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HILL-CLIMBING POWERED GATED RECURRENT UNIT NETWORK TO PREDICT STOCK TRADING SIGNALS USING MEAN AVERAGE CONVERGENCE DIVERGENCE INDICATOR

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ABSTRACT

This paper proposed a hill-climbing powered gated recurrent unit (HC-GRU) network to predict stock trading signals using the mean average convergence divergence (MACD) indicator. The proposed model was compared with the Buy/Hold Strategy, a benchmark strategy, and the traditional MACD indicator based trading strategy. All three models were evaluated in terms of the annualized rate of return, sharp ratio, and the number of profit/loss trades executed by the strategies. The experiments were conducted on twenty randomly selected stocks from the Bombay Stock Exchange, Nepal Stock Exchange, New York Stock Exchange, and the Shanghai Stock Exchange. From the experimental results, we observed that the HC-GRU outperformed the other two models in terms of all three measures. ARR obtained from HC-GRU strategy was 22.44% to 62.76% higher than the ARR obtained from the traditional MACD indicator based trading strategy and it was 14.69% to 71.72% higher than the Buy/Hold strategy. On the other side, 66.67% to 100% trades made by the HC-GRU strategy were profit trades but only 27.78% to 62.5% trades executed by the traditional MACD indicator based trading strategy were profit trades. From this observation, we concluded that the proposed HC-GRU approach is a superior strategy for automated stock trading whereas the traditional MACD indicator based strategy is not suitable for automated stock trading.

Keywords: *Stock Trading, Trading Signals, Gated Recurrent Unit, Hill Climbing, Mean Average Convergence Divergence*

1. INTRODUCTION

Basically, stock markets can be divided into two types: primary stock market and secondary stock market. In the primary market, companies sell stocks and bonds to the general public through an initial public offering (IPO) or further public offering (FPO), while, in the secondary market, peoples Buy/Sell stocks at the current prevailing stock price without the involvement of the company. The place where stock traders meet together, negotiate for the stock prices, and Buy/Sell stocks is called stock exchange. The Bombay Stock Exchange (BSE) is one of the pioneer stock exchange of India. There is only one stock exchange in Nepal called the Nepal Stock Exchange (NEPSE). New York Stock Exchange (NYSE) and Shanghai Stock Exchange (SSE) are two leading stock exchanges of the United States and China respectively.

Stock investors and traders always want to buy undervalued stocks and sell overvalued stocks. For this, they use their knowledge and experience to predict future stock prices of stocks and take actions accordingly. However, correctly forecasting stock prices and taking stock trading actions accordingly is a very difficult task as the stock price is the function of many known and unknown parameters like demand and supply, present and projected financial performances of companies, current and projected economic conditions, interest rate, growth rate, performance of peer companies, dividend history and capacity, rumors, political changes, etc. [1]-[3].

The schools of thought used to predict stock prices can be broadly divided into two categories:

fundamental analysis and technical analysis [4]. Fundamental analysis is generally used by value investors for long-term forecasting while technical analysis is generally a preferred tool for short-term traders. Technical analysts use historical trading data to identify trading patterns and use those patterns to estimate future direction of stock prices. However, it is very difficult for stock traders to analyze the large volume of the historical trading data and identify useful patterns from it. Hence machine learning algorithms are becoming popular for predicting stock price movements and performing automatic trading [5],[6]. The efficient market hypothesis (EMH) [7] and the random walk hypothesis [8] argued that stock prices never depend upon past trading patterns but are driven by entirely new information and therefore it is impossible to predict stock prices. However, John [9] and Burton [10] have provided evidence contrary to this and concluded that stock markets can be predicted to some degree.

The research work performed by Apostolos et al. [11] is probably the first research work that predicted stock prices using machine learning models. Since then researchers have proposed several models to predict stock prices and stock trading signals [6]. Researches related to stock market prediction are mainly focused into three areas (1) prediction of stock prices [12]-[15] (2) prediction of stock market index [16]-[20] and (3) prediction of stock trading signals [21]-[23]. Evolutionary or heuristic algorithms are used in many researches for estimating the optimal values of the hyperparameters of the machine learning model used for stock forecasting [21],[24]-[26]. Further, many researchers used technical indicators for predicting stock market trends and achieved improved prediction performance [14], [16], [19], [27]-[31]. These researches have just used technical indicators as input feature to machine learning strategies developed for predicting directions of stocks. None of these machine learning strategies simulated the approaches used by technical analysts for predicting stock prices and stock trading signals. Thus, there is clear gap between the machine learning based stock forecasting strategies and the forecasting approach used by technical analysts.

Technical indicators are preferred tools for financial analysts to predict future movements of stocks. Primarily technical indicators are calculated from stock prices and volume of past trading data [32],[33]. Broadly technical indicators can be divided into five categories [34]: Trend Indicators, Momentum Indicators, Volume Indicators, Volatility Indicators, and Other Indicators. The major trend indicators used by technical analysts are average directional index (ADX), mean average convergence divergence (MACD), mass index (MI), moving Averages (MA), parabolic SAR, Trix, vortex indicator (VI), and know sure thing (KST) Oscillator and the major momentum indicators are momentum, RSI, stochastic oscillator, and Williams %R [35],[36].

This research paper proposed a Hill-climbing powered gated recurrent unit (HC-GRU) network model for predicting stock trading signals using mean average convergence divergence (MACD) indicator. The proposed model was evaluated by conducting an automatic stock trading simulation based on the predicted signals. Performance of the model was compared with the Buy/Hold strategy, a benchmark strategy, and the traditional MACD indicator based trading strategy. Although many researchers have proposed intelligent stock trading strategies [21]-[23], the proposed HC-GRU model is the first intelligent stock trading strategy developed on the basis of MACD indicator based trading strategy used by technical analysts. One problem with this indicator is that it gives false trading signals frequently. Therefore, technical analysts cannot depend solely upon this indicator for predicting stock trends. The HC-GRU strategy is devised with the hope that it will be able to filter false trading signals.

The rest of the paper is structured as follows. Section 2 briefly describes the theories and models that were used for formulating the HC-GRU strategy. Section 3 discusses the proposed HC-GRU model. Section 4 sheds light on the materials and methods used to carry out this research work. Section 5 presents and interprets the experimental results. Finally, the conclusion of this research work is provided in Section 6.

2. RELATED THEORY

This section briefly described the concept of MACD indicator, Hill-climbing strategy, and gated recurrent unit (GRU) network. These concepts were used for formulating the proposed HC-GRU strategy.

2.1 Mean Average Convergence Divergence (MACD)

MACD is a widely used stock trading indicator that shows the trend and momentum of the stock price. MACD is calculated using historical closing prices of stocks [36]. This indicator is a

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combination of three time-series data: MACD series, MACD Signal, and MACD histogram. It is calculated using exponential moving averages (EMA's) of different periods as given in Equation 1. EMA is the type of moving average that puts greater weight and significance on recent closing prices.

$$\begin{aligned} &\text{MACD} = 12 \text{ day EMA(Close)} - 26 \text{ day EMA(Close)} \\ &\text{MACD Signal} = 9 \text{ day EMA(MACD)} \\ &\text{MACD Histogram} = \text{MACD} - \text{MACD Signal} \end{aligned} \qquad (1)$$

Relationship between MACD and MACD signal functions as the trigger for Buy/Sell actions. The general stock trading strategy is that buy a stock when MACD crosses above the MACD signal and sell the stock when MACD crosses below the MACD signal line. MACD histogram is a series that shows the strength of bullish and bearish momentum of stocks. Figure 1 demonstrates the point of Buy/Sell actions based on of crossover between MCAD and MACD signal.

2.2 Hill Climbing(HC) Strategy

Hill Climbing (HC) is a heuristic search algorithm used for solving optimization problems. It is a type of local search algorithm that uses a greedy strategy for solving problems. It explores all its neighbors and chooses the best one among them. This process continues until the specified number of iterations is reached or the specified level of accuracy is achieved. Although HC is the simplest approach for solving optimization problems, it may get stuck in local optima and hence may not give global optimal solution [37],[38]. To cope with this problem stochastic HC or simulated annealing strategy can be used. This study used a simple HC strategy for finding optimal values of thresholds for the proposed feature generation model (see Section 3.1). The main reason behind choosing simple HC is that threshold values are always near to the point where MCAD line and MACD signal line crosses each other (see Figure 1) and we took the crossover point as the starting point in this study.

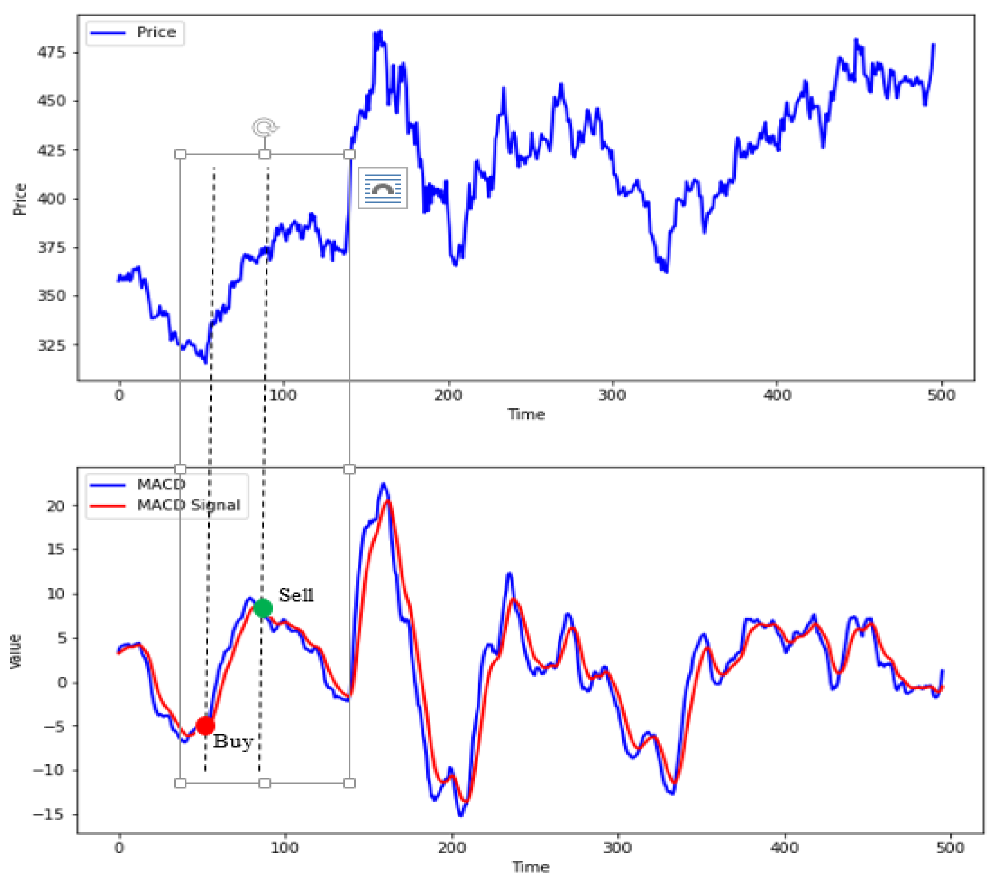

Figure 1: MACD Indicator based Trading Strategy

2.3 Gated Recurrent Unit (GRU) Network

Recurrent neural networks (RNNs) suffers from the vanishing/exploding gradient descent problem. GRU and long short-term memory (LSTM) are types of RNN that can cope with this type of problem. GRU is similar to LSTM network but its structure is simple [39]. It uses only two gates and fewer parameters than LSTM. Therefore it can be trained faster than LSTM as well as it can be generalized with fewer data. Research by Gail et al. [40] argued that LSTM has higher expressive power than GRU and hence yields better results when working with a huge amount of data. However, GRU performs well when working with a moderate volume of data. The mathematical formulation of the network is provided in Equation 2 [39].

$$
\begin{aligned}
Z_t &= \sigma(W_z x_t + U_z H_{t-1}) \\
R_t &= \sigma(W_r x_t + U_r H_{t-1}) \\
H_t' &= \tanh(W_h x_t + (R_t \times H_{t-1}) U_h) \\
H_t &= (Z_t \times H_t') + ((1 - Z_t) \times H_{t-1})
\end{aligned}
\tag{2}
$$

where, Z and R are update and reset gates, H_t' is candiadte hidden state, H_t is hidden state, W and U are weights, and σ is sigmoid function

3. PROPOSED MODEL

The proposed model has three parts: target generation model, HC-GRU strategy, and automated trading simulation. Figure 2 shows the schematic diagram of the proposed model.

3.1 Target Generation

This study proposed a model for generating the target feature "Action". The model generates Buy/Sell/Hold signals based on the values of MACD indicators as given in Equation 3. It generates Buy and Sell signals alternately. Thus, the model generates a sequence of Buy, Hold, and Sell actions. The optimal values of threshold δ1 and δ2 for the model were determined using HC strategy.

$$
\begin{cases}
\text{if } m_i - ms_i > \delta_1 & \text{then} \quad action[i:i+3] = \text{'Buy'} \\
\text{if } ms_i - m_i > \delta_2 & \text{then} \quad action[i:i+3] = \text{'Sell'} \\
\text{otherwise} & \qquad\quad\; action[i] = \text{'Hold'}
\end{cases}
\tag{3}
$$

where δ_1 and δ_2 thresohold values and m & ms are MACD and MACD Signal respectively

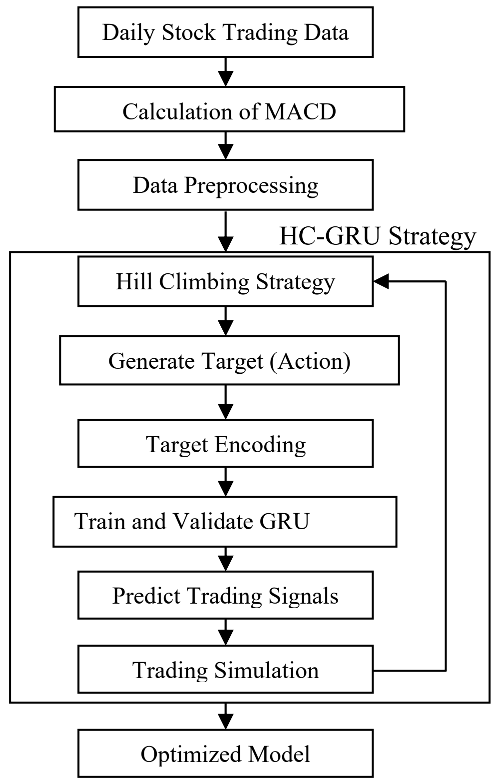

Figure 2: Schematic Diagram of the Proposed HC-GRU Model

3.2 HC-GRU Strategy

The proposed HC-GRU is basically a GRU network that uses a hill-climbing strategy to find optimal values of thresholds δ1 and δ2, so as to make the maximum profit from trading. HC strategy starts with δ1=0 and δ2=0 and evaluates each of its neighbors to reach optimal values of thresholds. The GRU network employed in the HC-GRU model has two hidden layers with ReLU activation function and a final dense layer with the softmax activation function. Each hidden layer of the GRU network is followed by a dropout layer. The model was trained, validated, and tested using MACD indicators as input attributes and 'action' as the target attribute. The sliding window approach with window size 5 was used for model training and testing as suggested by Saud and Shaky [41]. Thus the shape of input data was (L, N, 3), where 3 is the number of features used for training, L is the length of the dataset, and N is the window Size (i.e. N=5).

3.3 Automated Trading Simulation

HC-GRU model was used for predicting trading signals for test data and these trading signals were used by the automatic trading simulator. The simulator performs Buy and Sell operations on the assumption that stock investors initially holds no stocks. Hence the first trading operation of the simulator should be 'Buy' operation. Thus, the simulator performs a sequence of Buy and Sell operations. If the last trading operation is 'Sell' operation, then the sequence consists of the same number of 'Buy' and 'Sell' operations. However, if the last trading operation is 'Buy' operation, then the sequence includes one more 'Buy' operation than the number of 'Sell' operations. In such a situation, the simulator discards last 'Buy' operation and performs profit/loss calculation derived from automated trading. The simulator uses the close price as 'Buy/Sell' price. The formula used to calculate gross profit/loss from the trading is given in Equation 4. This equation does not include transaction cost and income gain tax.

$$pl = \sum_{i=0}^{len(s)} (s_i - b_i) \quad (4)$$

where b and s are vectors representing buy and sell prices for trading sequnce

After calculating the gain/loss, the simulator calculates average investment amount and percentage profit/loss using Equations 5 and 6, respectively.

$$ai = \frac{1}{len(b)} \sum_{i=0}^{len(b)} b_i \quad (5)$$

$$plp = \frac{pl}{ai} \times 100 \quad (6)$$

The above mentioned technique of calculating profit/loss percentage is also used for the traditional MACD indicator based trading strategy. On the other hand, the 'Buy/Hold' strategy operates 'Buy' and 'Sell' operations only once during the test period. The assumption for the strategy is that the 'Buy' operation is performed at the first day and the 'Sell' operation is performed last day of the test period. Therefore, the profit/loss percentage for the 'Buy/Hold' strategy was calculated using Equations 7 and 8.

$$pl = (C_L \times (1+k) - C_{L*0.9+1}) + \sum_{i=1}^{n} cd_i \quad (7)$$

where C_i is close prices of i^{th} trading dayk denotes number bonus shares issued during test period cd_i is the i^{th} cash divided provided during the test period

$$plp = \frac{pl}{C_{L*0.9+1}} \times 100 \quad (8)$$

4. Materials and Methods

This research work was carried out by using experimental research method. This research work was carried out by using an experimental research method. This section describes the data, tools, and data analysis techniques used while conducting this research work.

4.1 Stock Data

In this research, BSE, NEPSE, NYSE, and SSE stocks were used for experimentation. Historical trading data of BSE stocks was downloaded from BSE India [42], historical trading data of NEPSE stocks was collected from Nepal Stock Exchange [43], and historical trading data of NYSE and SSE stocks was downloaded from yahoo finance [44]. Five stocks were randomly chosen from each of four stock exchanges. Stocks representing different sectors were chosen for the experiment. Thus, in total 20 stocks were experimented in this research work. The data for NEPSE stocks was daily data from 15 August 2007 to 12 March 2020. The five NEPSE stocks used in this research work were Nabil Bank (Nabil), Himalayan Bank (HBL), Nepal Life Insurance (NLIC), Life Insurance Company (LICN), and Everest Bank Limited (EBL). Downloaded data of BSE, NYSE and SSE stocks was daily data from 1st January 2000 to 1st January 2020. The five BSE stocks experimented in this research work were ICICI Bank, Dabur India, HCL Technologies, Reliance Industries and Infosys. The five NYSE stocks were Harmony Gold Refinery (HMY), Coca Cola (KO), Fedex (FDX), Taiwan Semiconductor (TSM), and Bank of Hawai (BOH). And the five SSE stocks were Anhui Conch Cement (ACC), China Minsheng Bank Corporation (CMBC), Dongfang Electric Corporation (DEC), Fosun Pharmaceuticals (FP), and SAIC Motor Corporation.

4.2 Data Preprocessing

First, the data was arranged in the order of oldest to newest date, the MACD indicators (MACD Series, MACD Signal, and MACD Histogram) were calculated from the data, and all other features were dropped from the dataset. The target feature 'Action' was then generated using the proposed target generation model given in Equation 3. Finally, the input features were normalized using standard scalar and the target attribute was encoded using one-hot encoding strategy.

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4.3 Data Preparation

The data were divided into training, validation, and test sets in 8:1:1 ratio. The aim of this study was to predict trading signal for the day t+1 using input features from (t-N+1)th day to tth day, where t is the current trading day and N is window size. Therefore the input data used in this research work was a combination of N independent variables $d_{t-N+1} \ldots d_{t-1}$, d_t and a dependent variable a_{t+1}, where d_i is a tuple (m_i, ms_i, mh_i) and a_i represents trading action for the ith day. The symbols m_i, ms_i, and mh_i, denotes MACD, MACD signal, and MACD histogram respectively for the ith trading day. Thus, $t \in [1, L*0.8]$ for the training set, $t \in [L*0.8+1, L*0.9]$ for the validation set, and $t \in [L*0.9+1, L]$ for the test set, where L is the length of the dataset.

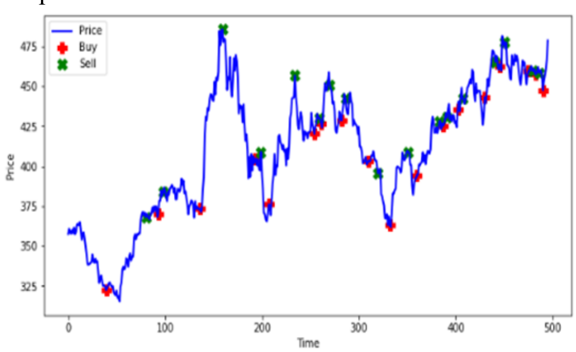
4.4 GRU Configuration

GRU network was used as machine learning tool for predicting stock trading signals. Configuration of the GRU network used in this research work was 3×100×100×3. In addition, Adam optimizer was used with the GRU network. Although this configuration is not fine tuned, some random experiments were conducted with different configuration and finally, this configuration was adopted.

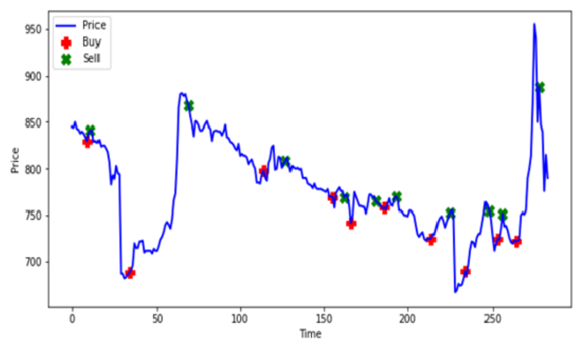
5. RESULTS AND DISCUSSION

In this research work, experiments were carried out in three directions to evaluate the proposed model: (1) annual rate of return (ARR) obtained from trading (2) sharp ratio (SR) of the return obtained from trading and (3) profit/loss percentage of total trades. Further, the performance of the proposed model was compared with the Buy/Hold strategy and the traditional MACD indicator based trading strategy. HC-GRU strategy was not evaluated in terms of classification accuracy because the target feature (Action) was generated using the MACD indicator. Thus, the generated class labels are only rough estimates because, as already mentioned, the MACD indicator gives false trading signals frequently. It was expected that the proposed HC-GRU strategy will be able to learn true Buy/Sell patterns and will be able to filter out false patterns from the dataset. Therefore, accuracy calculation is not relevant to judge the performance of the proposed HC-GRU strategy.

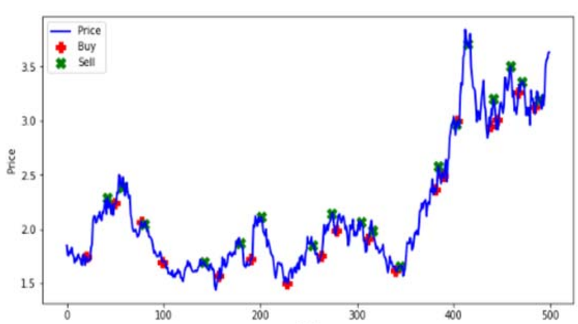
The Buy/Sell actions generated by the HC-GRU strategy and the traditional MACD indicator based trading strategy for Dabur, Nabil, HMY, and ACC is presented in Figure 3 and Figure 4 respectively. In the Figures, the x-axis is the time dimension that represents the number of trading days in the test period and the y-axis represents the close price of the stock over time.



(a)



(b)



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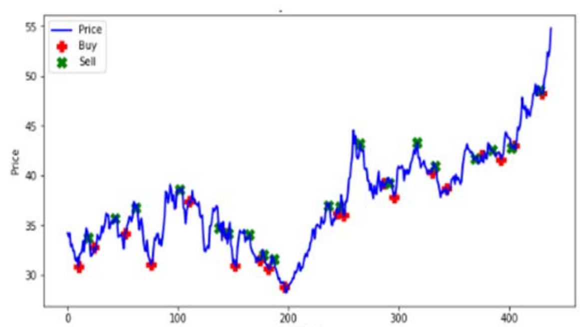

(d)

Figure 3: Buy/Sell Actions generated by HC-GRU mode for (a) Dabur (b) Nabil (c) HMY and (d) ACC

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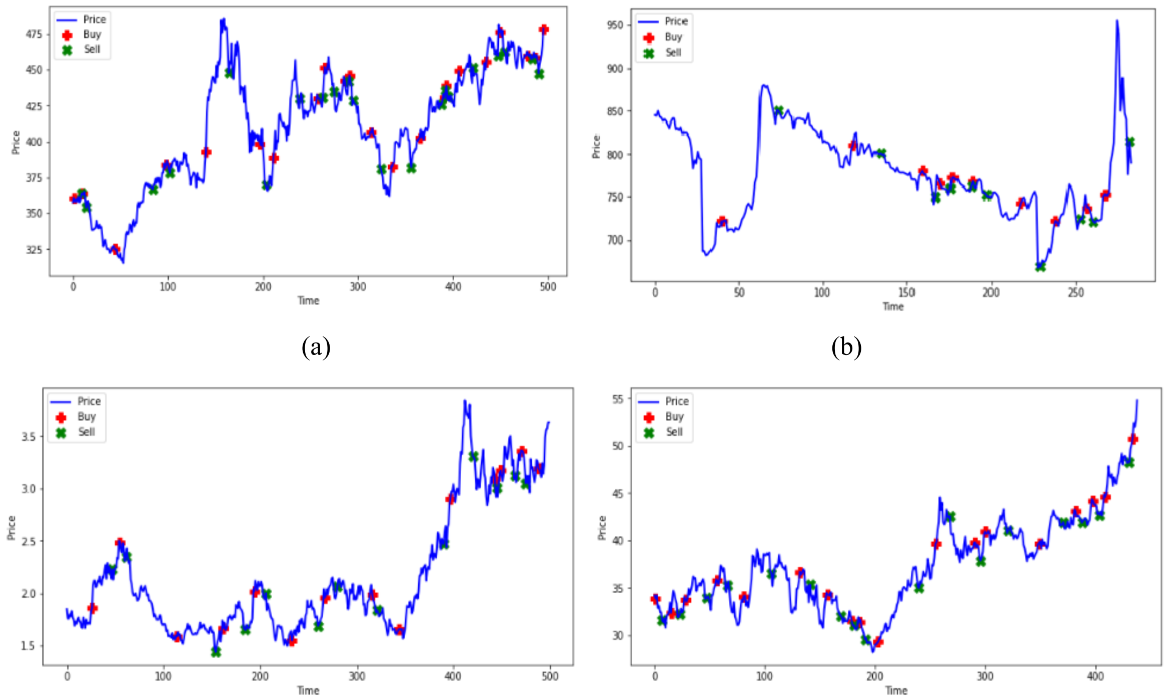

Figure 4: Buy/Sell Actions generated by MACD model for (a) Dabur (b) Nabil (c) HMY and (d) ACC

5.1 Evaluation of Trading Return and Risk

A trading simulation was carried out on the test data using trading signals generated by the HC-GRU strategy and the traditional MACD indicator based strategy. Furthermore, profit/loss earned from the Buy/Hold strategy was computed. Then, for each of the strategy, ARR (Table 1) and SR(Table 2) was calculated using Equations 9 and 10 respectively and the obtained result is plotted in Figures 5 and 6 respectively.

$$\mathrm{ARR} = (1+\mathrm{Return})^{1/n} - 1 \quad (9)$$

where, n is the number of years

$$\mathrm{SR} = \frac{R_t - R_f}{\sigma} \quad (10)$$

where, R_t is return from stock trading R_f is return from risk free investment and σ is standard deviation of return from stock trading

Table 1. Annual Rate of Return of Stocks

Company	ARR		
	HC-GRU	MACD	Buy/Hold
Dabur	44.62	4.41	16.96
HCL	38.87	3.96	15.92
Infosys	37.11	-0.25	21.53
ICICI	54.72	22.65	31.25
Reliance	58.38	1.17	28.67
Nabil	52.91	14.85	6.22
HBL	68.02	27.88	38.25
NLIC	53.21	30.77	29.88
LICN	37.22	3.60	17.08
EBL	72.15	29.28	38.06
HMY	81.60	18.84	39.32
KO	27.61	-0.43	12.92
FDX	46.35	-8.13	-20.87
TSM	43.22	7.97	23.76
BOH	36.47	1.18	7.79
ACC	67.71	5.66	38.59
CMBC	22.96	-4.18	-5.69
DEC	47.79	-8.67	-6.99
FP	50.70	0.92	-21.03
SAIC	37.96	-1.97	-9.26

Table 2. Sharp Ration of Stocks

Company	SR		
	HC-GRU	MACD	Buy/Hold
Dabur	10.15	-2.34	10.21
HCL	18.90	-2.79	9.17
Infosys	5.63	-7.00	14.78
ICICI	6.38	15.90	24.50
Reliance	8.11	-5.58	21.92
Nabil	22.57	8.10	-0.53
HBL	40.01	21.13	31.50
NLIC	28.98	24.02	23.13
LICN	5.73	-3.15	10.33
EBL	42.77	22.53	31.31
HMY	4.78	12.09	32.57
KO	4.75	-7.18	6.17
FDX	16.24	-14.88	-27.62
TSM	6.90	1.22	17.01
BOH	17.30	-5.57	1.04
ACC	6.38	-1.09	31.84
CMBC	5.37	-10.93	-12.44
DEC	2.96	-15.42	-13.74
FP	3.69	-5.83	-27.78
SAIC	8.98	-8.72	-3.22

The graphs of Figure 5 and 6 clearly shows that the HC-GRU model outperformed the Buy/Hold strategy and the traditional MACD based trading strategy in terms of ARR and SR. The HC-GRU strategy yielded the highest ARR and SR for all companies. The model achieved 22.96% to 81.60% ARR. This ARR was achieved with SR 2.96 to 42.77. Negative SR was not obtained for any stock. This shows that stock trading using HC-GRU strategy is almost risk free strategy. On the other hand, the traditional MACD based trading strategy yielded the lowest ARR for 14 stocks and second lowest ARR for remaining 6 stocks. The model achieved -8.67% to 30.77% ARR. This ARR was achieved with SR -15.42 to 22.53. In case of the model, positive SR was obtained only for 7 stocks whereas negative SR was obtained for 13 stocks. This observation indicates to the fact that stock trading using traditional MACD strategy is riskier. Further, the Buy/Hold strategy yielded the lowest ARR for 6 stocks and second lowest ARR for the remaining 14 stocks. The model yielded -20.87% to 39.32% ARR. This ARR was achieved with SR -27.78 to 32.57. In case of the model, positive SR was obtained for 14 stocks whereas negative SR was obtained for 6 stocks. This observation indicates to the fact Buy/Hold strategy is safer than traditional MACD based trading strategy and riskier than HC-GRU trading strategy.

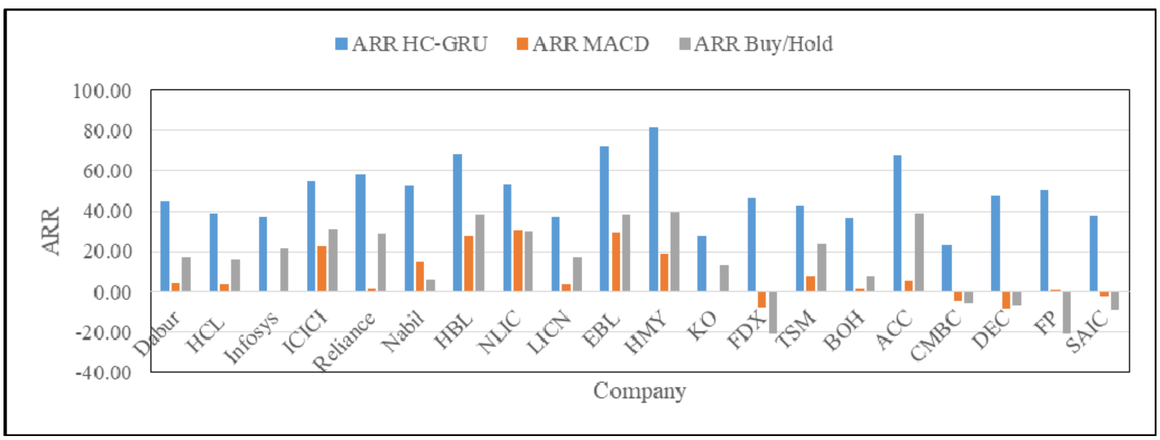

Figure 5: Annual Rate of Return (ARR)

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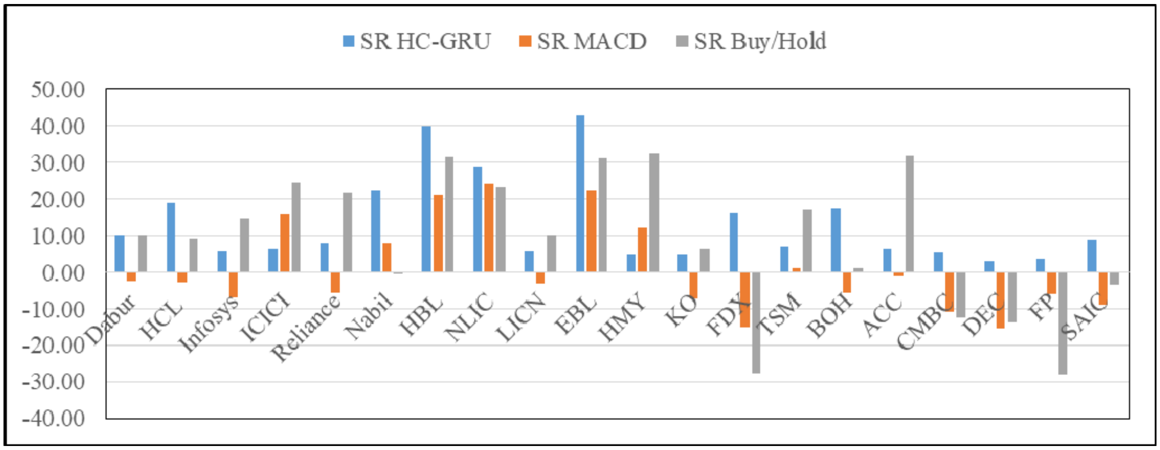

Figure 6: Sharp Ratio (SR)

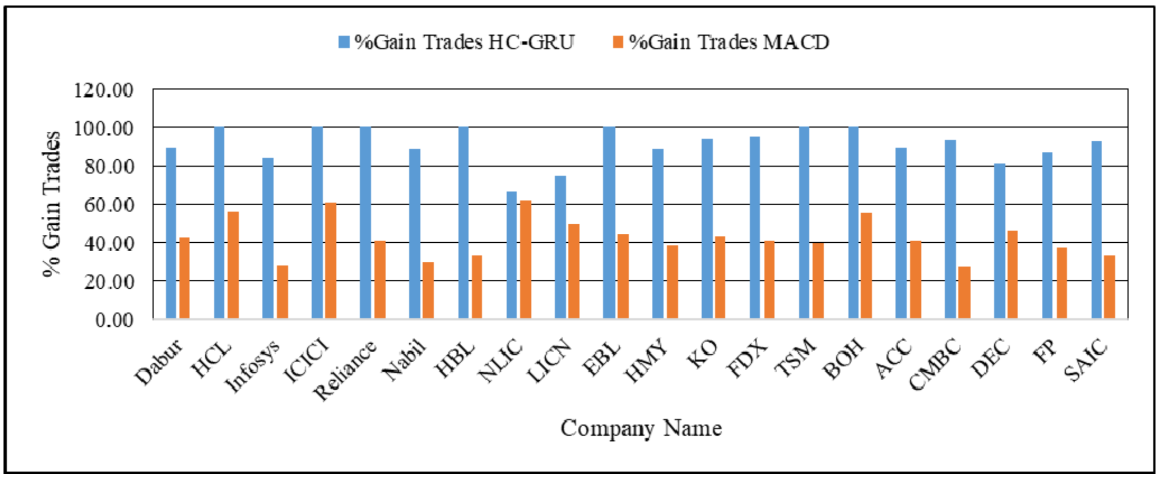

Figure 7: Percentage Gain Trades

5.2 Evaluation of Gain/Loss Trades

The percentage of profit/loss trades is one of the key parameters for any stock trading strategy. This measure was therefore tracked through the automated trading simulation module. The graph of Figure 7 provides a comparison between the percentage of profitable trades with HC-GRU and traditional MACD indicator based trading strategy. The analysis of the Buy/Hold strategy is not included in this regard as it always conducts only one trade for each stock during the test period.

The interesting facts that can be seen from the graph of Figure 7 is that very high percentage (i.e. 66.67% to 100%) of trades made by the HC-GRU strategy are gain trades. However, very low percentage (i.e. 27.78% to 62.5%) of trades made by the traditional MACD indicator based trading strategy are profitable trades. This observation indicates to the fact that the large number of trade signals given by MACD indicators were false signals (noise signals). This fact again leads to another fact that the HC-GRU trading strategy is able to filter the false trading signals significantly and hence is able to learn true Buy/Sell signals from the dataset.

As already mentioned, many researchers proposed intelligent stock market trading strategies [21-23] that were able to generate a satisfactory return from stock trading. This research work has used a different approach than existing intelligent trading strategies. We generated trading signals on the basis of the relationship between MACD line and MCAD signal line, which is the strategy used by technical analysts, and then used this data for training and testing of the machine learning strategy. None of the machine learning strategies developed yet has adopted this approach. However, some researchers used technical indicators simply as input features to the devised machine learning strategy. The experimental results discussed above show that intelligent trading strategy can be devised according to the proposed approach and good return

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can be earned from the intelligent stock trading along with minimizing the risk.

6. CONCLUSION

This research work proposed a hill-climbing powered gated recurrent unit (HC-GRU) network for predicting stock trading signals using the MACD indicator. Performance of the proposed model was compared with the Buy/Hold strategy, a benchmark model, and the traditional MACD indicator based trading strategy. The trading strategies were evaluated and compared in terms of the annual rate of return (ARR), sharp ration (SR), and percentage of profit/loss trades executed by the trading strategies.

From the experimental results, it was observed that the HC-GRU strategy significantly outperformed the other two models in terms of all three measures. ARR obtained from HC-GRU strategy was 22.44% to 62.76% higher than the ARR obtained from traditional MACD indicator based trading strategy and it was 14.69% to 71.72% higher than the Buy/Hold strategy. Meanwhile, HC-GRU strategy obtained this ARR with positive SR for all stocks whereas traditional MACD indicator based strategy generated return with positive SR only for 7 stocks and Buy/Hold strategy generated return with positive SR only for 14 stocks. On the other hand, 66.67% to 100% trades made by the HC-GRU strategy was profitable trades but only 27.78% to 62.5% trades executed by the traditional MACD indicator based trading strategy was profitable trades. From these facts, we concluded that the proposed HC-GRU strategy is a safer and better strategy for automated stock trading whereas traditional MACD indicator based strategy is not a good strategy for automated stock trading.

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