An Effective Feature Selection With Generative Adversarial Network (GAN) Model For Stock Market Prediction

S. Punitha, dr. M. Jeyakarthic

Abstract: At present days, the prediction of stock prices is very complicated as it depends on various factors. Several researches have been done to foresee the stock prices which will be helpful for users to identify the direction of stock price movement. Recently, machine learning and bio-inspired algorithms are employed for precise Stock market prediction (SMP). Though classification methods perform wells on SMP, the presence of numerous factors in the stock process decreases the efficiency of the applied classification algorithm. So, feature selection methods are applied to reduce the computation complexity and enhance the classification accuracy of SMP. This paper projects a novel new feature selection based classification model for forecasting the stock prices in an effective way. The proposed algorithm employs particle swarm optimization (PSO) algorithm to select the features properly which will enhance the classifier performance. In addition, we employ a novel architecture of Generative Adversarial Network (GAN) based classifier for forecasting the closing price of stocks. The presented model is validated using Borsa Istanbul Index (BIST) dataset. The simulation outcome showed that the projected model is the compared methods under several aspects.

Keywords: Stock prices; Feature selection; Classification; GAN; PSO.

1. INTRODUCTION

Recently, prediction of stock prices gains more importance in the rising economical sector, as a practically accurate prediction holds the probability to gain more financial advantages and be cautious against market risk factors. Because of the advanced development of Internet and computation approaches, the possibility to perform functions on the stock market had raises to a fraction of seconds [1]. In 2009, Brazilian stock exchange operated high frequencies and has increased from 2.5-36.5% from the year 2009 to 2013. [2] estimated that high-frequency trading takes place in 2016 where average of 10%–40% of trading quantity in equities and 10%–15% of amount in foreign exchange and commodities. These values recommended that the high frequency stock market is a world wide style.

Under diverse scenarios, the assessment of prediction performance takes place in two distinct ways namely forecast error which can be determined by the use of Root Mean Square Error (RMSE) among actual and predicted prices. The next one indicates the predictive accuracy implies the proportion of accurate forecast of price series direction like up and down actions are actually needed to make decisions. A slight increase in the predictive results can also be highly beneficial. But, the SMP is a difficult task owing to the complex and hectic adaptive nature of the market and unstable parameters are employed. Several research works from diverse fields have examined the active pattern in the economic time series and presented models to forecast stock prices. For obtaining significant results, various models need cautious choice of input parameters, constructing predictive model with qualified financial facts, and employing distinct algebraic models for arbitrage investigation, that makes it hard for normal people to utilize these techniques for SMP. It can be treated as a classification problem and diverse methods can be employed to solve itGenerative adversarial network (GAN) is presented in [3], where patch of images were created from arbitrary noise by the use of a pair of networks which undergo training concurrently. Particularly, in GAN, a discriminative net undergo learning process for distinguishing if the provided data sample is real or unreal, and a generative net performs learning process through the generation of high quality data. Though this model is famous and employed in diverse domains like image inpainting, semantic segmentation, and video prediction [4], it can find useful in the SMP. In this study, the fundamental technical index data is considered as an input variable that could be gathered straightaway from a trading program, hence, the people outside the financial domain performs the prediction of stock process using this model. A forecast error as well as direction prediction loss is utilized and indicated that the training of GAN might be effectively applied to combine the loss for achieving reasonable prediction performance. Based on the existing studies presented in SMP, the methods can be classified to two ways. The former type is based on econometric model that comprises econometric methods to predict data. The widely employed models are moving average (MA), autoregressive (AR), AR moving average (ARMA), and so on. Generally, these approaches take every new signal as a noisy linear integration of the previous signals and self-regulating noise term. But, many methods are based on the assumption based on the noise term as well as loss function whereas the actual financial data might not completely fulfil the considerations. Through the application of a generalized autoregressive conditional heteroscedastic (GARCH) approach for conditional variances, [5] employed ARIMA-GARCH approach to predict the financial time series. The next type comprises artificial intelligence that is inspired from the biological processes. Some of them are fuzzy logic (FL), artificial neural networks (ANN), support vector regression (SVR), and so on. Several works are based on the integration of fuzzy concepts with the arbitrariness in option pricing techniques. [6] introduced the fuzzy concepts and [7] showed the effectiveness of the fuzzy based prediction

- *S. Punitha, Assistant Professor, Department of Computer Science, Dharmapuram Gnanambigai Govt, College For Women, Mayiladuthural, spddeprof@gmail.com.*
- *Dr. M. Jeyakarthic, Assistant Director (Academic), Tamil Virtual Academy, Chennai, jeya_karthic@yahoo.com.*

and designed membership functions for the stock prices in Europe using the fuzzification of the interest rate, instability, and opening stock price. Lately, significant attention is provided to the area of deep learning where the fundamental organization is defined as a multilayer neural network [8]. Few methods which have applied deep learning models for improving the classification capability of high-frequency financial time series is presented here [9]. The capability of deep learning lies in the extraction of needed features from the provided data is also significant. [10] employed a deep feature learning-based SMP technique that extracts the details from the stock return time series with no dependency on earlier information of the prediction models and validated it on high frequency data from Korean SMP. [11] developed a dual layer neural network (NN) to forecast data using the connections particularly developed for capturing dependency structures between stock returns in diverse business domains. Earlier methods using deep learning can also be applied for identifying the relationship among earlier news events and stock market motions. But, many models need an expert for imposing particular limitations on the input variables like integration of related stocks together as entry data, provide distinct index data to various layers of DNN, and transforming the news content to organized representation as input. Contrastingly, the presented forecast model utilizes the data offered by the trading program as input that reduces the limitation of normal people. Several researches have been done to foresee the stock prices which will be helpful for users to identify the direction of stock price movement. Recently, machine learning and bio-inspired algorithms are employed for precise Stock market prediction. Though classification methods perform wells on SMP, the presence of numerous factors in the stock process decreases the efficiency of the applied classification algorithm. So, feature selection methods are utilized to reduce the computation complexity and enhance the classification accuracy of Stock market prediction. This paper projects a new feature selection based classification model for forecasting the stock prices in an effective way. The proposed algorithm employs particle swarm optimization (PSO) algorithm to select the features properly which will enhance the classifier performance. In addition, we employ a novel architecture of GAN with the Multi-Layer Perceptron (MLP) as the discriminator and the Long Short-Term Memory (LSTM) as the generator for forecasting the closing price of stocks. An extensive validation takes place on Borsa Istanbul Index (BIST) dataset. The simulation results showed that presented model is superior to other ones on the applied BIST dataset. The paper organization is provided here. The presented SMP model is elaborated in Section 2 and the simulation analysis takes place in Section 3. Section 4 concludes the work.

2. PROPOSED SMP MODEL

The presented SMP model involves two stages namely feature selection and classification. At the initial stage, the feature selection process is executed using PSO algorithm to pick out the required features from the available feature set. Then, the GAN classifier is employed to foresee the stock prices in an effective way.

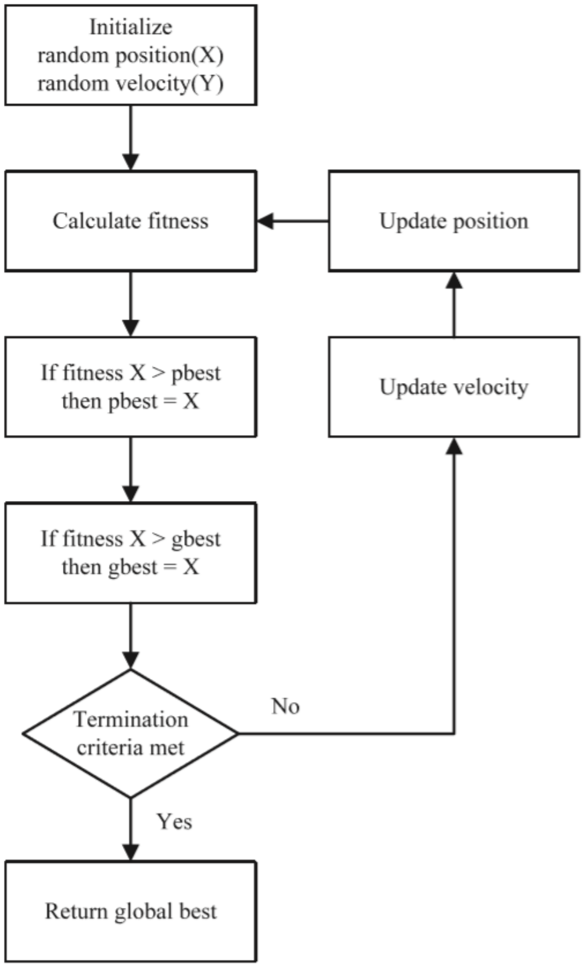
2.1. PSO based feature selection

Here, PSO algorithm is applied to select the required features. It is initially developed by Kennedy and Eberhart in 1995 [12]. It is based on the foraging nature of flocking of birds and schooling of fishes. The basic idea of PSO algorithm lies in the optimization of information through social communication in the population where thoughts are individual as well as social. It depends upon the concept that every solution is defined as a particle in the swarm. Every individual particle holds a position in the search space that is indicated using a vector $x_i= (x_{i1}, x_{i2}, . . . , x_{iD})$, where D indicates the dimensionality of the search space. The process involved in the PSO algorithm is demonstrated in Fig. 1. The particles move in the search space for identifying the optimum solution. As a result, each particle holds a velocity defined by $v_i= (v_{i1}, v_{i2}, . . . , v_{iD})$. In the motion process, every individual particle will update the position and velocity depending upon the knowledge and adjacent particles. The earlier best particle's position is known as personal best p_{best}, and optimal position attained by the population is named as global best g_{best}. Utilizing p_{best} and g_{best}, PSO will find the optimum solution through updating of velocity and the position of every particle as follows

$$x_{id}^{j+1} = x_{id}^{j} + v_{id}^{j+1} \quad (1)$$

$$v_{id}^{j+1} = w * v_{id}^{j} + c_1 * r_{1.} * (p_{id} - x_{id}^{j}) + c_2 * r_{2.} * (p_{gd} - x_{id}^{j}) \quad (2)$$

where j indicates the j^{th} round in the evolution procedure, $d \in D$ denotes the d^{th} aspect in the search space. w represents inertia weight, c_1 and c_2 are acceleration constants. r_1 and r_2 are arbitrary values which undergo uniform distribution in [0, 1]. p_{id} and p_{gd} indicates the components of the p_{best} and g_{best} in d^{th} dimension. The velocity is restricted using a fixed maximum velocity, v max, and $v_{id}^{j+1} \in [-vmax, vmax]$. This procedure will be terminated upon the satisfaction of the fixed criteria that could be optimal fitness value or predefined maximum iteratio



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count.

***Fig. 1**. PSO based Feature Selection*

2.2. GAN based classification

2.2.1. Principle

GAN is a novel model that performs training of two models: generative model which gathers the distribution of data and discriminative model which performs the possibility that a instance comes from the training data instead of G [13]. The training process for G lies in the maximization of generating a mistake. It represents a min-max two-player game. At the domain of random functions and D, an exclusive solution is present by retrieving the training data distribution and is identical to 0.5. During the adversarial procedure, the generator could be viewed as a cheater for generating the identical data as the real world data whereas the discriminator acts a part of differentiating the real time and produced data. It could attain an optimal point where the discriminator has the inability to distinguish two kinds of data. In this case, the generator could gather the data distribution from this game. Using this concept, the GAN model can be applied for the classification and prediction of stock market prices.

2.2.2. The Generator

The generator of GAN is developed using LSTM using its effective capability to process time series data. The daily data is gathered from the earlier two decades using a set of seven financial parameters for predicting the upcoming future closing prices. The set of seven parameters are important and noteworthy in SMP with the concept of technical examination, Mean Reversion, or MAR. So, the parameters which could be employed as seven features of the stock data for SMP. Let us consider the input $X = \{x_1, \dots, x_t\}$comprisingdaily stock data of t days. Every$x_k$in$X$is a vector consists of a set of seven features and is represented below.

$$\left[x_{k,i}\right]_{i=1}^{7} = \begin{bmatrix} x_{k,High}, x_{k,Low}, x_{k,Open}, x_{k,Close}, \\ x_{k,TurnoverRate}, x_{k,Volume}, x_{k,Ma5} \end{bmatrix} \quad (3)$$

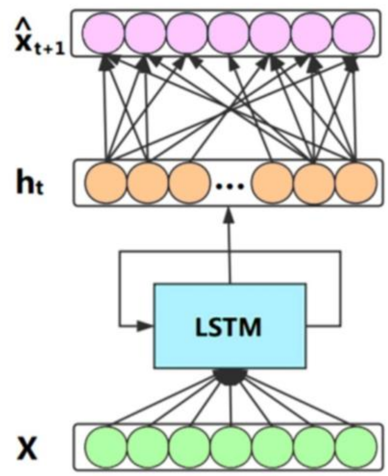

***Fig. 2**. Generator developed using LSTM*

The generator model is clearly provided in Fig. 2. For simplicity, the description of the LSTM model is eliminated. Using the generator, the output $h_t$of the LSTM will be extracted and given it to the fully connected layer with 7 neurons for the generation of the $\hat{x}_{t+1}$.It intends to the approximation of x_{t+1} and $\hat{x}_{t+1,\text{Close}}$ can be predicted from $\hat{x}_{t+1}$as the prediction of closing price on the $t+1$ day. The outcome of the generator $G(X)$can be represented here.

$$h_t = g(X) \quad (4)$$

$$G(X) = \hat{x}_{t+1} = \delta(W_h^T ht + b_h) \quad (5)$$

where $g(\cdot)$ indicates the outcome of the LSTM and $h_t$represents the outcome of the LSTM with $X = \{x_1, \dots, x_t\}$as the input. δindicates the for the Leaky Rectified Linear Unit (ReLU) activation function. $W_h$and $b_h$indicates the weight and bias in the fully connected layer. A dropout function is also employed as a regularization model for eliminating overfitting. In addition, the upcoming $\hat{x}_{t+2}$with $\hat{x}_{t+1}$and X can also be predicted.

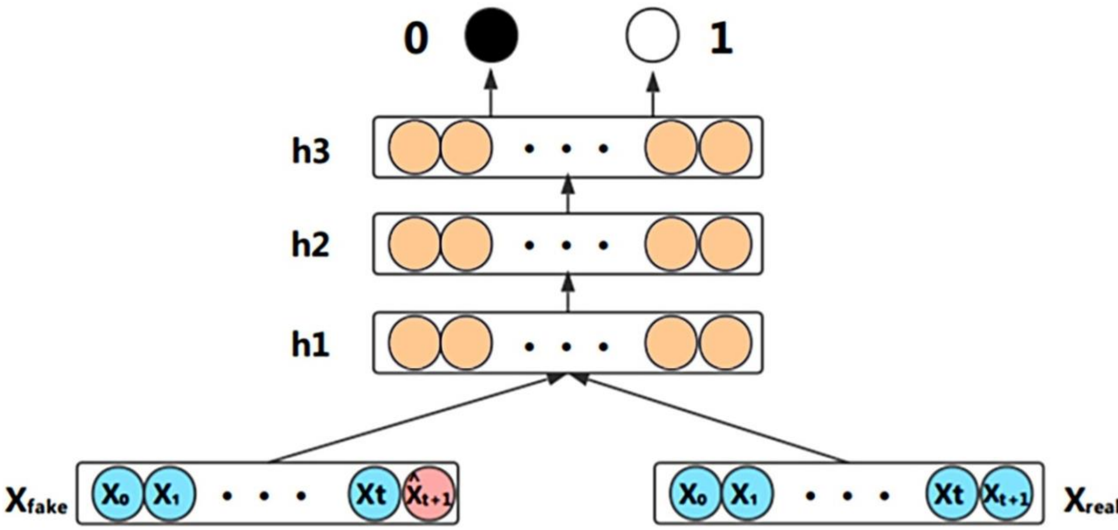

***Fig. 3**. Design of Discriminator utilizing MLP*

2.2.3. The Discriminator

The goal of the discriminator lies in the constitution of a differentiable function D for the classification of the input data. The discriminator is expected to output 0 when a fake data is provided as input and outcome will be one in case of providing real time. In this case, MLP is chosen as a discriminator along with a set of 3 hidden layers h_1, h_2 *and* h_3 comprising a set of 72, 100, 10 neurons, correspondingly. The Leaky ReLU is utilized as an activation function between the hidden layers and sigmoid function is applied in the output layer. Additionally, cross entropy loss is selected as the loss function for the optimization of the MLP.

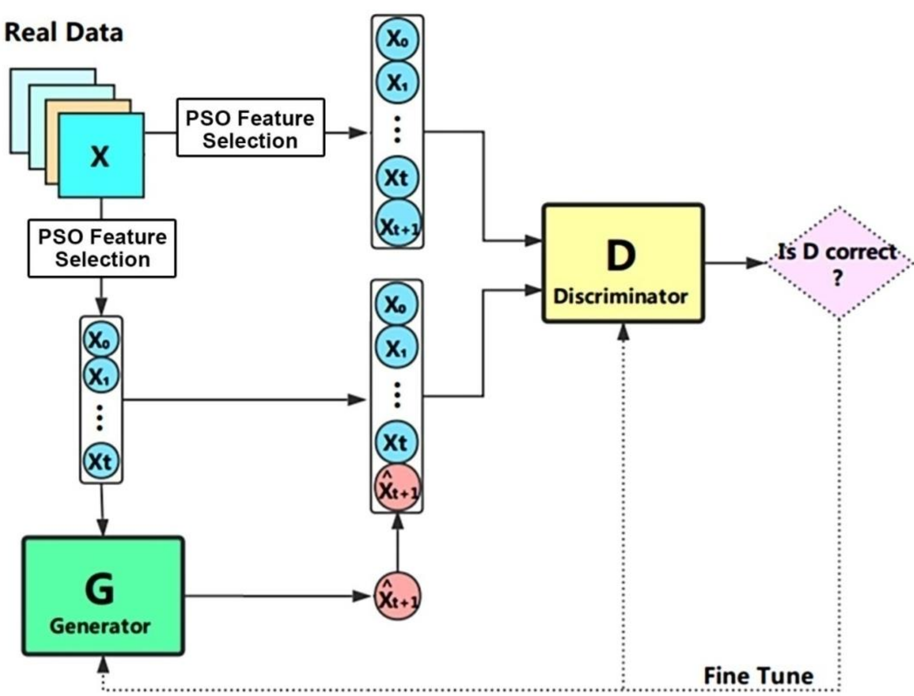

***Fig. 4.** GAN architecture*

Particularly, the $X = \{x_1, \dots, x_t\}$ and $\hat{x}_{t+1}$ *are concanated to* $\{x_1, \dots, x_t, \hat{x}_{t+1}\}$ as fake data X_{fake}. Likewise, $X = \{x_1, \dots, x_t\}$ and x_{t+1} are concatenated to generate a $\{x_1, \dots, x_t, x_{t+1}\}$ as the real data X_{real}. The outcome of the discriminator can be represented by:

$$D(X_{fake}) = \sigma\left(d(X_{fake})\right) \qquad (6)$$

$$D(X_{real}) = \sigma\left(d(X_{real})\right) \qquad (7)$$

where $d(\cdot)$ and σ indicates the outcome of the MLP and sigmoid activation function. The X_{fake} and X_{real} will be provided a single scalar. Fig. 3 displays the discriminator of GAN.

2.3. The Architecture of GAN

Using the two models explained in the previous subsections, the GAN model is presented. Based on [5], in the two-player min-max game, G as well as D is tried for the optimization of the value function. Likewise, the optimization of the value function V(G,D) is also defined in:

$$\underset{G}{min}\ \underset{D}{max} V(G,D) = E[logD(X_{real})] + E\left[\log\left(1 - D\left(x_{fake}\right)\right)\right] \quad (8)$$

Two set of losses namely generator loss $G_{loss}$and discriminator loss $D_{loss}$are applied for the optimization of the value function. Principally, Mean Square Error (MSE) is combined with the generator loss of a traditional GAN for constituting the G_{loss}. These two losses can be represented as given in Eqs. (9)-(13):

$$D_{loss} = -\frac{1}{m}\sum_{i=1}^{m} logD\left(X_{real}^{i}\right) - \frac{1}{m}\sum_{i=1}^{m}\log\left(1 - D\left(X_{fake}^{i}\right)\right) \quad (9)$$

$$g_{MSE} = \frac{1}{m}\sum_{i=1}^{m}\left(\hat{x}_{t+1}^{i} - x_{t+1}^{i}\right)^2 \quad (10)$$

$$g_{loss} = \frac{1}{m}\sum_{i=1}^{m}\log\left(1 - D\left(X_{fake}^{i}\right)\right) \quad (11)$$

$$G_{loss} = \lambda_1 g_{MSE} + \lambda_2 g_{loss} \quad (12)$$

Here, G_{loss} containsg_{MSE} and gloss with λ_1 and λ_2, correspondingly. Here, λ_1 andλ_2 represents the hyperparameters which can be set in a manual way. Fig. 4 provides the architectural model of GAN. The $X_{fake}$and X_{real} is used instead of $\hat{x}_{t+1}$ and x_{t+1}in the discriminator because of the fact that it is expected that the discriminator captures the correlation and time series information between $x_{t+1}$and X.

3. PERFORMANCE EVALUATION

a. Dataset details

	A	B	C	D	E	F	G	H	I	J
1		TL BASED	USD BASED				imkb_x			
2	date	ISE	ISE	SP	DAX	FTSE	NIKKEI	BOVESPA	EU	EM
3	5-Jan-09	0.0357537	0.03837619	-0.00468	0.002193	0.003894	0	0.03119	0.012698	0.028524
4	6-Jan-09	0.0254259	0.03181274	0.007787	0.008455	0.012866	0.004162	0.01892	0.011341	0.008773
5	7-Jan-09	-0.028862	-0.02635297	-0.03047	-0.01783	-0.02873	0.017293	-0.0359	-0.01707	-0.02002
6	8-Jan-09	-0.062208	-0.0847159	0.003391	-0.01173	-0.00047	-0.04006	0.028283	-0.00556	-0.01942
7	9-Jan-09	0.0098599	0.00965811	-0.02153	-0.01987	-0.01271	-0.00447	-0.00976	-0.01099	-0.0078
8	12-Jan-09	-0.029191	-0.04236116	-0.02282	-0.01353	-0.00503	-0.04904	-0.05385	-0.01245	-0.02263
9	13-Jan-09	0.0154453	-0.00027218	0.001757	-0.01767	-0.00614	0	0.003572	-0.01222	-0.00483
10	14-Jan-09	-0.041168	-0.03555248	-0.03403	-0.04738	-0.05095	0.002912	-0.0403	-0.04522	-0.00868
11	15-Jan-09	0.0006619	-0.01726784	0.001328	-0.01955	-0.01433	-0.05045	0.030314	-0.01207	-0.02343
12	16-Jan-09	0.0220373	0.03227803	0.007533	0.006791	0.006289	0.025453	0.004867	0.008561	0.010917
13	19-Jan-09	-0.022692	-0.04434878	-0.05426	-0.01155	-0.00935	0.003239	-0.01315	-0.01205	-0.00403
14	20-Jan-09	-0.013709	-0.02966137	0	-0.01783	-0.00417	-0.02341	-0.0409	-0.01509	-0.02411
15	21-Jan-09	0.0008647	0.00152943	0.042572	0.005011	-0.00773	-0.02056	0.033532	-0.00334	-0.00509
16	22-Jan-09	-0.003815	0.00504316	-0.01528	-0.00984	-0.0019	0.018818	-0.01698	-0.00655	-0.00323
17	23-Jan-09	0.0056613	-0.01000795	0.005363	-0.00964	7.40E-05	-0.03881	0.006261	-0.00362	-0.00808
18	26-Jan-09	0.0468313	0.06170818	0.005538	0.034787	0.037891	-0.00818	0.009838	0.0328	0.01032
19	27-Jan-09	-0.006635	0.01094866	0.010866	-0.0008	-0.00347	0.048148	0.004922	-0.00264	0.006344
20	28-Jan-09	0.034567	0.03587086	0.033007	0.044182	0.023748	0.005594	0.038725	0.029974	0.022104
21	29-Jan-09	-0.020528	-0.02027185	-0.03368	-0.02026	-0.02477	0.017723	-0.01475	-0.02311	0.000409
22	30-Jan-09	-0.008777	-0.02345826	-0.02305	-0.02048	-0.00971	-0.03167	-0.00854	-0.0072	0.002243

orjinal data

***Fig. 5**. Sample dataset*

To validate the presented model, the Istanbul stock exchange data or BIST dataset is employed. The Istanbul stock exchange gains interest among foreign investors and is considered as top ten largest emerging markets. The experiments are carried out on the BIST's 100 index because of low frequency of trading. Every public sector company shows exclusive trading on BIST and it reflects zero market fragmentation. The short selling is obtainable for every listed stock without one in the watch list. Istanbul stock exchange data is utilized here due to various facts. The financial market status in Turkey shows high volatility. The Turkish currency lira has the past information that it drops by 5% in a day whereas the Istanbul current has reduced upto 10% of its value in seven days. The economic level of a country faces a hard patch because of recession accompanying with high inflation, shrinking the economy [14]. Any of the presented models dealing with the Istanbul stock data is assumed as proficient whereas other stock exchanges are non-volatile in nature [15]. A sample data instances from the applied dataset is shown in Fig. 5. The ISE dataset is obtained from UCI repository and the dataset includes a set of 7 parameters collected from ISE in the period of June 5, 2018 to February 16, 2019. The information related to the dataset is shown in Table 1.

***Table 1.** Details of BIST parameters*

Parameter	Details
Sp	S&P 500 Index (New York Stock Exchange)

Parameter	Details
Dax	Deutscher Aktien Index (Frankfurt Stock Exchange)
Ftse	FTSE 100 Index (London Stock Exchange)
Nikkei	Nikkei Index (Tokyo Stock Exchange)
bovespa	Bovespa Index (Brasil Sao Paulo Stock Exchange)
Eu	MSCI Europe Index
Em	MSCI Emerging Markets Index

b. Results analysis

Figs. 6 and 7 shows the feature selection results of two algorithms namely genetic algorithm (GA) and presented PSO algorithm respectively. Generally, the performance of the feature selection model can be validated interms of best cost. Fig. 6 demonstrates that the GA algorithm attains the best cost value of 0.052. At the same time, Fig. 7 illustrates that the presented PSO algorithm obtains the best cost value of 0.0345. The significant reduction in the best cost value of the PSO algorithm implies that it exhibits effective feature selection performance on the applied BIST dataset.

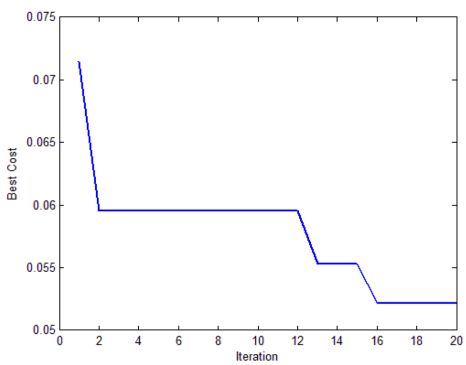

***Fig. 6**. Best cost analysis of GA based feature selection*

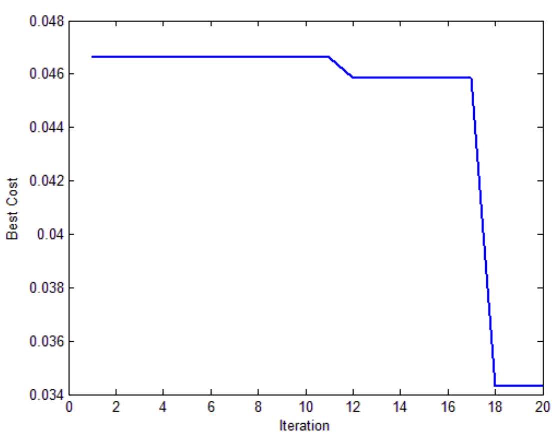

***Fig. 7**. Best cost analysis of PSO based feature selection*

Fig. 8 shows the comparative analysis of the predicted results with the actual results on different dates. For comparison purposes, SVR and ANN models are employed. The table 2indicates the data, open price, closing price and actual result whether 0 or 1 (i.e. down or up). On the date of 11-05-2019, it is shows that the open price and close price are 247.6 and 250.35. These values indicate that the prices are up. The presented and compared methods are also properly predicted that the stock prices are increased. Similarly, on the date of 14-05-2019, it is depicted that the open and close prices are 249.95 and 253.6. These values indicate that the prices are up. However, the compared methods SVR and ANN provide an identical outcome of 0 indicating that the prices are down. Interestingly, the presented model accurately performs SMP accurately by predicting the increased stock price. In the same way, on the date of 15-05-2019, it is noted that the open price and close price are 253 and 248. These values indicate that the prices are down. It can be shown that the presented and compared method accurately forecast that the stock prices are decreased. Similarly, on the date of 16-05-2019, it is depicted that the open and close prices are 245.5 and 243.1. These values indicate that the prices are down. But, the compared methods SVR and ANN provide a false outcome of 1 indicating that the prices are increased. Besides, the presented model accurately performs SMP accurately by predicting the decreased stock price.

Table 2 *Comparative analysis of various SMP methods*

Date	Open Price	Close Price	SVR Result	ANN Result	Proposed	Actual Result
2019-05-11	247.6	250.35	1	1	1	1
2019-05-14	249.95	253.6	0	0	1	1
2019-05-15	253	248	0	0	0	0
2019-05-16	245.5	243.1	1	1	0	0
2019-05-17	244.2	242.7	1	1	0	0
2019-05-18	243	238.85	1	0	0	0
2019-05-21	243.55	244.45	1	1	1	1

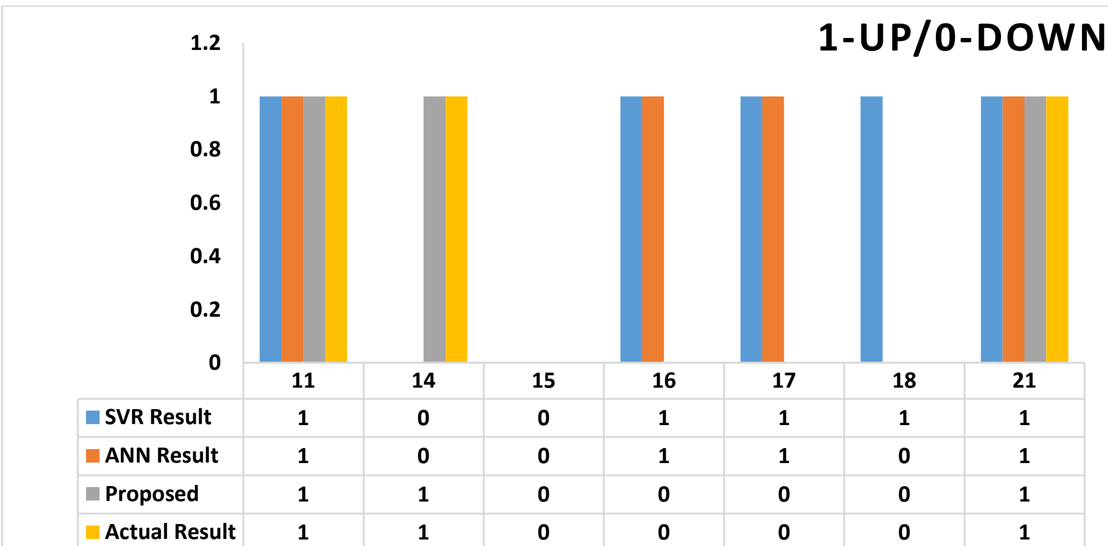

Fig. 8. *Comparative analysis of various SMP models*

On the date 17-05-2019, it is noted that the opening and closing stock prices are 244.2 and 242.7 respectively. It implies that the stock prices are decreased. Similar to the previous dates, the compared SVR and ANN model wrongly predicts the outcome whereas the presented model properly predicted that the stock prices gets reduced. On looking into the date 18-05-2018, it is shown that the stock prices begin with 243 and is reduced to 238.85. This decrease in stock prices is properly predicted by the presented model and ANN. But, the SVR model provides false forecast indicating that the increased stock price. Finally, on the date 21-05-2019, it is noted that the opening and closing stock prices are 243.55 and 244.45 indicating that the stock prices are increased. All the other methods such as existing and presented ones properly forecast the stock prices on the particular day. By observing the values presented in the table and figure, it is noted that the presented model shows proper forecasting over other methods in a significant way. Fig. 9 investigates the simulation outcome attained by the presented and compared models with respect to MAE. The figure shows that the ANN model shows poor forecast and attains the highest MAE value of 7.3029. At the same time, the SVR model tries to performs well by achieving moderate forecasting results by achieving moderate MAE of 4.9285. But, the presented model achieves superior results by obtained minimum MAE of 3.1247. From the above tables and figures, it is observed that the presented model shows better forecasting performance over the compared methods on the applied dataset.

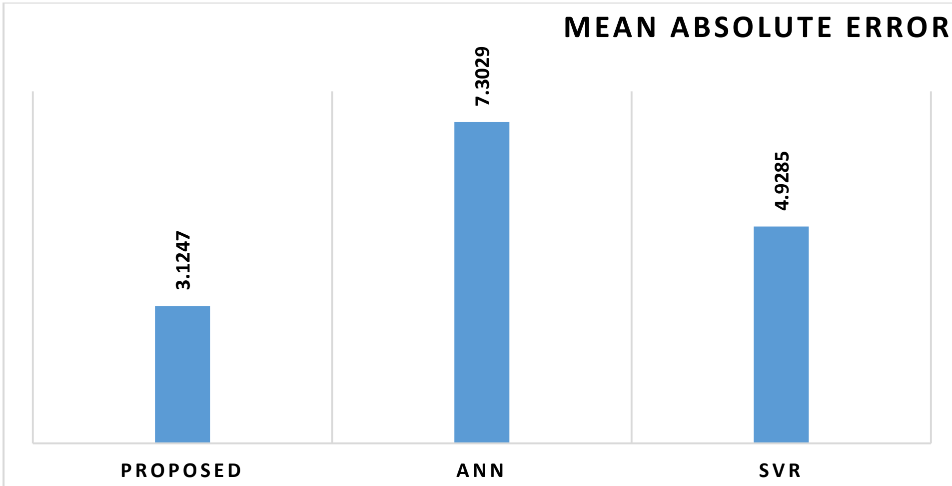

***Fig. 9**. MAE analysis of diverse SMP models*

4. CONCLUSION

Several researches have been done to foresee the stock prices which will be helpful for users to identify the direction of stock price movement. Though classification methods perform wells on SMP, the presence of numerous factors in the stock process decreases the efficiency of the applied classification algorithm. So, feature selection methods are applied to reduce the complexity level and enhance the classification accuracy of SMP. To achieve this, a novel feature selection based classification model for SMP is presented in an effective way. At the initial stage, the feature selection process is executed using PSO algorithm to pick out the required features from the available feature set. Then, the GAN classifier is applied to predict the stock market prices. An extensive validation takes place on BIST dataset. By observing the values presented in the table and figure, it is noted that the presented model shows proper forecasting over other methods in a significant way.

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