Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol.44 No. 6 (2023)

A Systematic Review on Artificial Neural Networks for Stock Market Prediction

*K. Kalaiselvi , *Vasantha Kalyani David

[1]*Department of Computer Science, Krupanidhi Degree College, Bengaluru, Karnataka, India*

Research Scholar, Department of Computer Science, Avinashilingam University for Women, Coimbatore, Tamilnadu, India

[2]*Professor, Department of Computer Science, Avinashilingam University for Women, Coimbatore, Tamilnadu, India*

Abstract: Prediction of the stock market price is one of the most problematic tasks in the financial sector because its time series is complicated, chaotic, noisy, volatile dynamic, and non-parametric. However, investors and professional analysts can use the computation intelligence technique to help them reduce the risk of their investments. Artificial neural network (ANNs) models have received a lot of attention, and various research works have looked into how these models might be used to predict the stock price based on chronological data.Because the goal is to generate financial market forecasts, the method must be validated using profitability indicators, and performance was evaluated. Therefore, this systematic review focuses on ANNs models for stock market prediction. The reviews of systematic were based on four essential components: a prediction algorithm, financial analyst technique, performance indicators, and prediction strategy. Therefore, even though they have been extensively studied, there are still exciting research and development opportunities.

Keywords: *artificial neural networks, machine learning, stock market prediction, systematic review*

1. Introduction

Stock price prediction is widely considered a problem in many domains, such as trading, finance, statistics, and computer science so that stocks can be sold and bought at profitable prices [1]. The stock's closing price is an important factor in predicting the stock price on the next trading day. Stock market forecasting has always played an important role. Investment brokers, private investors, and academic researchers are constantly on the lookout for a precise formula or a rule of thumb for expecting stock market trends. Because of the stochastic character of the stock market and the randomness of its behavior, forecasting stock indices in a realistic approach appears to be prone to failure to capture discontinuities, non-linearity, and high dataset complexity in a time series analysis of data [2].

In the earlier stage, various statistical methods have been applied for stock market prediction future features based on the past datasets. for example, simple moving average (SMA),Exponential Smoothing (ES), and auto-recursive integrated moving average (ARIMA)[3].Statistical approaches, in general, do not offer an easily automated process since they require adaptation and modifications at each stage, as well as certain regularities and stationary nature in the target data. Hence, typical statistical methods cannot be employed to solve the problem of identifying the sensitivities of stock market industries [4]. However, conventional statistical approaches are extremely difficult to apply to it because of the non-stationary nature of stock market data. Many research efforts have been studied with the use of various computational intelligence technologies to overcome the above addressing inadequacies. Stock market analysts and research investors have investigated various computational intelligent techniques for stock market prediction and making various trading decisions. Many computational intelligent methods have been employed to replace the conventional statistical methods in obtaining the solution includinggenetic algorithms (GA) [5], ant colony optimization (ACO)[6], particle swarm optimization (PSO) [7], artificial neural networks (ANNs)[8], fuzzy logic (FL)[9], and support vector machine (SVM)[10].

However, because of the non-stationary nature of stock market data, statistical approaches are extremely difficult to apply to stock market behavior. To overwrite the above speaking shortcomings, many research works have been investigated with the help of various computational intelligence methods. The ANNs are used in this research to predict the future movements of the stock market. ANNs are more efficient to handle the nonlinear stock market datasets due to their high acceptance ability with high accuracy[11]. Various researches have been carried out using the ANNs learning algorithm on stock market indices data. The several ANN methods used for stock market analysis include radial basis function (RBF)[12, 13], extreme learning machine (ELM) [14], recurrent neural networks (RNN)[15], time-delay neural networks (TDNN) [16]and multilayer perceptron (MLP)[17]. Hence, this systematic review focused on ANNs methods. The goals of this systematic review are to collect and analyses existing articles in the literature, with an emphasis on ANNs methodologies for stock market prediction, to emphasize the accuracy, performance measures used to validate the model and data analysis. In the final stage of this article, the reader can get some answers to the following questions,

a) Which approach is most commonly used to forecast stock market prices?

b) What timeframe is most commonly utilized to forecast stock prices?

c) What are the most often utilized performance metrics for validating the performance of prediction algorithms?

2. Prediction methodology

One of the most difficult things to do is to predict how the stock market will perform. The various factors can affect the performance of stock prices such as political, government policies, and natural threats. All of these factors combine to make stock values extremely volatile and difficult to predict accurately. Stock market forecasting is done using a variety of methods, including stock price or index forecasting, stock movements, risk analysis, and stock trend forecasting (up or down).The systematic review is conducting combine these above-stated prediction factors to make a review analysis.

The stock closing or index price prediction is a predicting the price of the stock at end of the trading day. Investors who buy for intraday trades will benefit from this. The technique of examining current patterns to forecast future trends is known as stock trend prediction (up or down price). You can attempt to predict if a market sector that is nowincreasing will continue to grow in the future using share market trend analysis.For instance, Wanget al. (2017) developed a combination of sentimental analysis with mutual information (MI)and an extreme learning machine (ELM) to improve forecast performance[18]. The developed method also proposed a new sentimental analysis approach based on MI uses to increase the effectiveness of feature selection, which is unlike the conventional sentimental analysis procedure. Then, selected appropriate features are considered as input to the ELM algorithm for a fast prediction process. This developed model combines the advantages of statistical sentimental analysis and ELM to achieve a good balance of prediction speed and accuracy.

F. Wang et al. (2018) perform a comparative investigation of a linear classification model that includes logistic regression classification (LR), partial least square discriminant analysis, linear discriminant analysis, nearest Shrunken discriminant analysis, and penalized discriminant analysis to compare and predict the stock market prices of Bangladesh's top six banks[19].LR, on the other hand, has a lower misclassification rate (MR) and apparent error rate (AER). As a result, if there is a strong correlation, multivariate normality, multicollinearity, and high-dimensionality among predictors, this study suggests using LR as a linear classification model.M. Göçken et al . (2018)analyze the performance comparisons among the five dissimilar machine learning methodsfor stock market prediction [20]. The five different models are established on five supervisedtechniques i.e., SVM, RF, KNN, NB, and Softmax. E. Chong et al. (2017)[21]developed a deep learning algorithm for stock market predictive analysis. Three unsupervised feature removalmethods, such as principal component analysis (PCA), autoencoder (AE), and the restricted Boltzmann machine (RBM), on the network's overall capability to predict future market performance, were investigated using high-frequency intraday stock returns as input data.

O. D. Madeeh et al. (2021) developed three-stage efficient stock market prediction approach-based machine learning algorithms[22]. The first stage involves pre-processing; the second stage involves using the machine learning algorithm for prediction, and the third stage involves evaluating the accuracy and competence of the forecast methods for the two models.M. Nabipour et al. (2020) [23] proposed a comparative study based on nine machine learning algorithms to significantly reduce the risk of trend prediction. The inputs are 10 technical indicators derived from ten years of historical data, and they are designed to be used in two ways. To begin, the indicators are based on stock trading values, such as continuous data, and then transformed to binary data before use.

M. Jiang et al. (2020) [24]developed a new stock prediction techniqueusing the two-stage collaborative method by combining variational-mode decomposition (VMD) and empirical mode decomposition (EMD), ELM and developed a harmony search (IHS) algorithm. The comparisons results were obtained by other methods, including VMD-based ELM (VMD–ELM), EMD based ELM (EMD–ELM), ARIMA, multi-layer perception (MLP), SVM, and long short-term memory (LSTM) models, to validate the effectiveness and performances.

K. Velusamy et al. (2021) [25] developed a new stock index prediction method cascade correlation neural network (CCNN) which is enhanced by deterministic weight modification (DWM). The newly presented method can improve the conventional CCNN's global convergence capabilities while also lowering system error.E. K. Ampomah et al. (2020) [26] developed a new Tree-Based Collaborative method for stock price movements comparison made against tree-based ensemble algorithms such as RF, XG Classifier, Bagging Classifier (BC),Extra Trees Classifier (ET), AdaBoost Classifier (Ada), and Voting Classifier (VC). D. Wu et al. (2021) [27]proposed hybrid stock trend prediction model usingELM and discrete wavelet transform (DWT). The DWT method is used to de-noise the data and then ELM is used for predicting stock trends using de-noisedstock market data. The suggested stock trend analysis algorithm was compared to the performance of 12 different machine learning algorithms.

S. Rohatgi et al. (20201) [28] performs a comparison against six various approaches for the Indian stock market i.e., DT, RF, SVM, Generalized Linear Model (GLM), Deep Learning (DL), and Gradient Boosted Trees (GBT). GBT was picked as the most efficient model out of all the ones used.I. R. Parray et al. (2020) [29] developed three machine learning techniques used for predicting the next day stock trend such as SVM, perceptron, and LR. S. T. Z. de Pauli et al. (2020) [30]compare five alternative neural network architectures such as multiple LR (MLR), Elman, Jordan, RBF, and MLP that have been proposed for predicting the Brazilian stock exchange. The forecast of the closing price of the next day is using historical datasets.

S. K. Chandar et al. (2021) [31]developed a new hybrid prediction method for intraday stock price prediction based on ANN and meta-heuristic algorithms. The developed new hybrid model compared with eight hybrid approaches such as GA-BPNN, GA- RBFNN, PSO-RBFNN, ABC-BPNN, PSO-BPNN, ABC-RBFNN, GA-TDNN, ABC- TDNN, and PSO-TDNN used for predicting intraday stock price. Hybrid prediction models were developed, all of which had the same attributes for projecting intraday stock prices. Various numbers of training and testing samples are used to assess the prediction accuracy of the created models.P. Gao et al. (2021)[32] introduced four different stock prediction methods such as three typical models MLP, LSTM, Convolutional Neural Network (CNN), and one attention-based neural network. The leading task is to forecast the next day's index according to the past data.

Y. Wang et al. (2020) [33]develop a new version of ElmanNN(ENN) for stock market index prediction. The developed method introduces direct input-to-output connections (DIOCs) into the ElmanNN. The KOSPI, SSE,Nikkei225, and SPX are all used to authenticate the value of the Elman-DIOCs.S. K. Chandar et al. (2020) [34] introduced a new enhanced version of ENN with a grey wolf optimization (GWO) algorithm to enhance the parameters of ENN.

S. Das et al. [35] developed an efficient stock predictor using an incorporating an improved crowsearch algorithm (CSA) and ELM. Using performance measurements, technical indicators, hypothesis testing, and the influence of the hybrid PGCSA ELM model on predicting the next day closing price of seven distinct stock indexes is examined (paired t-test). By adding data from the COVID-19 epidemic, the seven stock indices are analyzed.R. Bisoi et al. (2018) [36] developed a new stock price and trend prediction method using robust kernel-based ELM (RKELM) which is integrated with variational-mode decomposition (VMD) technique and the kernel function parameters are used to optimize with differential evolution (DE) method (DE-VMD-RKELM). K. Kalaiselvi et al. (2018) [37] developed a new stock index prediction method using BPNN based on the opposition-based learning (OBL) algorithm (OBL-BPNN). The OBL algorithm was used to adjust the weight of BPNN. The performance of OBL-BPNN was compared with ARIMA and BPNN prediction algorithms.

3. Financial analysis

The primary goal of stock market forecasting is to predict future behavior to help decision-making based on market activity. Fundamental analysis and technical analysis are two major factors which used for financial analysis.

3.1 Fundamental analysis

Fundamental analysis examines a company's data to determine whether it has medium- to long-term growth potential. Fundamental analysis is a technique used to assess a stock's intrinsic worth by looking at its financial statements, industry trends, economic indicators, and other qualitative elements. Based on the company's financial situation and future prospects, it seeks to assess if a stock is overpriced, undervalued, or appropriately valued. An in-depth understanding of financial accounts and the business environment is necessary for fundamental analysis. It's crucial to frequently update your analysis in order to take into account various viewpoints and reflect changing circumstances. Fundamental analysis offers insightful information, but when combined with other analytical techniques, including as technical analysis and sentiment analysis, it may offer a more complete picture of a stock's probable performance.The fundamental stock market attributes are open, low, high, and closing prices [38].

- The *open price* is the first share price at the start of the daily trading day
- The *close price* is the final share price after the day
- The *high price* is the highest share price during the day
- The l*owest*price share price during a trading day is known as the low price.

3.2 Technical analysis

Technical analysis is a technique used to make predictions about future stock and other financial asset price movements using previous price and volume data. It is predicated on the notion that market prices follow trends and patterns that may be recognized and applied to make predictions.It's vital to remember that technical analysis has its limits even if it might offer insights into short- to medium-term price changes. Stock prices can also be significantly influenced by basic considerations, unforeseeable events, and market psychology. To make wise investment selections, many investors mix technical analysis with fundamental research, risk management techniques, and other factors.The technical method assumes that market-moving information is received and reflected in share prices. Many technical indicators that are calculated using fundamental variables are used to analyze technical methods. The following subsections are discussed about the some of more important technical indicators which are shown in Table 4.

- **Simple Moving Average (SMA):**Moving averages provide a single flowing line that smooths out price data and makes it easier to see the underlying trend.
- **10-days Moving Average (10-MA):**A frequently used technical indicator called the 10-day moving average determines the average price of a stock or other financial asset over a 10-day period. It is a member of the moving averages family, which aids analysts and traders in identifying patterns and smoothing out price data.
- **Momentum:**It describes the rate and trajectory of price changes in a certain securities or market. Analysts and traders can assess a trend's strength and spot possible reversals with the aid of momentum indicators. Making intelligent trading selections might benefit from having a solid understanding of momentum.
- **Stochastic K% and D %:**The momentum of a stock is shown by the stochastic%K and%D. To determine if a stock is in an overbought or oversold range, it considers the stock's closing price as well as its

high-low range. The indication is based on the presumption that prices would close close to the day's high in an upwardly going market and close close to the day's low in a downwardly rising market.

- **Relative Strength Index (RSI):**The momentum oscillator known as the RSI gauges how quickly and dramatically prices move. It is employed to detect overbought and oversold situations, providing possible turning points.
- **Williams (%R):** it measures circumstances that are overbought and oversold and can offer information about future reversals.
- **Moving Average Convergence Divergence (MACD):**A momentum trend-following indicator called MACD depicts the connection between two moving averages of the price of a security. It is employed to spot momentum shifts and probable trend reversals.
- **Commodity Channel Index (CCI):**A stock or other financial asset's price momentum, volatility, and possible overbought or oversold circumstances may all be evaluated using the technical indicator CCI in financial analysis.
- **Price Oscillator:**PO calculates and shows the percentage difference between two moving averages of price data. It is used to assess market momentum, spot trends, and spot probable buy or sell signals.

4. Performance Indicators

Each prediction model must be evaluated to determine its accuracy [39, 40]. The following sub sections are discussed some of the most often used performance indicators metricsin which formulas are shown Table 3. The most used performance indicators are shown in Table 4.

- **Mean Square Error (MSE):**The average of the squared variations between the expected and actual values is computed. Better performance is indicated by a lower MSE.
- **Root Mean Squared Error (RMSE):**This is the square root of the MSE. It gives you an idea of how much your predictions deviate from the actual values on average, and it's in the same unit as the target variable.
- **Mean Absolute Error (MAE):**It computes the average of the absolute differences between the predicted values and the actual values, unlike MSE, which just computes the difference between the two. It is less susceptible to outliers than MSE.
- **Mean Percentage Error (MPE):**The average percentage difference between the expected and actual values is determined by this measure. Understanding the average error magnitude as a proportion of the actual data is helpful.
- **Mean Absolute Prediction Error (MAPE):**It also gives a better idea of the average error magnitude and is given as a percentage.
- **F-Measures:**The harmonic mean of accuracy and recall is known as the F1-Score. It strikes a balance between recall and accuracy and is especially helpful when classes are unbalanced.
- **Accuracy:**The fraction of occurrences that were properly categorized out of all instances, which is the most fundamental statistic.
- **Recall:**The percentage of accurate positive predictions among all instances of positive behaviour is determined by recall. When you want to record as many real positives as you can, it is helpful.
- **Precision:**The percentage of accurate positive predictions compared to all positive forecasts is known as precision.When you wish to prevent false positives, it's a useful statistic.

5. Discussions

This systematic review is conducted on twenty articles which are collected from Google scholar websites. The keywords used are as follows, "*stock market price prediction + artificial neural network*", "*stock closing price prediction + artificial neural network*", and "*stock market index prediction + machine learning algorithm*". From the twenty articles, seven springer articles (35 %), four Elsevier articles (20%), four IEEE articles (20%), three articles (15%) from IOP, and two articles from MDPI (10 %) and articles respectively. Twelve articles (60%) predicted the closing price and index, four articles (20%) predicted the stock market trend, two articles (10%) predicted the stock index and the remaining two articles (10%) predicted stock return and movement.

Table 1 : Reviewed articles

Ref. No.	Proposed Methods	Datasets	Performance Indicators	Time	Predicting value	Input Types
[18]	MISA-K-ELM	HKE	Accuracy	Ten years	Closing price	Technical
[19]	LR	Bank	ME AER	January 2009 to June 2019	Closing price	Fundamental
[20]	RF and NB	Amazon, Bata,Bosch, Cipla and Eicher	Accuracy F-Measures	Ten years	Stock price	Technical
[21]	DNN +AE	KOSPI	NMSE, RMSE, MAE MI	04-Jan-2010 to 30-Dec-2014	Future stock returns	-
[22]	RF	NYSE	Precision, Recall, F-measure MAE and RMSE	4500 trading days	Stock price	Fundamental
[23]	RNN and LSTM	TSE	Precision, recall, and F-measure.	November 2009 to November 2019	Stock trend	Technical
[24]	EMD–ELM–IHS	SSEC S&P 500 HSIHKE	MAE, MSE and MAPE	January 4th 2010 to March 1st 2019	Stock price	Fundamental
[25]	DWM+CCNN	Nifty 50 S&P BSE	RMSE, MAE, and DS	January 3, 2005 to June 30, 2018	Closing price	Fundamental
[26]	AdaBoost (training datasets) ETC (Test datasets)	NYSE, NASDAQ, NSE	Accuracy, Precision, Recall, F1-score, specificity, and AUC-ROC	Janauary 2005 to December 2019	Stock price movement	Technical
[27]	ELM- DWT	SSE	Accuracy,Precision, Recall, F1 score, and AUC	1 January 2001 to 3 December 2020	Stock trend	Fundamental

Table 2 : Reviewed articles (Continued..)

Ref. No.	Proposed Methods	Datasets	Performance Indicators	Time	Predicting Value	Input Types
[28]	GBT	BSE	RMSE	April 2015 to 31st March 2020	Stock price	Fundamental
[29]	SVM	NIFTY 50	Accuracy Recall, Precision F1 score	January 1, 2013, to December 31, 2018,	Trend prediction	Technical
[30]	MLR	Brazilian Stock data	RMSE	March 2019 to April 2020	Closing price	Fundamental
[31]	PSO-BPNN	SBIN NPTC TATASTEEL INFY	RMSE Hit Rate Error Rate Accuracy	01/01/2018to 28/02/2018	Stock price	Fundamental
[32]	Attention-based model	SP500 CSI300 Nikkei225	MAPE, RMSE, and Correlation Coefficient	July 2008 to September 2016	Next day Stock index	Fundamental macroeconomic
[33]	ElmanNN-DIOCs	SSE, KOSPI, Nikkei225 S & P 500 Index	RMSE, MAE and MAPE	10/12/2005 up to 31/12/2013	Daily closing index	Fundamental
[34]	GWO-ENN	NYSE and NASDAQ	MSE, RMSE, MAE, SMAPE and ARV	January 2009 to December 2018	Stock price	Technical
[35]	PGCSA ELM	DJI, HIS, IXIC, N 100, NSEI, RUT and GDAXI	MAE MSE MAPE	1st January 2004 to 10th May 2020	Stock index closing price	Fundamental
[36]	VMD-RKELM	S&P BSE HIS FTSE 100	RMSE MAE MAPE	04 January 2010 to 12 January 2016	day ahead and daily trend	Technical
[37]	OBL+BPNN	Nifty 50 S & P 500	MSE RMSE	January 3, 2005 to June 30, 2018	Closing price	Fundamental

---

Table 3 : Reviewed performance indicators

Measures	Formula	Article
MSE	$=\frac{1}{N}\sum_{i=1}^{N}\left(t_{(i)}-y_{(i)}\right)^{2}$	[24, 34]
RMSE	$=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(t_{(i)}-y_{(i)}\right)^{2}}$	[21, 22, 25, 28, 30-32, 34, 36]
MAE	$=\frac{1}{N}\sum_{i=1}^{N}\left\lvert t_{(i)}-y_{(i)}\right\rvert$	[21, 22, 24, 25, 34, 36]
MAPE	$=\frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{t_{(i)}-y_{(i)}}{t_{(i)}}\right\rvert$	[24, 32, 36]
F-Measures	$=\frac{TP^{2}}{(TP+FP)(TP+FN)}\Big/\frac{TP}{(TP+FP)}+\frac{TP}{(TP+FN)}$	[20, 22, 23, 26, 29]
Precision	$=\frac{TP}{TP+FP}$	[22, 23, 26, 27, 29]
Recall	$=\frac{TP}{TP+FN}$	[22, 23, 26, 27, 29]
Accuracy	$=\frac{TP+TN}{TP+TN+FP+FN}$	[18, 20, 26, 27, 29, 31]

According to the datasets, leaven articles (55%) have used ten and more than ten years datasets. Three articles (15%) have been used for five to ten years detests. Similarly, five articles (25%) have been used for one to five years datasets, and one article (5%) has been used for two-month datasets. In terms of performance indicators, eight articles were used RMSE, seven articles were used accuracy, and MAE, recall, and precision performance indicators are used in five articles. Finally, technical indicators were employed in seven articles, fundamental variables were used in twelve articles, and one article was not mentioned. Some well-known technical indicators are shown in Table 4**.**

6. Conclusion

The paper aims to conduct academic reviews on financial time series prediction using ANNs methods. The analysis and discussion are conducted based on four major points of view: prediction methodology, financial analysis, performance indicators, and trading strategy. In the prediction methodology, it was noted that the ELM algorithm is a fast algorithm and quite easy to use and comprehend. When compared to conventional neural networks, its simple architecture—a single hidden layer with random weights—reduces the difficulty of training and parameter adjustment.Financial analysis methods are two types such as fundamental and technical analysis. However, most of the articles have been used technical analysis. The performance indicators are used to analyze the performance of prediction algorithms. Therefore, many of the articles have used RMSE and accuracy as performance indicators. Finally, the trading strategy is another important method for predicting the stock market data. So, many of the articles used closing stock price prediction is considered to predict the stock market's future behavior. Therefore, some research gaps are identified from the reviewed articles in future works, such as efficient weight updating methods, selecting appropriate technical indicators, adapting trading strategy, and performance metrics. Specifically, it's crucial to remember that while ELM has many advantages, it also has certain drawbacks. For instance, under some circumstances, the random weight initialization of ELM may result in unexpected performance. In comparison to conventional neural networks, it could take more hidden neurons to reach the same levels of accuracy. Furthermore, ELM might not be as effective for challenging tasks that call for deep learning capabilities like hierarchical representations and high-level feature learning.Still, it will take more computation cost and high memory consumptions. Hence, the new weight updating strategy can reduce the above-stated shortcoming of ELM.However, the precise issue you're seeking to resolve and the resources at your disposal will determine whether you should use an ANN or an ELM in practice. ANNs could be a better option if you have a challenging situation with plenty of data and are looking for the best results. ELM could be a better choice, though, if you want speedy results with little effort in terms of hyperparameter adjustment and training time.

Table 4 : Technical Indicators

S.No	Technical Indicators	Formulas
1	SMV	$= \frac{x_1 + x_2 + \ldots + x_n}{n}$
2	10-days Moving Average	$= \frac{x_1 + x_2 + \ldots + x_n}{n}$
3	Momentum	$= C_t - C_{t-4}$
4	StochasticK%	$= \frac{C_t - LL_{t-4}}{HH_{t-n} - LL_{t-n}} \times 100$
5	Stochastic D%	$= \frac{\sum_{i=0}^{n-1} K_{t-1}\%}{n}$
6	RSI	$= 100 - \frac{100}{1+(\sum_{t=0}^{n-1} UP_{t-1}/n)/(\sum_{t=0}^{n-1} DW_{t-1}/n)}$
7	Williams (%R)	$= \frac{H_n - C_t}{H_n - L_n} \times 100$
8	MACD	$= MACD(n)_{t-1} + \frac{2}{n+1}(Diff_t - MACD(n)_{t-1})$
9	CCI	$= \frac{M_n - SM_t}{0.015 D_t} \times 100$
10	PO	$= \frac{MA_5 - MA_{10}}{H_n - L_n} \times 100$

C_t - closing price L_t - Lowest price

H_t - high price

LL_t - Lowest Low price

HH_t -Highest high price

UP_t Upward price

DW_t - Downward price

References

[1] BoxGE, JenkinsGM,ReinselGC andLjungGM(2015).wiley.series. pb and stat.5,p-9781118675021

[2] Patel J, Shah S, Thakkar P and Kotecha K (2015).Expert Syst. with Appl, 42, issue 1, p. 259 - 68

[3] Babu C N and Reddy B E (2014)Appl. Soft Comput. **23** 27-38

[4] Asadi S, Hadavandi E, Mehmanpazir F and Nakhostin M M (2012)Know. Based Syst. **35** 245-58

[5] Potter M A (1992)IEEE Computer Society press, 123-33

[6] UthayakumarJ, MetawaN, ShankarK and Lakshmanaprabu S (2020) ,Int.J.Inf. Manage. **50**538-56

[7] Ecer F, Ardabili S, Band S S and Mosavi A (2020)Adv. comput. int**22** 1239

[8] Göçken M, Özçalıcı M, Boru A and Dosdoğru A T (2016)Expert Syst. Appl **44** 320-31

[9] Atsalakis G S and Valavanis K P (2009)Expert Syst. Appl. **36** 10696-707

[10] Hao P-Y, Kung C-F, Chang C-Y and Ou J-B (2021)Appl. Soft Comput. **98** 106806

[11] Velusamy K and Amalraj R (2018)Int. J. Eng. and Technol.**7** 3485-8

[12] Lin C-L, Wang J, Chen C-Y, Chen C-W and Yen C (2009) Expert Syst. with Appl.**36** 12049-53

[13] Rajasekaran S and Amalraj R (2002)Computers and Struct.**80** 2495-505

[14] Mohanty D K, Parida A K and Khuntia S S (2020)Appl Soft Comput. 106898

[15] Kohara K (2003) Knowledge-Based and Intell. Inf. and Eng. Syst. pp 141-7

[16] Khansa L and Liginlal D (2011)Decis. Support Syst. **51** 745-59

[17] Kara Y, Boyacioglu M A and Baykan Ö K (2011) Expert syst. with Appl.**38** 5311-9

[18] Wang F, Zhang Y, Rao Q, Li K and Zhang H (2017)Soft Comput. **21** 3193-205

[19] Karimuzzaman M, Islam N, Afroz S and Hossain M M (2021)Annals of Data Sci.**8** 21-38

[20] Kumar I, Dogra K, Utreja C and Yadav P (2018) Second Int. Conf. on InventCommun. and Comput. Technol. p 1003-7

[21] Chong E, Han C and Park F C (2017) Expert Syst. with Appl. **83** 187-205

[22] Madeeh O D and Abdullah H S (2021)J. Phys. Conf. Ser. : IOP Publishing p 012008

[23] Nabipour M, Nayyeri P, Jabani H, Shahab S and Mosavi A (2020),2212832866**8** 150199-212

[24] Jiang M, Jia L, Chen Z and Chen W (2020) Annl. Oper. Res. 10.1007/s10479-020-03690-w

[25] Velusamy K and Amalraj R (2021)IOP Conf. Ser.: Mater. Sci. Eng.**1110** 012005

[26] Ampomah E K, Qin Z and Nyame G (2020),2078-2489, *11*(6), 332

[27] Wu D, Wang X and Wu S (2021) 1099-4300 **23(4)** 440

[28] Rohatgi S, Singh K K and Jasuja D (2021) Int. Conf. Adv. Compt and Technol. in Eng.278-83

[29] Parray I R, Khurana S S, Kumar M and Altalbe A A (2020) Soft Comput. **24** 16509-17

[30] de Pauli S T Z, Kleina M and Bonat W H (2020)Annl. of Data Sci. **7** 613-28

[31] Chandar S K (2021)Pattern Recognit. Lett.**147** 124-33

[32] Gao P, Zhang R and Yang X (2020)Math. Comput. Appl.**25** 53

[33] Wang Y, Wang L, Yang F, Di W and Chang Q (2021)Inf. Sci**547** 1066-79

[34] Chandar S K (2021) Soft Comput.**25** 649-58

[35] Das S, Sahu T P, Janghel R R and Sahu B K (2022)Neural Comput.Appl. 34(1) 555-591

[36] Bisoi R, Dash P and Parida A (2019) Appl. Soft Comput. **74** 652-78

[37] Kalaiselvi K, Velusamy K and Gomathi C (2018)J of Physics: IOP p 012008

[38] Velusamy K and Amalraj R (2017) Int. Conf. on Electr., Comput. and Commun. Technol. pp 1-6

[39] Selvamuthu D, Kumar V and Mishra A (2019)Financ. Innovation **5** 1-12

[40] Rajkumar N and Chithra S (2021) Bull. Env. Pharmacol. Life Sci., 10 [12] 44-49.