An Optimized Machine Learning Model for Candlestick Chart Analysis to Predict Stock Market Trends

Satyakam Behar*, Dr.Anurag Sharma
* Research Scholar, Dept. of CSE, MATS School of Engineering and Information Technology, Aarang
Professor, Dept. of CSE, MATS School of Engineering and Information Technology, Aarang

* skbehar@gmail.com, anusiraag@gmail.com

Abstract:

Stock market prediction is challenging due to its complex behaviour. Various theories are available for stock trend prediction. Technical analysis is widely used by researchers in which various charts and statistics are used to analyse the market trend. Candlestick charts are a useful tool in technical analysis. However, utilizing candlestick charts with machine learning techniques is still a matter of research. This paper proposes a model which uses candlestick chart patterns for the trend prediction of Indian and US stock indices. At first, candlestick patterns are extracted from the historical stock data which results in the generation of a large number of features. In this work, the Gaussian-modified PSO (g-PSO) is proposed for feature selection and an optimized K-Nearest Neighbour (KNN) model for trend prediction. The proposed model is tested on the four stock indices BSE, NIFTY50, S&P500, and DJIA. The performance metric Accuracy, Precision, Recall, and F1-score are used for the model assessment. The proposed model gives an average accuracy of 61.4%. The proposed model is compared with the state-of-the art methods and comparatively provides better results.

Keywords: Stock Market Forecasting, Candlestick Chart, Machine Learning (ML), K-nearest Neighbour (KNN), Particle Swarm Optimization (PSO), Grid Search.

DOI Number: 10.14704/nq.2022.20.13.NQ88145 **Neuro Quantology 2022; 20(13):1132-1143**

1. Introduction

In the modern digitized era, the stock market and associated activities play important role in people's wealth [1]. A stock market is a place where people can earn a handsome amount of money if a well-planned investment is done. The general phenomenon is to buy a stock when the prices are expected to rise in the future and sell the stock at a higher price at some later point [2]. This kind of financial act requires predictive knowledge of market trends which insists naive investors to take help from market analysts or automated predictive modules. Predictive modelling of stock market trends is a difficult task and nobody is able to get 100% accurate prediction. Stock market prediction has always been an interesting area of research and aimed to get the maximum return with minimized loss. The stock market forecast is a puzzling task due to the numerous factors affecting the prices of the stock market. Some of these factors are investor sentiments (from social media), NEWS articles, economic policies, political scenarios, pandemic situations, etc. [3]–[5]. However, the Efficient Market Hypothesis (EMH) contradicts this fact and states that the historical stock prices completely reflect the market information, and one can use this information to predict the future market trend [6]. ML techniques have grown tremendously and provided good results in almost every field including stock market forecasting.

Stock market forecasting can be done via technical analysis, financial analysis, or sentiment analysis [7]. Technical analysis is commonly used when historical stock prices are studied to get the prediction of future stock prices [8]. Stock market forecasting by ML techniques are in practice since a decade. In the initial phase of computational research, conventional ML algorithms were used by the researchers. With the progression in computational algorithms and huge dataset availability, researchers proposed a number of advancements in conventional algorithms. Advancement started with the variability in the dataset format [9]. Initial research is carried out on the historical stock data, technical indicators and financial indicators where all of these are having numeric values. Later on, the dataset formats are evolved with the usage of texts, image, video, and audio [10]. Researchers also played with the pre-processing step because a well-thought pre-processing technique can improve the performance of the vanilla ML model too [4]. Apart from the above mentioned modifications (dataset format and pre-processing technique), researchers proposed versions of conventional ML models which proved better than the baseline models [9].

Recently DL models have gained popularity due to its superior performance over the ML models [11]. Also, DL models are capable of handling nonlinear relationships that exists in the stock market data [12]. The beauty of DL models is that it can inherently selects the features and has self-learning capacity which makes it prominent for the classification tasks [13]. Also, DL models are suitable for all kinds of data format. One such data format is image which can be used not only for classification but for prediction too. Some of the common images/charts generated from the historical data are candlestick chart, bar chart, line chart, point and figure charts. In the literature, candlestick charts are commonly used for the stock market forecasting. Candlestick charts are generated from historical data through mathematical computations. Candlestick charts are easy to visualize, compute, and modify making it advantageous to bridge the gap between researchers and market practitioners [10]. Also, the representation of data plays an important role in predictive modelling because not every investor is capable to understand the financial times series data. In this situation, charts are helpful to have an understanding of these numerical data obtained from the stock time series.

Keeping all the above points in mind, this paper proposes a stock market forecasting framework that has a strong data representation format (images) to identify the stock market pattern and predict the stock prices in more accurate way. The paper contributions are as follows:

1. Generation and visualization of candlestick chart images from the historical stock market data.
2. Feature extraction from the candlestick chart images based on the candle pattern and then ranking of extracted features.
3. Proposed modified PSO to select the most prominent features for stock market forecasting.
4. Parameter tuning of KNN is performed with Grid Search optimization.

The rest of the paper is organized as follows: section two provides the literature review; section three provides the detailed methodology of the proposed work; section four discusses the results obtained from the proposed model; section five concludes the paper and discusses the limitations of the proposed model and possible future direction to overcome these limitations.

2. Literature Review

This section discusses the related literature that used ML and DL techniques for stock market forecasting. The research articles that used candlestick charts for financial time series analysis are considered for the review. For financial research, candlestick data is commonplace, but combining candlestick data with computational methods does not always produce satisfying results. There is no doubt that this is an interesting phenomenon that is easily verifiable. [14] proposed an expert system that analysed the chart pattern to know market movement for buy, sell, and hold strategy. [15] did analysis of Brazilian stock market utilizing candlestick charts. [16] mentioned in their paper that previously none of the researchers has utilized image processing techniques for stock market analysis. The author used Content-Based Image Retrieval (CBIR) technique for stock forecasting. In this direction, the author contributed by performing image retrieval operation on candlestick chart to get the wavelet-based texture features and predicted the stock movement based on charts and associated features. CBIR is quite useful in extracting the visual features from input images [17]. [16] utilized CBIR for low level feature extraction using wavelets and canny edge detection which is then used for stock trend prediction.

ML models are quite useful in financial forecasting. One of the popular ML model is Support Vector Machine (SVM). [18] proposed optimized SVM for candlestick chart analysis to predict stock market trend. The author proposed Imperialist Competition Algorithm (ICA) for parameter optimization of SVM and Genetic Algorithm (GA) for feature selection. [19] proposed a Particle Swarm Optimized (PSO)-SVM to analysis the candlestick chart patterns generated from technical analysis. The author tested their model for 48 datasets with two approaches (raw-based and signal-based) and mentioned that their model worked better than the Artificial Neural Network (ANN). [20] used charts and graphs (generated from technical analysis) to analyse the market trend. K-Nearest Neighbour (KNN) was used by the author for bullish and bearish interpretation. [21] used Gramian Angular Field (GAF) images for candlestick charts and empirically tested Random Forest (RF), XGBoost, AdaBoost, Multilayer Perceptron (MLP), and Convolution Neural Network (CNN) on these images. The author mentioned that the DL models worked better than the RF and AdaBoost but not XGBoost (for GAF images).

In recent decades, DL has attracted a lot of attention for studying forecasting problems in time series. A lot of DL models exists in the literature and proved to be efficient for financial forecasting [5]. [22] proposed two-step method for automatic recognition of candlestick patterns. The author first used GAF for encoding of time series (historical stock data) into images and then used CNN to learn from these images. [23], [24] proposed a DL framework for analysing candlestick chart patterns. Both the author first decomposed the candlestick chart into sub-charts and then used CNN autoencoder to get features from sub-charts and finally a DL predictor. [24] used 1D-CNN for stock price movement prediction whereas [23] used Gated Recurrent Unit (RNN) due to its better training efficiency in comparison to other DL models. Although training of RNN is challenging mainly because of gradient vanishing, apart from its power [25]. A gradient vanishing network is one that cannot be trained due to its gradient components approaching zero. This issue can be solved by modifying RNN architectures with Long Short-Term Memory (LSTM) and GRU [26].

Plain ML/DL models may not provide excellent results [27], [28]. Hybrid stock market forecasting models are evaluated using candlestick chart data and predefined patterns [4]. ML model works tremendously when hybridized with the optimization techniques. Optimization techniques can be applied for feature optimization or model optimization. Optimizing features and model both significantly improve the model performance. This paper targets to propose an optimized KNN for stock trend prediction utilizing candlestick chart patterns.

3. Data and Methodology

This section provides the discussion for the proposed methodology which is illustrated in the figure 1. The objective is to extract the candlestick chart images from the historical stock data which is collected from the website of Yahoo Finance (https://finance.yahoo.com/). The features are extracted from the candlestick image based on the candle pattern ranking which results in the generation of new feature set. In the next step, proposed Gaussian modified PSO (g-PSO) is used to get the optimal feature subset. The stock market trend prediction is performed by the optimized KNN where hyper-parameters of KNN are optimally selected with the help of Grid Search Optimization.

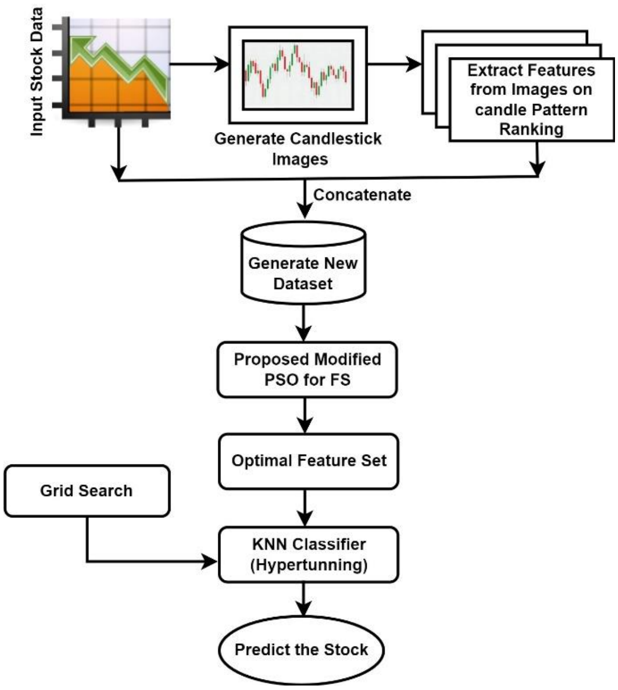


Figure 1. Proposed Methodology

The datasets of two Indian stock indices (BSE and NIFTY50) and two US stock index (S&P500 and DJIA) is used for the experimental evaluation of the proposed model. The dataset is collected for the duration of five years (1-Oct-2017 to 30-Sep-2022). Summary statistics of the dataset (for close price) is given in the table 1, where count provides the total number of observations, min and max provides minimum and maximum value respectively, mean and std. dev. provides mean and standard deviation respectively.

Table 1: Summary statistics of Close price

Stock	Count	Min	Max	Mean	Std. Dev.
BSE	1230	25981.240234	61765.589844	43303.537325	9403.484396
NIFTY	1231	7610.250000	18477.050781	12940.078476	2768.520805
S&P500	1258	2237.399902	4796.560059	3387.082671	686.226935
DJIA	1258	18591.929688	36799.648438	28613.275499	4104.733721

In the subsequent sections, the main modules of the proposed model are discussed.

3.1 Candlestick Chart

Candlestick charts are used by the technical analysists to demonstrate the price movements for a particular time frame. Each candlestick pattern illustrates the trading information of a day therefore a month's pattern illustrates that month's trading candlestick pattern. These charts is provided to the proposed prediction model in the form of image. Candlestick charts are useful in identifying the early and exist plan for a particular stock. There are three basic components of the candlestick charts: upper, lower, and main body. When the close price is lower than the open price then the main body is filled by red colour. The main body is filled by the green colour when the close price is higher than the open price. The upper and lower body of the chart represents the high and low prices respectively. The chart is interpreted as bullish when the close price is greater than the open price, and interpreted as bearish when the close price is lesser than the open price [29]. Candlestick charts for the four dataset is provided from figure 2 to 5.

Figure 2. Candlestick chart for BSE

Figure 3. Candlestick chart for NIFTY50

Figure 4. Candlestick chart for S&P500

Figure 5. Candlestick chart for DJIA

3.2 Optimized Feature Selection

Features play important role in any kind of classification or regression task. Therefore, feature selection plays a crucial role in model designing. PSO is a well-known feature optimization technique and is used in the proposed model. Next, we discuss the basic PSO and the proposed g-PSO.

Particle Swarm Optimization (PSO): PSO is one of the most effective swarm optimization algorithms introduced by Kennedy and Eberhart [30]. The core idea is to model flocking behaviour of birds using a population of randomly started particles that collectively use the search space to locate the best possible outcome. PSO is an iterative process in which particles constantly relocate to their optimal solution (i.e., location). Particles undergo two processes, exploration and exploitation, to find their optimal placement and the optimal location for all particles. To accomplish these two tasks, particles change their positions in the search space depending upon their velocities and the parameters for updating those positions using equation (1) and (2).

$$V_i^k(\tau+1) = \omega_1 V_i^k(\tau) + c_1 r_1 \left(POS_{Lbest_i^k} - D_i^k(\tau)\right) + c_2 r_2 \left(POS_{Gbest_i^k} - D_i^k(\tau)\right) \quad (1)$$

$$D_i^k(\tau+1) = D_i^k(\tau) + V_i^k(\tau+1) \quad (2)$$

Where, τ denotes the number of iteration; ω_1 as the initial weight which is used to regulate the searching inclinations either for local or global solutions; $V_i^k(\tau)$ stands for the present velocity at iteration τ for k^{th} dimension in i^{th} particle; $D_i^k(\tau)$ is the k^{th} dimension in i^{th} particle; *r1* and *r2* represent two random values between zero and one, whereas c_1 and c_2 represent the impact of individual and social aspects, respectively; $POS_{Lbest_i^k}$ and $POS_{Gbest_i^k}$ refer to local and global best solution for each particle respectively. PSO has a quick convergence characteristic when performing the exploration and exploitation operations since each response will follow the $POS_{Lbest_i^k}$ and $POS_{Gbest_i^k}$ solution. While dealing with complicated and multi-modal optimization issues, PSO may get imprisoned in local optima in certain circumstances [31]. Taking the advantage of early convergence and to solve the local optima problem of PSO, this paper come up with the solution by modifying the PSO which is discussed next.

Gaussians modified Particle Swarm Optimization (g-PSO): In the context of selecting features, the removal of key features traits may have a major impact on classification performance. As a result, a swarm boosting technique based on Gaussian distributions is presented to provide $Gbest$ with additional discriminative skills to circumvent local optima traps. Such Gaussian distributions and random walk techniques have also been extensively used in previous research for leader or swarm augmentation [32]–[35]. As stated in equation (3), $Gbest$ is modified repeatedly based on three Gaussian distributions with varied skewness settings. According to the $Gbest$ solution, the Gaussian distribution with a positive right-skewed is more likely to exclude unwanted features, while the operation with a negative left-skewed is more likely to contain more discriminative characteristics.

$$Gbest_d^{\tau} = Gbest_d + \alpha \times Gaussian\,(h) \times (UB - LB) \qquad (3)$$

Where, $Gbest_d^{\tau}$ states the enhanced global best solution; α represents the step size, and is assigned as 0.1 based on previous studies [36]. The $'h'$ is the skewness parameter of Gaussian distribution which is selected form the set [-1,1,0] as left, right and non- skewed Gaussian distribution respectively. UB and LB represents the upper bound and lower bound of the dimension. $Gbest$ will be the new solution which is generated by Gaussian distribution.

Algorithm 1: Pseudo-Code of g-PSO

```
Population Initialization of particles with UB and LB
while Termination condition is not fulfilled do
    for Each particle i do
        Obtain the fitness value for all particles
        Update the velocity of all the particles from the population using Eq. (1);
        Update the position of all the particles from the population using Eq. (2);
        Conduct swarm enhancement using Gaussian distribution using Eq. (3);
        Evaluate the fitness value f(P_i^k)
        if f(P_i^k) < f(Lbest_i^k) then
            Lbest_i^k ← P_i^k
        end
        if f(P_i^k) < f(Gbest_i^k) then
            Gbest_i^k ← P_i^k
        end
    end
end
Return Gbest
```

3.3 Optimized KNN

KNN is a popular similarity-based learning method and proved efficient in solving variety of problems [37]. KNN belongs to the class of supervised learning, which can be used for classification or regression. Distance with all the neighbours is computed where distance computation identifies the nearest neighbour from the training sample for prediction. A commonly used method for distance computation is the Euclidean Distance measure. The important parameters of the KNN model are number of neighbours, weight, and distance measure. The problem is how to choose these values to get the optimal solution. A popularly known optimization method called Grid Search is used to find the optimal values of these parameters

Grid Search Optimization: Grid search is basically an optimization technique that allows to find the optimum parameters for particular optimization issue from a list of parameter alternatives provided, therefore streamlining the 'trial-and-error' process. Although it may be used to a wide range of optimization issues, it is well recognised for its usage in machine learning to determine the parameters within which the model performs best. By taking the advantage of easy to implementation and understanding of grid search, proposed model used to optimize the parameter of K-NN classifier.

The selection of hyper-parameter to optimize the K-NN classifier is shown in table 2 on which the proposed model evaluated and gives best results; wherein the number of neighbours are selected 5 from the provided range of parameters. Weight is selected by uniformly instead of distance based. And the generalised vector space found by Minkowaski distance measure.

Table 2: Hyper-parameter Selection

Parameters	Range of Parameters	Selected Parameters
Number of Neighbors	(2, 3, 4, 5, 6, 7, 8)	5
Weight	(Uniform, Distance)	Uniform
Distance Measure	(Manhattan, Euclidean, Minkowski)	Minkowaski

4. Experiments and Results

The experiments are performed in the Anaconda framework with Python 3.7. The proposed model is tested on the datasets of BSE, NIFTY50, S&P500, and DJIA. The python library "talib" is used to generate the candlestick charts which results in the generation of 61 features. These features are large to process therefore useful features are selected with the help of the proposed g-PSO. The g-PSO selects 28, 25, 23, 26 features for the BSE, NIFTY50, S&P500, and DJIA respectively. The convergence graph obtained from g-PSO for the four datasets are provided in figures 6-9. It can be observed from the convergence graph that error rate is minimized over the iterations for all the datasets.

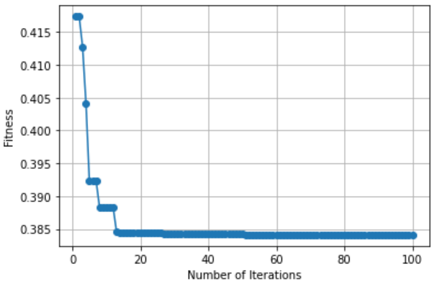


Figure 6. Convergence graph for BSE

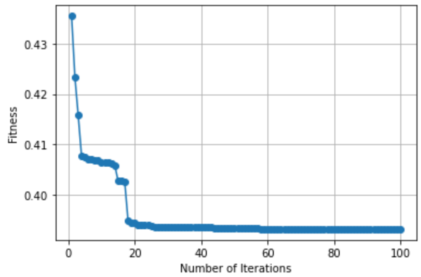


Figure 7. Convergence graph for NIFTY50

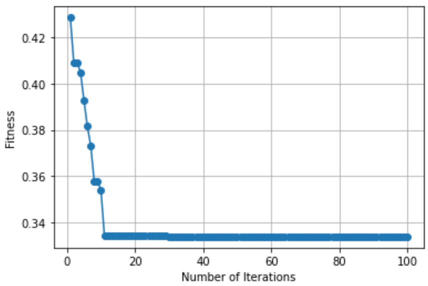


Figure 8. Convergence graph for S&P500

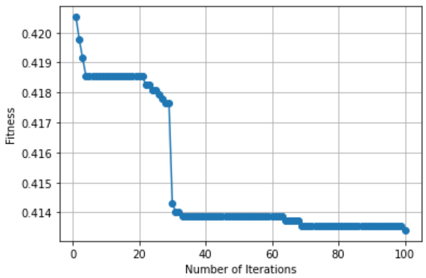


Figure 9. Convergence graph for DJIA

Table 3 provides the performance metric for the four dataset. The proposed model performed well for all the dataset. The highest prediction performance (66.66% accuracy) is attained for the S&P500 index. The proposed model is also compared with the conventional ML models. It can be observed from the table that the proposed model outperforms the conventional ML techniques.

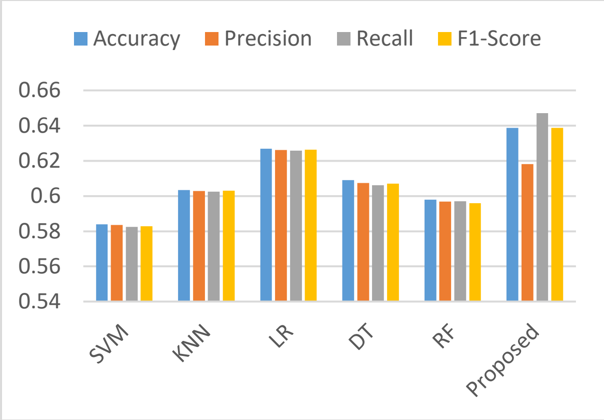
Table 3. Comparative Performance Metric with conventional ML methods

Dataset	Method	Accuracy	Precision	Recall	F1-Score
BSE	SVM	0.5847	0.5824	0.5849	0.5810
	KNN	0.5961	0.5929	0.5960	0.5885
	LR	0.5512	0.5480	0.5510	0.5498
	DT	0.5796	0.5760	0.5790	0.5780
	RF	0.5821	0.5815	0.5820	0.5820
	Proposed	**0.6056**	**0.6037**	**0.6056**	**0.6030**
NIFTY50	SVM	0.5941	0.5943	0.5951	0.5945
	KNN	0.5813	0.5794	0.5804	0.5810
	LR	0.5627	0.5590	0.5617	0.5620
	DT	0.5798	0.5746	0.5764	0.5781
	RF	0.5926	0.5912	0.5918	0.5923
	Proposed	**0.6153**	**0.6138**	**0.6153**	**0.6141**
S&P500	SVM	0.6455	0.6441	0.6413	0.6448
	KNN	0.6540	0.6515	0.6528	0.6425
	LR	0.6411	0.6408	0.6390	0.6304
	DT	0.6470	0.6461	0.6440	0.6465
	RF	0.6485	0.6480	0.6465	0.6470
	Proposed	**0.6666**	**0.6655**	**0.6666**	**0.6657**
DJIA	SVM	0.5840	0.5835	0.5824	0.5828
	KNN	0.6035	0.6028	0.6026	0.6030
	LR	0.6270	0.6262	0.6258	0.6264
	DT	0.6090	0.6074	0.6062	0.6070
	RF	0.5979	0.5968	0.5971	0.5960
	Proposed	**0.6388**	**0.6182**	**0.6472**	**0.6388**

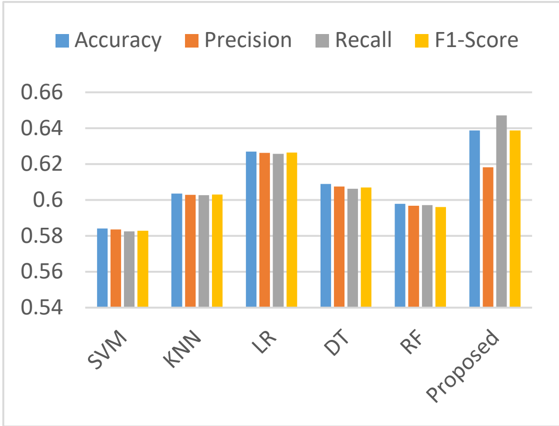
Table 4 provides the comparison of proposed model with the existing work where average performance of the proposed model is compared with the reported performance of the existing work. The result is also analyzed and displayed graphically in figure 10 for all the used stock indices. From the tables and figure it can be observed that the proposed model outperforms the existing work.

Table 4. Comparison with existing work

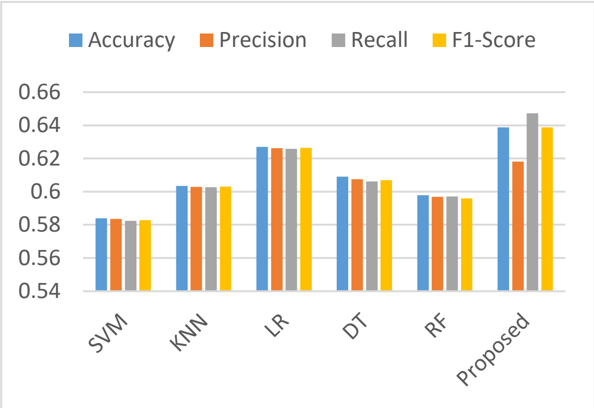
Reference	Method	Accuracy (%)
[38]	CNN	56.0
[39]	LSTM	55.9
[40]	PCA	57.5
[41]	DEEP Q-NETWORK	51
[42]	Ensemble Learning (XGBoost)	53.8
Proposed	**g-PSO Optimized KNN**	**61.4**



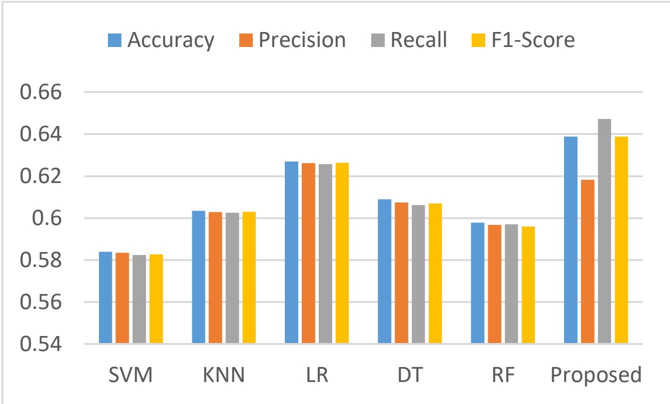
(a) BSE



(b) NIFTY50



(c) S&P500



(d) DJIA

Figure 10: Performance analysis of proposed model on different stock indices

5. Conclusion

Candlestick chart is very important tool for analysis and prediction of stock trend. This paper proposed a model which used pattern of candlestick chart for Indian and US stock market prediction. The model is evaluated on features which were generated from candlestick pattern of historical stock data. As the generated feature vector had high dimensionality problem and it was difficult to analysis and predict the trending stock. To solve this problem, the proposed feature selection model utilized the Gaussian based modified Particle Swarm Optimization (g-PSO) for selecting optimal features. In which, the grid search optimizer was incorporated to optimize the parameters of K-NN classifier. The proposed model worked well for all the datasets (BSE, NIFTY50, S&P500, and DJIA). The performance metric Accuracy, Precision, Recall, and F1- score was used to measure the performance of proposed model. The model successfully achieved 61.4% average accuracy, which is highest accuracy as compared to the existing models. The limitation of proposed model is that the model needs historical stock data. In future, the proposed model will be evaluated on the live stock data so that the investor can get clear analysis of stock market.

References

[1] M. Yusup, M. I. Suhaepi, and R. Ramadhan, “Blockchain Technology for Cashless Investments and Transactions in Digital Era With SWOT Approach,” *Blockchain Front. Technol.*, vol. 2, no. 1, pp. 17–23, 2022.

[2] O. A. Lamont, “Investment plans and stock returns,” *J. Finance*, vol. 55, no. 6, pp. 2719–2745, 2000.

[3] S. C. Nayak, C. Sanjeev Kumar Dash, A. K. Behera, and S. Dehuri, “Improving Stock

Market Prediction Through Linear Combiners of Predictive Models BT - Computational Intelligence in Data Mining," 2020, pp. 415–426.

[4] G. Kumar, S. Jain, and U. P. Singh, *Stock Market Forecasting Using Computational Intelligence: A Survey*, vol. 28, no. 3. Springer Netherlands, 2021.

[5] S. Verma, S. P. Sahu, and T. P. Sahu, "Stock Market Analysis of Beauty Industry During COVID-19 BT - Advances in Data Computing, Communication and Security," 2022, pp. 157–168.

[6] E. F. Fama, "Efficient Market Hypothesis: A Review of Theory and Empirical Work," *The Journal of Finance*, vol. 25, no. 2. pp. 383–417, 1970.

[7] A. Picasso, S. Merello, Y. Ma, L. Oneto, and E. Cambria, "Technical analysis and sentiment embeddings for market trend prediction," *Expert Syst. Appl.*, vol. 135, pp. 60–70, 2019, doi: 10.1016/j.eswa.2019.06.014.

[8] R. D. Edwards, J. Magee, and W. H. C. Bassetti, *Technical analysis of stock trends*. CRC press, 2018.

[9] N. Rouf *et al.*, "Stock market prediction using machine learning techniques: A decade survey on methodologies, recent developments, and future directions," *Electron.*, vol. 10, no. 21, 2021, doi: 10.3390/electronics10212717.

[10] R. M. I. Kusuma, T.-T. Ho, W.-C. Kao, Y.-Y. Ou, and K.-L. Hua, "Using deep learning neural networks and candlestick chart representation to predict stock market," *arXiv Prepr. arXiv1903.12258*, 2019.

[11] M. Nikou, G. Mansourfar, and J. Bagherzadeh, "Stock price prediction using DEEP learning algorithm and its comparison with machine learning algorithms," *Intell. Syst. Accounting, Financ. Manag.*, vol. 26, no. 4, pp. 164–174, 2019, doi: 10.1002/isaf.1459.

[12] S. Verma, S. Prakash Sahu, and T. Prasad Sahu, "Ensemble Approach for Stock Market Forecasting Using ARIMA and LSTM Model," in *Proceedings of Third International Conference on Intelligent Computing, Information and Control Systems*, 2022, pp. 65–80.

[13] Z. H. Kilimci *et al.*, "An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain," *Complexity*, vol. 2019, 2019.

[14] K. H. Lee and G. S. Jo, "Expert system for predicting stock market timing using a candlestick chart," *Expert Syst. Appl.*, vol. 16, no. 4, pp. 357–364, 1999, doi: https://doi.org/10.1016/S0957-4174(99)00011-1.

[15] H. A. do Prado, E. Ferneda, L. C. R. Morais, A. J. B. Luiz, and E. Matsura, "On the Effectiveness of Candlestick Chart Analysis for the Brazilian Stock Market," *Procedia Comput. Sci.*, vol. 22, pp. 1136–1145, 2013, doi: https://doi.org/10.1016/j.procs.2013.09.200.

[16] C.-F. Tsai and Z.-Y. Quan, "Stock prediction by searching for similarities in candlestick charts," *ACM Trans. Manag. Inf. Syst.*, vol. 5, no. 2, pp. 1–21, 2014.

[17] S. Khokhar and S. Verma, "Content based image retrieval with multi-feature classification by back-propagation neural network," *Int. J. Comput. Appl. Technol. Res*, vol. 6, pp. 278–284, 2017.

[18] E. Ahmadi, M. Jasemi, L. Monplaisir, M. A. Nabavi, A. Mahmoodi, and P. Amini Jam, "New efficient hybrid candlestick technical analysis model for stock market timing on the basis of the Support Vector Machine and Heuristic Algorithms of Imperialist Competition and Genetic," *Expert Syst. Appl.*, vol. 94, pp. 21–31, 2018, doi: 10.1016/j.eswa.2017.10.023.

[19] A. Mahmoodi, L. Hashemi, M. Jasemi, J. Laliberté, R. C. Millar, and H. Noshadi, "A novel approach for candlestick technical analysis using a combination of the support vector machine and particle swarm optimization," *Asian J. Econ. Bank.*, 2022, doi: 10.1108/ajeb-11-2021-0131.

[20] M. Ananthi and K. Vijayakumar, "RETRACTED ARTICLE: Stock market analysis using candlestick regression and

market trend prediction (CKRM)," *J. Ambient Intell. Humaniz. Comput.*, vol. 12, no. 5, pp. 4819–4826, 2021, doi: 10.1007/s12652-020-01892-5.

[21] C. Xu, "Image-based candlestick pattern classification with machine learning," *ACM Int. Conf. Proceeding Ser.*, pp. 26–33, 2021, doi: 10.1145/3468891.3468896.

[22] J. H. Chen and Y. C. Tsai, "Encoding candlesticks as images for pattern classification using convolutional neural networks," *Financ. Innov.*, vol. 6, no. 1, 2020, doi: 10.1186/s40854-020-00187-0.

[23] C. C. Hung and Y. J. Chen, "DPP: Deep predictor for price movement from candlestick charts," *PLoS One*, vol. 16, no. 6 June 2021, pp. 1–22, 2021, doi: 10.1371/journal.pone.0252404.

[24] S. J. Guo, F. C. Hsu, and C. C. Hung, "Deep Candlestick Predictor: A Framework toward Forecasting the Price Movement from Candlestick Charts," *Proc. - Int. Symp. Parallel Archit. Algorithms Program. PAAP*, vol. 2018-Decem, pp. 219–226, 2018, doi: 10.1109/PAAP.2018.00044.

[25] R. Pascanu, T. Mikolov, and Y. Bengio, "On the difficulty of training recurrent neural networks," in *International conference on machine learning*, 2013, pp. 1310–1318.

[26] H. Sak, A. W. Senior, and F. Beaufays, "Long short-term memory recurrent neural network architectures for large scale acoustic modeling," 2014.

[27] B. Akay, D. Karaboga, and R. Akay, "A comprehensive survey on optimizing deep learning models by metaheuristics," *Artif. Intell. Rev.*, pp. 1–66, 2021.

[28] S. Sun, Z. Cao, H. Zhu, and J. Zhao, "A survey of optimization methods from a machine learning perspective," *IEEE Trans. Cybern.*, vol. 50, no. 8, pp. 3668–3681, 2019.

[29] T.-H. Lu, Y.-M. Shiu, and T.-C. Liu, "Profitable candlestick trading strategies—The evidence from a new perspective," *Rev. Financ. Econ.*, vol. 21, no. 2, pp. 63–68, 2012.

[30] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of ICNN'95 - International Conference on Neural Networks*, 1995, vol. 4, pp. 1942–1948, doi: 10.1109/ICNN.1995.488968.

[31] A. Sahu, S. K. Panigrahi, and S. Pattnaik, "Fast convergence particle swarm optimization for functions optimization," *Procedia Technol.*, vol. 4, pp. 319–324, 2012.

[32] A. R. Jordehi, "Enhanced leader PSO (ELPSO): a new PSO variant for solving global optimisation problems," *Appl. Soft Comput.*, vol. 26, pp. 401–417, 2015.

[33] Z. Zhang, Y. Yu, S. Zheng, Y. Todo, and S. Gao, "Exploitation enhanced sine cosine algorithm with compromised population diversity for optimization," in *2018 IEEE International Conference on Progress in Informatics and Computing (PIC)*, 2018, pp. 1–7.

[34] X. Yu, X. Yu, Y. Lu, G. G. Yen, and M. Cai, "Differential evolution mutation operators for constrained multi-objective optimization," *Appl. Soft Comput.*, vol. 67, pp. 452–466, 2018.

[35] Y. Zhang, L. Zhang, S. C. Neoh, K. Mistry, and M. A. Hossain, "Intelligent affect regression for bodily expressions using hybrid particle swarm optimization and adaptive ensembles," *Expert Syst. Appl.*, vol. 42, no. 22, pp. 8678–8697, 2015.

[36] X.-S. Yang, *Nature-inspired optimization algorithms*. Academic Press, 2020.

[37] L. Yang and A. Shami, "On hyperparameter optimization of machine learning algorithms: Theory and practice," *Neurocomputing*, vol. 415, pp. 295–316, 2020.

[38] H. Gunduz, Y. Yaslan, and Z. Cataltepe, "Intraday prediction of Borsa Istanbul using convolutional neural networks and feature correlations," *Knowledge-Based Syst.*, vol. 137, pp. 138–148, 2017.

[39] D. M. Q. Nelson, A. C. M. Pereira, and R. A. De Oliveira, "Stock market's price movement prediction with LSTM neural networks," in *2017 International joint conference on neural networks (IJCNN)*, 2017, pp. 1419–1426.

[40] X. Zhong and D. Enke, "Forecasting daily

stock market return using dimensionality reduction," *Expert Syst. Appl.*, vol. 67, pp. 126–139, 2017.

[41] J. Lee, R. Kim, Y. Koh, and J. Kang, "Global stock market prediction based on stock chart images using deep Q-network," *IEEE Access*, vol. 7, pp. 167260–167277, 2019.

[42] Y. SANTUR, "Candlestick chart based trading system using ensemble learning for financial assets," *Sigma J. Eng. Nat. Sci. – Sigma Mühendislik ve Fen Bilim. Derg.*, vol. 40, no. 2, pp. 370–379, 2022, doi: 10.14744/sigma.2022.00039.