rules below.

Rule 1:

The values of MACD can be positive, negative or zero, and when these values are plotted against time on the *xy*-plane, they oscillate around the 0-line (the *x*-axis). When the MACD curve crosses the 0-line from the lower half plane to upper half plane, then a buy-signal is generated, and when it crosses the 0-line from upper half plane to lower half plane, then a sell-signal is generated. Mathematically, it is defined as follows:

Buy: $M_{t-1} < 0$ and $M_t > 0$

Sell: $M_{t-1} > 0$ and $M_t < 0$

Rule 2:

Given a sequence of MACD, $\{M_t\}_{t=1}^{N}$,first calculate the 9-day EWMA of MACD sequence. It yields a new sequence which is denoted by $\{E_t^M\}_{t=1}^{N}$.The values of the new sequence can be positive, negative or zero, and these are plotted against time on the *xy*-plane, along with the MACD sequence. The MACD curve is called the momentum curve and the 9-day EWMA of MACD is called the signal curve. A buy signal is marked for MACD curve crossing the signal line from bottom and when it crosses the signal line from top, we take it as sell signal. It is expressed as follows:

Buy: $M_{t-1} < E_{t-1}^M$ and $M_t > E_t^M$

Sell: $M_{t-1} > E_{t-1}^M$ and $M_t < E_t^M$

3.1.5 Relative Strength Index (RSI)

It is a powerful indicator to determine the strength of the trend. It is defined in the following way. First, we define two sequences named as upper (U_t) and lower sequences (L_t) for time period of N days i.e., *t=1 to N* as follows:

$$U_t = \begin{cases} C_t - C_{t-1} & \text{if} \quad C_t > C_{t-1} \\ 0 & \text{otherwise} \end{cases}$$

$$L_t = \begin{cases} C_{t-1} - C_t & \text{if} \quad C_{t-1} > C_t \\ 0 & \text{otherwise} \end{cases}$$

Both the sequences $\{U_t\}_{t=1}^{N}$ and $\{L_t\}_{t=1}^{N}$ are nonnegative sequences. Next, we take simple moving averages for the period *p* of these sequences.

$$\overline{U_t} = \frac{1}{p}\sum_{i=t-(p-1)}^{t} U_i,$$

and

$$\overline{L_t} = \frac{1}{p}\sum_{i=t-(p-1)}^{t} L_i$$

It yields two new sequences $\{\overline{U}_t\}_{t=p}^{N}$ and $\{\overline{L}_t\}_{t=p}^{N}$. By using these sequences, we define another sequence by taking their ratio. It is named as the sequence of relative strengths and is defined by

$$\mathrm{RS_t} = \frac{\mathrm{\overline{U}_t}}{\mathrm{\overline{L}_t}} \tag{5}$$

It produces the sequence $\{RS_t\}_{t=p}^{T}$. Next, we define the relative strength index as follows:

$$RSI_t = 100 - \frac{100}{RS_t}.$$

It generates the sequence of relative strengths, that is, $\{RSI_t\}_{t=p}^{T}$. RSI value remains between 0 and 100. If the value of RSI is close to zero, it shows a downward trend and if the value of RSI is close to one hundred it shows an upward trend.

Rules:

RSI can be used in diverse ways to determine the strength of the trend. RSI is plotted against time on the *xy*-plane with the horizontal lines at *RSI* = 30, 50 and 70. The region below the line *RSI* = 30 is considered as the oversold region, and the region above the line *RSI* = 70 is considered as the overbought region. If the *RSI* curve crosses the line *RSI = 30* from below, and it is also increasing, then an upward trend is depicted and similarly if the *RSI* curve crosses the line *RSI* = 70 from above and it is also decreasing, then a downward trend is depicted. Most of the authors also consider the middle line *RSI* = 50 as a reference. For instance, a buy signal is generated if $RSI_t > 50$ and $RSI_{t-1} < 50$, and similarly a sell signal is generated if $RSI_t < 50$ and $RSI_{t-1} > 50$.

3.1.6 Directional Indicators

Directional indicators (*DI*) were developed by Wilder (1978) and are used to enter and exit a trade. The *DI* are constructed by using not only closing price of a stock but also the information about the intraday high and low prices of a stock. To define (DI), first we define two sequences named as upper move (UM_t) and lower move (LM_t) sequences as follows:

$$UM_t = \begin{cases} H_t - H_{t-1} & \text{if} \quad H_t > H_{t-1} \\ 0 & \text{otherwise} \end{cases}$$

$$LM_t = \begin{cases} L_{t-1} - L_t & \text{if} \quad L_{t-1} > L_t \\ 0 & \text{otherwise} \end{cases}$$

Both the sequences $\{UM_t\}_{t=1}^{N}$ and $\{LM_t\}_{t=1}^{N}$ are nonnegative sequences.

Positive Directional Movement (DM ⁺)

$$DM_t^+ = \begin{cases} UM_t & \text{if} \quad UM_t > 0 \quad \text{and} \quad UM_t > LM_t \\ 0 & \text{otherwise} \end{cases}$$

Negative Directional Movement (DM ⁻)

$$DM_t^- = \begin{cases} LM_t & \text{if} \quad LM_t > 0 \quad \text{and} \quad LM_t > UM_t \\ 0 & \text{otherwise} \end{cases}$$

Note that both $\{DM_t^+\}_{t=1}^{N}$ and $\{DM_t^-\}_{t=1}^{N}$ form sequences of nonnegative numbers and at least one of them must be zero at any given value of *t*.

True range is a term used to provide the price range of day-to-day trading, and it is defined as follows:

$$TR_t = \max\{H_t - L_t, \quad H_t - C_{t-1}, C_{t-1} - L_t\}$$

Where, TR_t represents true range on a particular trading day.

Next, we define the positive directional indicators DI_t^+, and negative directional indicators DI_t^- with the help of *DM* and *TR* for a period of *p* number of days.

Positive Directional Indicator (DI ⁺)

$$DI_t^+ = \frac{\sum_{i=t-(p-1)}^{t} DM_i^+}{\sum_{i=t-(p-1)}^{t} TR_i}$$

Negative Directional Indicator (DI ⁻)

$$DI_t^- = \frac{\sum_{i=t-(p-1)}^{t} DM_i^-}{\sum_{i=t-(p-1)}^{t} TR_i}$$

These indicators measure the upward and downward price movements as the fraction of trading range over a period of *p* number of days. Moreover, they are inversely proportional to each other, that is, if one of them increases the other decreases and vice versa.

Directional movement index is defined as the hundred times the ratio of the absolute values of the difference between the positive and negative directional indicators and the sum of the positive and negative directional indicators, that is,

$$DX_t = \left|\frac{DI_t^+ - DI_t^-}{DI_t^+ + DI_t^-}\right|$$

The values of *DX* lie between 0 and 100. It yields a sequence $\{DX_t\}_{t=1}^{T}$

3.1.6.1 Average Directional Movement Index (ADX)

The average directional movement index is obtained by taking the simple moving average of the sequence $\{DX_t\}_{t=1}^{T}$ for the period of *p* number of days, that is,

$$\mathrm{ADX_t} = \frac{1}{\mathrm{p}} \sum_{\mathrm{i=t-(p-1)}}^{\mathrm{t}} \mathrm{DX_i} \tag{6}$$

The range of *ADX* values is from 0 to 100. It is a powerful indicator to determine the strength of the trend.

Trading Rules: *ADX* is plotted against time *t* on the *xy*-plane. Two horizontal lines at *ADX* = 20 and *ADX* = 40 are drawn which are used to generate the signals. If *ADX* is greater than twenty and increasing, then the trend's strength is increasing, and if *ADX* is smaller than forty and decreasing, then the trend's strength is decreasing.

3.2 Smart Trading Strategy

The use of technical indicators without a strategy does not assure profits. Moreover, dependence on any single indicator is risky, and often multiple indicators are combined to determine the strength of the trend and momentum.

The goal of the deployed model is to develop a strategy which uses the most popular technical indicators. The idea is to use three or more indicators that generate buy and the sell signals within a predefined range. The potential signals are used to train a neural network model that learns the nature of the data that comprise signals. Later, the same neural network model works as stand-alone system to predict buy and sell signals. We adopt the default configuration of the neural network model [24]. The overall strategy is depicted through Fig. 2.

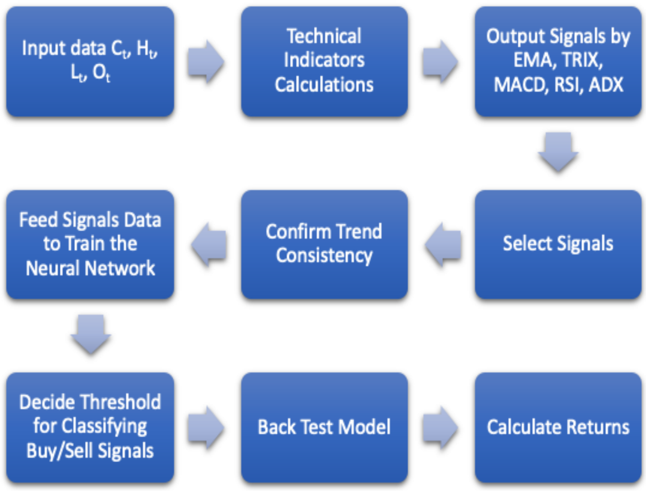

Fig. 2: Smart trading strategy

Here, we outline the composition of the strategy.

1. Apply the technical indicators, *ADX, EMA, MACD, RSI,* and *TRIX*.
2. Mark the initial signals by each indicator (may not be common).
3. Mark trend days based on the output of each indicator.
4. Define the search range to locate the same indexes in other indicators.
5. Define sensitivity i.e., at least how many indicators must confirm a signal.
6. Data comprising potential signals is used to train a neural network model.
7. Trained model is used to generate buy/sell signals depending on threshold values.
8. Smart trading is performed accordingly, and returns are calculated.

4. Simulations and Results

In this section we will apply the above strategy to show its effectiveness through backward and forward testing.

4.1 Data Collection

We have obtained the historical data of the companies from the online resources. For example, the stock data for Apple Inc., a US technology company is obtained from Yahoo Finance [30], and the data for the Saudi Cement Company (SCC) is obtained from Tadawul [31]. The data is collected for a period of ten years, from Jan 01, 2010, to Dec 31, 2019.

4.2 Backward Testing

Backward testing is a process to determine how well the new strategy will perform if it is applied on the historical data of the stock prices. In the first case we have applied the trading model on the stock prices of Saudi Cement Company and obtained the buy and sell signals. We will describe this in the form of an investment scenario. In the first problem, we consider an investment in the Saudi Stock Exchange, and in the second problem we consider an investment in the New York Stock Exchange.

Problem Statement 1:

Mr. Ali wants to invest SAR 10,000 for a tenure of 10 years. Suppose, he purchases the stocks of SCC. His risk tolerance level is 5% and he intends to achieve a return of 10% annually over his investments. Use the trading model defined in this paper to determine the entry and exit points, and also determine the success rate of this strategy.

1. Initial capital = 10,000 SAR
2. Investment time frame = 10 years
3. Risk tolerance = 5% of initial capital
4. Profit target = 10% annually
5. Entry point = buy signal
6. Exit point = sell signal
7. Assume no fees, no taxes, no cost
8. Determine the profit or loss

We collect the data of SCC from Jan 01, 2010, to Dec 31, 2019, and apply the above strategy to get the buy and the sell signals. We enter the first trade when we obtain the buy

Table 1: Backward Testing Results for Problem Statement 1

	Buy					Sell					
No. of Trades	Date	Price	No	Cost	Cash	Date	Price	No	Cost	Cash (new)	Return (%)
1	2/16/2010	40	250	10000	0	5/17/2010	49	250	12250	12250	22.5
2	7/5/2010	45	272	12240	10	7/9/2011	62	272	16864	16874	37.77
3	8/22/2011	58	290	16820	54	3/12/2012	92	290	26680	26734	58.62
4	4/14/2012	88.25	302	26652	82.5	5/5/2012	93.25	302	28162	28244	5.66
5	6/12/2012	90.75	311	28223	20.75	11/4/2012	88.25	311	27446	27466.5	-2.75
6	12/3/2012	90	305	27450	16.5	2/17/2013	97.25	305	29661	29677.75	8.05
7	4/24/2013	95.75	309	29587	91	12/2/2013	107	309	33063	33154	11.74
8	1/9/2014	102.25	324	33129	25	3/17/2014	114.5	324	37098	37123	11.98
9	4/23/2014	107.75	344	37066	57	9/22/2014	121.16	344	41679	41736.04	12.44
10	4/15/2015	91.82	454	41686	49.76	6/9/2015	95.91	454	43543	43592.9	4.45
11	11/19/2015	65.75	663	43592	0.65	12/7/2015	69	663	45747	45747.65	4.94
12	1/28/2016	50.41	907	45722	25.78	3/24/2016	67.16	907	60914	60939.9	33.22
13	5/26/2016	64.45	945	60905	34.65	6/16/2016	66.54	945	62880	62914.95	3.24
14	11/7/2016	52.93	1188	62881	34.11	1/5/2017	71.51	1188	84954	84987.99	35.1
15	5/17/2017	52.52	1618	84977	10.63	6/5/2017	53.23	1618	86126	86136.77	1.35
16	11/30/2017	38.59	2232	86133	3.89	3/29/2018	56.13	2232	125282	125286.05	45.45
17	9/20/2018	40	3132	125280	6.05	10/10/2018	43.1	3132	134989	134995.25	7.75
18	10/30/2018	38.3	3524	134969	26.05	7/23/2019	77	3524	271348	271374.05	101.04
19	9/19/2019	62.5	4341	271313	61.55	1/2/2020	69.9	4341	303436	303497.45	11.84

signal and exit the trade when we obtain the sell signal. We buy the shares so that the cost is less than the initial capital and the left-over amount remains in the account as a cash. We sell the shares when a sell signal is obtained, and the amount received is kept as a cash until the next buy signal is obtained. We repeat the process for the tenure of ten years. The results are shown in Table 1. The above strategy yields tremendous results. The initial capital SAR 10000 is turned into an amount of SAR 303497.45 which is a return of 3000%.

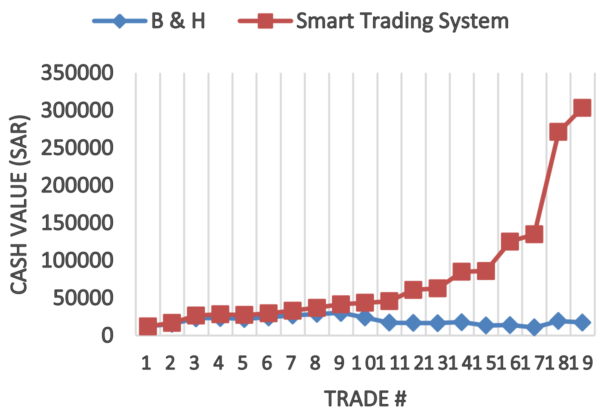

Fig. 3: The comparison of smart trading system with B&H (Problem-I)

As noticed in Fig. 3, the profits gained by smart trading system are higher in each trade than the profits by benchmark strategy i.e., Buy and Hold (B&H).

Problem Statement 2:

Mr. Neil wants to invest US$ 10,000 for a tenure of 10 years. Suppose he purchases the stocks of Apple Inc. His risk tolerance level is 5% and he intends to achieve a return of 10% annually over his investments. Use the strategy define in this paper to determine the entry and exit points, and also determine the success rate of this strategy.

1. Initial capital = $ 10000
2. Investment time frame = 10 years
3. Risk tolerance = 5% of initial capital
4. Profit target = 10% annually
5. Entry point = buy signal
6. Exit point = sell signal
7. Assume no fees, no taxes, no cost
8. Determine the profit or loss

We collect the data of Apple Inc. from Jan 01, 2010, to Dec 31, 2019, and apply the above strategy to get the buy and the sell signals. We enter the first trade when we obtain the buy signal and exit the trade when we obtain the sell signal. We buy the shares so that the cost is less than the initial capital and the left-over amount remains in the account as a cash. We sell the shares when a sell signal is obtained, and the amount received is kept as a cash until the next buy signal is obtained. We repeat the process for the tenure of ten years. The results are shown in Table 2. The above strategy yields tremendous results. The initial capital 10000$ is turned into an amount of 301834.2$ which is a return of almost 3000%.

Table 2: Back Testing Results for Problem Statement 2

	Buy					Sell					
No. of Trades	Date	Price	No	Cost	Cash	Date	Price	No	Cost	Cash (new)	Return(%)
1	2/26/2010	29.23	342	9997.14	2.85	5/20/2010	33.96	342	11616.27	11619.12	16.19
2	8/31/2010	34.72	334	11599.34	19.78	3/16/2011	47.14	334	15746.19	15765.97	35.75
3	7/1/2011	49.03	321	15740.92	25.05	10/3/2011	53.51	321	17178.08	17203.13	9.13
4	12/20/2011	56.56	304	17195.54	7.59	5/1/2012	83.16	304	25281.07	25288.66	47.02
5	7/2/2012	84.64	298	25224.42	64.24	10/5/2012	93.22	298	27781.68	27845.93	10.13
6	3/14/2013	61.78	450	27803.57	42.36	3/27/2013	64.58	450	29062.28	29104.64	4.52
7	4/26/2013	59.59	488	29084.79	19.84	6/12/2013	61.74	488	30129.81	30149.66	3.59
8	7/16/2013	61.45	490	30113.99	35.66	9/11/2013	66.81	490	32739.69	32775.36	8.71
9	10/7/2013	69.67	470	32748.92	26.43	1/6/2014	77.7	470	36521.01	36547.44	11.51
10	4/24/2014	81.11	450	36499.5	47.94	12/9/2014	114.1	450	51354	51401.95	40.69
11	1/26/2015	113.1	454	51347.39	54.55	6/8/2015	127.8	454	58021.2	58075.75	12.99
12	10/21/2015	113.8	510	58017.6	58.15	12/10/2015	116.2	510	59246.69	59304.85	2.11
13	3/2/2016	100.8	588	59241	63.85	4/15/2016	109.8	588	64591.79	64655.64	9.03
14	5/20/2016	95.22	679	64654.38	1.26	10/28/2016	113.7	679	77215.88	77217.14	19.42
15	12/9/2016	113.9	677	77144.14	73	6/9/2017	149	677	100859.5	100932.5	30.74
16	7/13/2017	147.8	683	100926.9	5.54	1/26/2018	171.5	683	117141.3	117146.9	16.06
17	2/14/2018	167.4	699	116991.6	155.2	4/20/2018	165.7	699	115838.3	115993.5	-0.98
18	5/1/2018	169.1	685	115833.5	160	10/23/2018	222.7	685	152570	152730.1	31.71
19	1/30/2019	165.3	924	152691	39.07	5/8/2019	202.9	924	187479.6	187518.7	22.78

20	6/6/2019	185.2	1012	187442.6	76.02	2/24/2020	298.2	1012	301758.2	301834.2	60.98

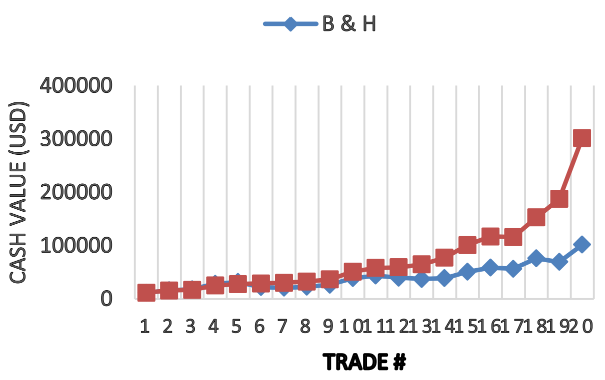

Fig. 4: The comparison of smart trading system with B&H (Problem-II)

As shown in Fig. 4, the profits gained by both the smart trading system and B&H are almost same for the first five trades. The profits of smart trading system are higher in each trade after the fifth trade. Our results show that the model is efficient to perform well during all market cycles like upward, downward, or sideways. As the model is trained on the confirmed buy and sell signals generated by different indicators, it is able to mark the relevant patterns in any sequence, and forecast the future trends.

5. Conclusions

We evaluated a smart trading model that uses a blend of different indicators taken from three well-known classes of technical indicators. The model is effective to exploit the patterns of price values, and it performs automated trading by generating buy/sell signals for positive returns. Our smart trading model utilizes distinguished features of LSTM neural network model. We trained LSTM model on the confirmed buy and sell signals generated by different technical indicators. We adopted unified trading strategy that helps to unify indicators and it can be customized according to the needs and preferences of the traders. The model was back-tested by feeding the historical data from the international stock markets and the buy and sell signal were obtained. These signals were used to enter or exit a trade according to the designed methodology. The performance of the model was compared with the performance of buy and hold benchmark strategy. The results show that the model outperforms under various market conditions, and it is able to gain outstanding profits.

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