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Know Sure Thing based Machine Learning Strategy for Predicting Stock Trading Signals

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Abstract: Although some studies employed technical indicators as input to machine learning models to forecast stock trading signals, there was a noticeable gap between how technical analysts and machine learning professionals used technical indicators. Based on this finding, this study suggested a know sure thing based machine learning (KST-ML) technique for anticipating stock trading signals and compared its results to KST-based trading and Buy-Hold strategies. The main idea behind the KST-ML strategy is to learn and then predict stock trading signals from the relationship between KST indicators such that more accurate predictions can be made. The strategies were assessed based on their annual rate of return (ARR), Sharpe ratio (SR), and percentage of profitable trades executed. In addition, the proposed strategy's performance was compared to that of several intelligent stock trading strategies proposed in the literature. The proposed method clearly outperformed the other two strategies in terms of all three evaluation measures. With a 5.6 SR value, the strategy generated a 67.73% ARR and made 79.38% profitable trades. The results were much better than the results from the KST-based and the Buy-Hold strategies. Furthermore, we found that the annual returns generated by the KST-ML approach were significantly higher than those generated by other intelligent techniques reported in the literature.

Keywords: Intelligent stock trading, KST indicator, KST-ML, Stock prediction, Stock trading signal.

1. Introduction

The primary market and secondary market are the two types of stock markets. The primary market is the stock market where public firms sell stocks to the general public via an initial public offering (IPO) or a follow-on public offering (FPO). Secondary market is the stock market where stock traders meet, negotiate, and trade stocks at the current prevailing market price. Stock traders always try to predict future direction of stocks and trade accordingly. Fundamental analysis and technical analysis are two schools of thought to forecast the direction of future stock prices [1]. Fundamental analysis focuses on overall economic, industry, and company analysis to predict future stock price movement, whereas technical analysis focuses on price action, which provides insight into supply-demand dynamics and aids in predicting future stock price movement. Technical analysts analyze past trading data to predict stock price direction [2-4]. Therefore, machine learning strategies to stock prediction are closely related with prediction strategies used by technical analysts.

Technical indicators and candlestick chart analysis are widely adopted by technical analysts and machine learning researchers to forecast stock price movement [5-8]. Technical indicators are computed from the historical price and volume of stock trading. Moving average convergence divergence (MACD) indicator, know sure thing (KST) oscillator, average movement directional indicator (ADMI), relative strength index (RSI), moving average (MA), momentum, bollinger band (BB), William %R, etc. are widely used technical indicators in the technical analysis community [9]. Although some machine learning models only used historical trading data to forecast financial markets [10-12], historical trading data along with technical indicators also being used to improve accuracy of financial market forecasting [13-16].

KST oscillator is a popular technical indicator among technical analysts to predict stock buy/sell signals. Although many machine learning researchers used this indicator as an input feature to the machine learning model to predict stock price movement [17-19], there was gap between the way of using this indicator by the machine learning experts and technical analysts. Therefore, this research work proposed a KST oscillator based machine learning strategy (KST-ML) to predict buy/sell signals. The proposed strategy integrated machine learning approach with the approach used by technical analysts. The KST-ML strategy is devised on the basis of KST-based trading strategy used by technical analysts. Basics of the trading strategy is introduced in section 2. They use relationship between KST indicators to predict stock trading signals. However, the biggest issue with the KST oscillator is that it frequently generates misleading trading signals and is also a lagging indicator. The main objective of the proposed strategy is to learn true patterns so that buy/sell signals can be generated in timely way and misleading trading signals can be filtered out. This study also evaluated the performance of the proposed strategy against the KST-based trading strategy and the Buy-Hold strategy. Furthermore, the study compared the results obtained from the KST-ML strategy with the various intelligent trading strategies found in the literature. The annual rate of return (ARR), Sharpe ratio (SR), and proportion of profitable trades executed by the strategies were used to assess their performance.

Although there were numerous intelligent trading methods devised in the literature [20], none of them was based on concepts used by technical analysts for forecasting stock trading signals. Another motive of the proposed KST-ML method is to demonstrate that more profitable intelligent trading strategies can be developed based on the theories that technical analysts use to forecast financial markets.

Time series modelling approaches like autoregressive integrated moving average (ARIMA) [20-21], and machine learning strategies like logistic regression (LR) [22-23], support vector machine (SVM) [24-25], random forest (RF) [26-28], decision trees [27-28], etc. are widely used by researchers to predict stock market. Besides, artificial neural network approaches like multilayer perceptron (MLP) are also used by many researchers to forecast financial markets [29-31]. The aforementioned strategies lack ability to remember the context in contrast to recurrent neural networks (RNNs). Meanwhile, due to the challenges of exploding/vanishing gradient descent associated with RNNs, its variations such as the long short-term memory (LSTM) network [32-38] and the gated recurrent unit (GRU) network [37-40] became state-of-the-art models for stock forecasting and other time series prediction problems. Therefore, the GRU network was employed as a machine learning tool in this study to forecast stock trading signals. The major reason behind using GRU network is its capability of generalizing in better way with moderate volume of data compared to LSTM network. Furthermore, GRU networks have a simpler structure than LSTM networks, allowing them to be trained faster.

The rest of the paper is organized as follows. Section 2 discusses the concept of the KST oscillator briefly. The proposed KST-ML strategy is illustrated in section 3. The methodology adopted to carry out the research work is described in section 4. Experimental results and discussions are provided in section 5. Finally, section 6 concludes the research outcome.

2. Know sure thing (KST) oscillator

The KST oscillator is a trend and momentum oscillator. It is calculated from rate of change (ROC) indicators. The ROC indicator is a momentum indicator that measures the difference in percentage between a stock's current price and its price N-periods ago. KST oscillator is merely the sum of simple moving averages (SMAs) of the ROCs of four different periods, and KST signal is simply the 9-period SMA of the KST oscillator. Eq. (1) gives the mathematical formulation for computing the oscillator. This oscillator is widely used for determining the stock market's primary swings. Buying stocks when the KST line crosses above the KST signal line and selling the stocks when the KST line crosses below the KST signal line is the standard KST indicator based swing trading strategy. In this article, this strategy is referred as KST-based trading strategy. If the KST lines continue above the zero line, the momentum is in favour of bulls, and if the KST lines stays below the zero line, the momentum is in favour of bears [9, 7-19].

$$
\begin{aligned}
ROC\#1 &= (CP_t - CP_{t-10})/CP_{t-10} \\
ROC\#2 &= (CP_t - CP_{t-15})/CP_{t-15} \\
ROC\#3 &= (CP_t - CP_{t-20})/CP_{t-20} \qquad (1) \\
ROC\#4 &= (CP_t - CP_{t-30})/CP_{t-30}
\end{aligned}
$$

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$$KST = SMA_{10}(ROC\#1) \times 1 + SMA_{10}(ROC\#2) \times 2 + SMA_{10}(ROC\#3) \times 3 + SMA_{15}(ROC\#4) \times 4$$

Where, $SMA_p(x)$ is p-period SMA of x and CP_t is close price of t[th] trading day.

3. Proposed strategy

This section describes the proposed target feature generation model used for producing buy/hold/sell signals, KST-ML strategy, and trading simulation model used for performing automated stock trading based on predicted signals.

3.1 Target feature generation

On the basis of crossover between the KST indicator line and the KST signal line, this study devised a model for producing target feature "Action". Eq. (2) is the mathematical formulation of the model. The model alternates between producing buy and sell signals. When the indicator line and the signal line intersect, the model puts three buy or sell signals in the target feature. The main motivation behind this is to make it easier for machine learning model to spot trade signals.

$$\begin{array}{ll} If\ K[i] > KS[i] & action[i: i+3] = 'Buy' \\ If\ K[i] < KS[i] & action[i: i+3] = 'Sell' \\ Otherwise & action[i] = 'Hold' \end{array} \quad (2)$$

Where K[i] and KS[i] are KST indicator and KST signal of i[th] trading day.

3.2 KST-ML strategy

The conceptual framework of the proposed KST-based machine learning (KST-ML) strategy for predicting stock trading signals is presented in Fig. 1. Calculation of KST indicators is discussed in section 2. The target feature generation model is presented in section 3.1. Scaling, encoding and data preparation strategies used in the research study are discussed in sections 4.2 and 4.3. The gated recurrent unit (GRU) network used for predicting stock trading signals is described in section 4.4. Finally, the trading simulation module performs automated trading on the basis of predicted signals as discussed in section 3.3.

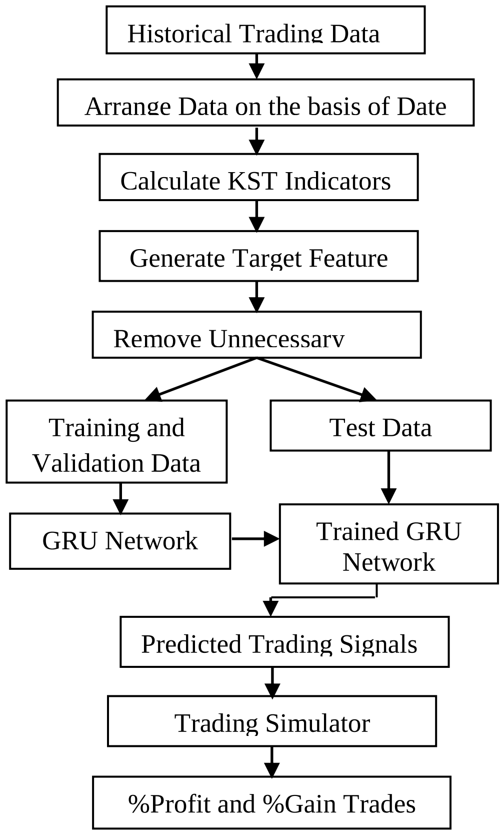

Figure. 1 Proposed KST-ML strategy

3.3 Trading simulation

This research work also designed and constructed a trading simulator that takes trading signals predicted by the KST-ML strategy or KST-based trading strategy and performs automated stock trading. The simulator buys and sells stocks based on the assumption that stock investors have no stocks at the start. Therefore, the simulator's first trading operation should be a buy operation. As a result, the simulator executes a series of buy and sell operations. The sequence consists of the equal number of both operations if the last transaction is a sell operation. However, if the last transaction is a buy operation, the sequence will include one more buy action than the number of sell actions. In this situation, the simulator discards the last buy operation and calculates profit/loss derived from automated trading. The "close price" is assumed to be the buy/sell price by the simulator. The simulator assumes that the investor has some seed money to invest in equities. It reinvests the entire sold value in the following buy transaction after the stocks are sold. Eq. (3) gives formula for calculating the gross profit/loss earned from trading. The cost of transactions and the tax on capital gains are not factored into the equation. Finally, the simulator uses Eq. (4) to compute profit/loss percentage.

$$pl = y - x \quad (3)$$

Table 1. Historical trading data of stocks

Stock Exchange	Stock Name	Date	
		From	To
NEPSE	Standard Chartered Bank Nepal (SCBN)	4/15/2010	7/01/2021
	Nepal SBI Bank Ltd.(NSBI)	4/15/2010	7/01/2021
	Muktinath Bikas Bank Ltd. (MNBBL)	11/3/2011	7/01/2021
	Prime Life Insurance (PLIC)	7/22/2010	7/01/2021
	Chilime Hydropower Company Ltd. (CHCL)	4/15/2010	7/01/2021
BSE	Housing Development Finance Corp. Ltd. (HDFC)	1/1/2000	7/01/2021
	Larsen & Toubro Ltd. (LT)	1/1/2000	7/01/2021
	Hindustan Zinc Ltd. (HZ)	1/1/2000	7/01/2021
	JSW Steels Ltd. (JSW)	1/1/2000	7/01/2021
	Vedanta Ltd. (VL)	1/1/2000	7/01/2021
NYSE	Baker Hughes Company (BKR)	1/1/2000	7/01/2021
	Carnival Corporation & plc. (CCL)	1/1/2000	7/01/2021
	Devon Energy Corporation (DVN)	1/1/2000	7/01/2021
	The Kroger Co. (KR)	1/1/2000	7/01/2021
	Nokia Corporation (NOK)	1/1/2000	7/01/2021
SSE	GuangYuYuan Chinese Herbal Medicine (GCHM)	1/1/2000	7/01/2021
	Hengtong Optic-Electric (HOE)	8/22/2003	7/01/2021
	Hua Xia Bank Limited (HB)	6/19/2003	7/01/2021
	Shanxi Coking Ltd. (SCC)	1/1/2000	7/01/2021
	Orient Group Incorporation (OG)	1/1/2000	7/01/2021

Where, y is the amount of money obtained from last sell operation and x is amount of seed money.

$$plp = pl/x \times 100 \quad (4)$$

4. Methodology

This section describes dataset, data preprocessing and preparation strategy, configuration of GRU network, and performance measures used in this research work.

4.1 Dataset

Historical stock trading data from four stock exchanges was used in this study: the Shanghai stock exchange (SSE), the New York stock exchange (NYSE), the Bombay stock exchange (BSE), and the Nepal stock exchange (NEPSE). Twenty stocks were experimented, five from each stock market. Table 1 gives description the stock data in detail. The start date of the data was varied due to data availability. The data of NEPSE and BSE stocks were obtained from the Nepal stock exchange [41] and the BSE India [42], respectively. Similarly, Yahoo finance [43] was used to obtain data on NYSE and SSE stocks.

4.2 Data preprocessing

Initially, the historical trading data was organized in chronological order from the oldest to the most recent date. The KST indicators were then generated, including the KST oscillator, KST signal, and KST histogram, and any superfluous features were removed from the dataset. Following that, the proposed target generation model in Eq. (2) was used to generate the target attribute 'Action'. Finally, standard scalar was used to normalize the input features, and one-hot encoding technique was used to encode the target feature.

4.3 Data preparation

The datasets were partitioned into train, validation, and test sets in an 8:1:1 ratio. The goal of this research work was to anticipate stock trading signals for $(t+1)^{th}$ day utilizing input features from day $(t+N-1)$ to day t, where t is current trading day and N is window size. Thus, the study's input data included a combination of N independent variables $d_{t-N+1,} \dots . d_{t-1}, d_t$ and a dependent variable a_t, where d_i is a tuple (k_i, ks_i, kh_i) and a_i reflects transaction activity for the i^{th} trading day. The symbols $k_{i\,,}\, ks_i$ and kh_i represents KST oscillator, KST signal, and KST histogram, respectively. The size of window (N) employed in the research study was 5 as suggested by Saud and Shakya [44].

4.4 Configuration of GRU network

The GRU network employed in this study had a configuration of $3 \times 100 \times 100 \times 3$. A dropout layer with a dropout rate of 0.2 was placed after each hidden layer of the network. The network's hidden layers employed the ReLU activation function, whereas the output layer used the Softmax activation function. With the GRU network, the Adam gradient descent optimizer was also used. This configuration of the GRU network is not guaranteed to be optimal; nonetheless, experiments were undertaken with many configurations before settling on this one.

4.5 Performance measures

The annual rate of return (ARR), Sharpe ratio (SR), and proportion of profit/loss transactions conducted by trading strategies were all used to analyze trading strategies in this study. SR measures performance of the stock trading against risk-free asset. Higher value of SR means higher excess return compared to risk-free asset. ARR and SR were computed from the profit earned from the trading strategies using the formulae given in Eqs. (5) and (6) respectively. Since the target feature 'Action' is simply an estimation based on the crossover between KST line and KST signal line, classification accuracy is not a relevant performance measure for the proposed strategy.

$$ARR = \{(1 + r)^{1/n} - 1\} \times 100 \tag{5}$$

Where, n is the number of years and r is return from stock trading.

$$SR = (R_t - R_f)/\sigma \tag{6}$$

Where, Rt is the return from stock trading, Rf is risk-free return, and σ is standard deviation of Rt.

5. Results and discussion

As already mentioned, this research work experimented 20 stocks. Price movement pattern of these stocks in the test period is shown in Fig. 2. From the figure we can see that the stocks SCBN, NSBI & NOK are in sideways pattern, stocks MNBBL, CHCL, PLIC, JSW, VL, KR & GCHM are in bullish pattern, stocks CCL, HOE & HB are in bearish pattern and stocks HDFC, LT, HZ, BKR, DVN, SCC & OG are in mixed pattern during the test period. In the figure x-axis represents number of trading days and y-axis represents price. Fig. 3 shows buy/sell operations for the stocks SCBN, HDFC, BKR, and HOE that were carried out using a trading simulator based on forecasted signals by the KST-ML approach.

5.1 Analysis of returns

The trading simulator executed buy/sell operations on the test data on the basis of predicted signals and computed returns obtained from stock

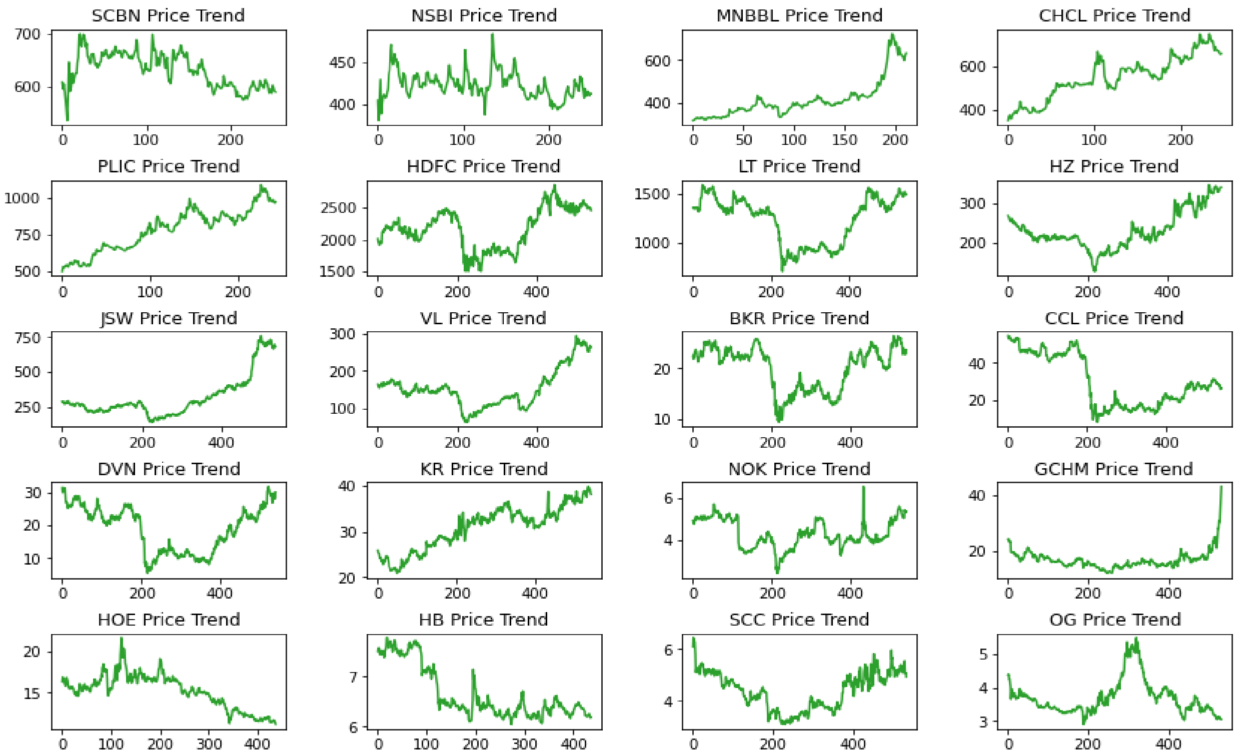

Figure. 2 Price trend of stocks in test period

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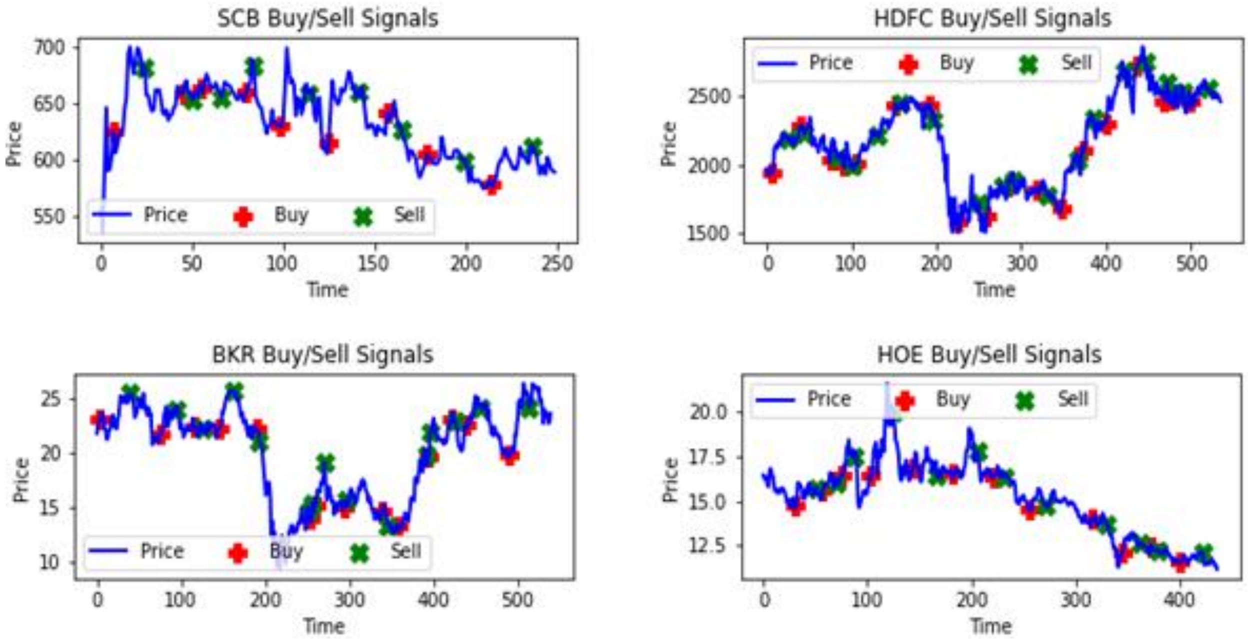

Figure. 3 Buy/Sell signals of stocks

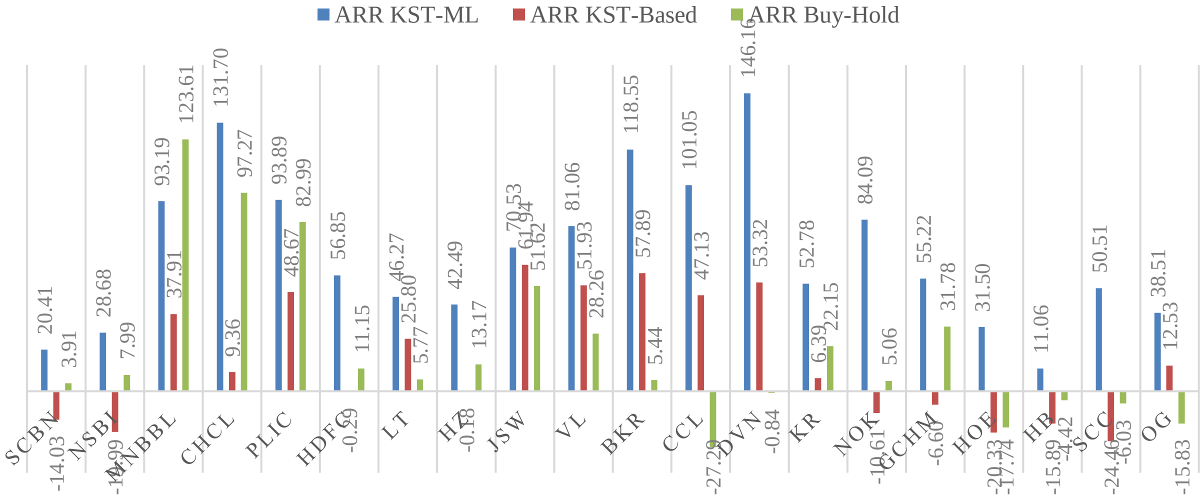

Figure. 4 ARR obtained from trading strategies

Figure. 5 SR obtained from trading strategies

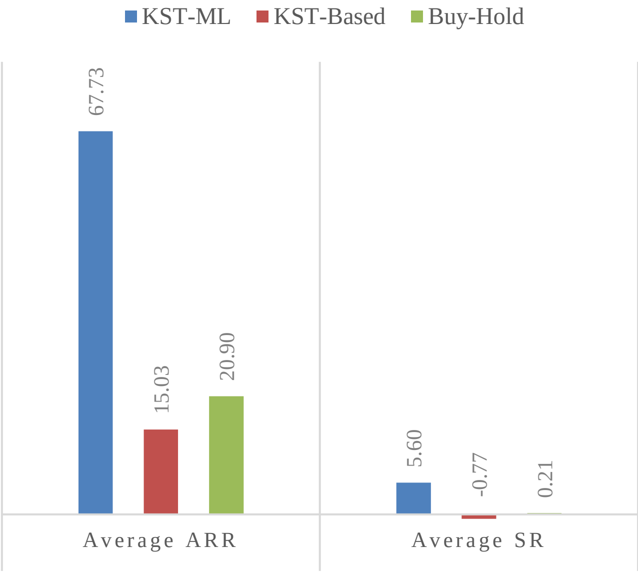

Figure. 6 Average ARR and SR

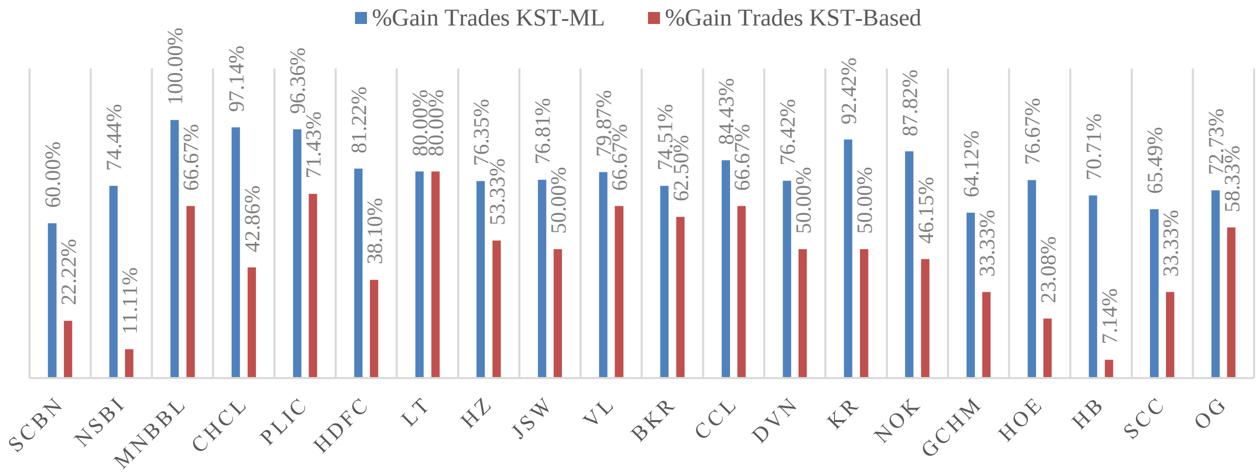

Figure. 7 Percentage gain trades

trading. Thereafter, ARR was calculated using Eq. (5) and the result is presented in Fig. 4. In order to quantify the risk associated with stock trading, SR was then calculated using Eq. (6) and the result is presented in Fig. 5. Treasury bill rates from the respective countries were used as risk-free returns in the SR calculation. Furthermore, the standard deviation of trading returns was utilized in the KST-ML and KST-based strategies, and the standard deviation of the past 10 years annual returns was employed in the Buy-Hold strategy.

The KST-ML trading approach clearly outperformed the KST-based trading strategy and the Buy-Hold strategy in terms of ARR and SR, as shown in Figs. 4 and 5. The strategy yielded 11.06 % to 146.16 % ARR from stock trading. This ARR was achieved with SR range of 2.47 to 12.69. The Buy-Hold strategy achieved ARR from -27.29 % to 123.61 % with SR value ranged from -1.09 to 1.98. The KST-based trading strategy performed worst and yielded ARR from -24.46 % to 61.94 % with SR range -10.74 to 2.59. In summary, the KST-ML strategy yielded 67.73 % average ARR with 5.6 average SR value. Meanwhile, the Buy-Hold and the KST-based strategy achieved average ARR 20.9% and 15.03% with SR values 0.21 and -0.77 respectively as shown in Fig. 6. From the observation of ARR, we saw that the Buy-Hold strategy obtained satisfactory returns only from bullish stocks. The KST-based method exhibited unpredictable behaviour. With certain stocks, the technique produced satisfactory returns, while with

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others, it produced disappointing returns. However, the KST-ML strategy achieved satisfactory returns from all stocks regardless of the stock trend.

From Fig. 5, we also observed that the KST-ML strategy achieved SR above 3 for 18 stocks and below 3 only for 2 stocks. However, SR values obtained from the Buy-Hold strategy and the KST-based strategy was always below 3. Furthermore, the Buy-Hold strategy achieved positive SR for 13 stocks and negative SR for remaining 7 stocks and the KST-based strategy achieved positive SR for 11 stocks and negative SR for remaining 9 stocks. Based on these observations, it is clear that the KST-ML approach is the most profitable and safest trading method of the three.

5.2 Analysis of gain trades

The percentage of gain trades executed by trading strategies is one of the important measure. The trading simulator counts total number of trades and total number of profitable trades executed by the trading strategies. Then, percentage of profitable trades executed by the strategies were calculated and the result is presented in Fig. 7. The Buy-Hold strategy is not analyzed in this regard because it only conducts one trade per stock during the test period.

The percentage of profitable trades conducted by the KST-ML trading strategy is substantially higher than the percentage of such trades done by the KST-based strategy, as shown in Fig. 7. The KST-ML strategy executed 60 % to 100 % profitable trades whereas the KST-based strategy executed only 7.14 % to 80 % such trades. On average, the trading strategies executed 79.38 % and 46.65 % profitable trades respectively. This observation leads to the fact that a considerable percentage of trade signals generated by the KST indicator were misleading signals that were significantly filtered by the KST-ML approach.

5.3 Comparison with other intelligent trading strategies

Stoen, Paja, and Sandita proposed HC-LSTM and HC-CNN strategies for stock price prediction along with trading simulation based on heuristic-based approach and found that the HC-LSTM strategy performed better than the HC-CNN strategy. The HC-LSTM strategy was able to achieve 10.61 % more return than the Buy-Hold strategy & 14.17 % more return than the bollinger band based trading strategy [35]. Yang, Hao, Cai, Chen, and Ren predicted stock trading signal based on multi-indicator channel convolutional neural networks (MICNN) and found that the MICNN strategy achieved 6.2 % more return than the RSI based trading strategy [45]. Kroha and Friedrich compared genetic algorithms for trading strategies and found that the genetic programming based trading strategy achieved 2.72 % more return than the Buy-Hold strategy [46]. Song and Lee predicted stock price movement with LSTM neural networks and reported 81.6 % accuracy and profit near to zero [47]. Matsubara, Akita, and Uehara predicted stock price by deep neural generative model of news articles and obtained accuracy above 60 % and 22 % loss [48]. Vargas, Anjos, Bichara and Evsukoff used deep learning for stock market prediction using technical indicators and financial news articles and obtained 10.72 % more profit than the than the Buy-Hold strategy [49]. Tan and Wang proposed SDNN for optimized trading strategy that was able to generate 33.3 % annualized return [50]. Sezer and Ozbayoglu utilized 2-D deep CNN and technical indicator to develop algorithmic trading system that generated 5.85 % more annualized return than the Buy-Hold strategy [51]. Oncharoen and Vateekul added risk-reward function into loss function to train deep neural network and reported 21.56 % annualized return [52]. From this survey, we found that most of intelligent trading strategies compared performance with Buy-Hold strategy and related technical indicator based trading strategy. Thus, in this study, the proposed KST-ML approach has been compared to the Buy-Hold strategy and the KST-based trading strategy.

As presented in section 5.1, we observed that the proposed KST-ML strategy yielded 52.7 % and 46.82 % more return than the KST-based and Buy-Hold strategy respectively. The results are far superior to those produced using the aforementioned intelligent trading strategies. The strength of the KST indicator, on which the KST-ML strategy was designed, is the main reason for the proposed approach's improved performance. Technical experts have been using this indicator for a long time. Its strength, on the other hand, is not exploited in any intelligent stock trading method. From these discoveries, we claim that the proposed KST-ML strategy not only outperformed the Buy-Hold and KST-based strategies but also excelled other intelligent trading methods proposed in the literature in terms of annualized return.

6. Conclusion

This paper proposed a know sure thing based machine learning (KST-ML) strategy for predicting buy/hold/sell signals in stock trading and compared the model's performance to that of a Buy-Hold strategy and a KST-based trading strategy. The annualized rate of return (ARR), Sharpe ratio (SR), and percentage of gain trades executed were used to analyze the strategies.

Experimental results revealed the fact that the KST-ML strategy performed better than the other two strategies in terms of all three evaluation measures. The approach's average ARR was 52.7 percent and 46.82 percent greater than the average ARR of the KST-based trading strategy and the Buy-Hold strategy, respectively. The KST-ML strategy yielded the 5.6 average SR from the trading which was only -0.77 and 0.21 for the other two strategies. This finding demonstrated that the KST-ML strategy is both more profitable and less risky than the other two trading methods. The strategy was able to generate satisfactory returns from the stock trading regardless of the stock trend. The KST-ML method, on the other hand, averaged 79.38 percent profitable trades, while the KST-based approach averaged only 46.65 percent profitable trades. This discovery leads to the fact that the KST-ML approach may effectively filter out a large number of false trade signals generated by the KST indicator. Furthermore, we found that the KST-ML approach generated significantly greater annual returns than other intelligent trading techniques reported in the literature. Thus, we conclude that the proposed KST-ML method is superior to other trading strategies for automatic stock trading. This research conclusion has a significant implication: it is possible to develop intelligent trading strategies based on correlations between technical indicators that have long been used by technical analysts.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Arjun Singh Saud played a key role in framing conceptual design, implementation, result analysis, and research report writing. Subarna Shakya played the role of advisor in this research work. He provided feedback, validated the result and reviewed the research report.

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