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Stock Market Analysis using ART-SVR based on Technical Parameters

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Abstract-In this research work, a soft computing or machine learning approach is used to design an algorithm which is a basic hybridized framework of the feature reduced adaptive resonance theory (ART) and support vector regression (SVR) to effectively predict stock market price as well as behaviour from the historical dataset.Ten different technical indicators are extracted and reduced using particle swarm optimization (PSO). Simulation results on different well-known stock market price like Adani Powers, BHEL, Reliance Industries, SBI and Infosys, stock exchange price is finally presented to test the performance of the established model. With the proposed model, it can achieve a better prediction capability to stocks. The proposed algorithm is compared with ART algorithm and analyzed that proposed model predicts better stock position behavior.

Keywords-Machine learning, ART, SVR, PSO, Stock Market Indices, Technical indicators, Stock Prediction.

I. INTRODUCTION

Trading stocks is the process of buying and selling shares of a company on a stock exchange with the aim of generating profitable returns. The stock exchange operates like any other economic market; when a buyer wants to buy some quantity of a particular stock at a certain price, there needs to be a seller willing to sell the stock at the offered price. Transactions in the stock market are processed by brokers who mediate sales between buyers and sellers [1],[2].

The benefits involved in accurate prediction have been motivating motivated researchers to develop newer and more advanced tools and methods. With regard to the techniques used to analyze the stock markets, some are based on statistical methods, others are artificial intelligence and machine learning methods [3],[4].

Generally the financial time series data, being chaotic, noisy and nonlinear in nature [5],[6], does not necessarily follow a fixed pattern. and thus the statistical approaches, such as moving average, weighted moving average, Kalman filtering, exponential smoothing, regression analysis, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), and autoregressive moving average with exogenous, do not perform very well in predicting stock market indices accurately. In contrast to the statistical techniques, artificial intelligence methods can handle the random, chaotic, and nonlinear data of the stock market and have been used widely for accurate prediction of stock market indices[7],[8].

II. RELATED WORK

A lot of artificial intelligence methods have been developed and applied to forecast stock market indices, for instance, Artificial Neural Network (ANN, Support Vector Machines (SVMs), Rough Set Theory, Bayesian Analysis (BA)and K-Nearest Neighbors (KNN), Particle Swarm Optimization (PSO), Decision Tree (DT), and the evolutionary learning algorithms like Genetic Algorithm (GA).

Table 1: Existing Contributions in Stock Price Prediction

Author Name	Description	Result and Conclusion
Yu, H et al. (2014) [2]	Applied Feature reduction using principal component analysis (PCA) and Support vector machine classifier (SVM)	Achieved an accuracy of 75.4464% in training set and of 61.7925% in test set. This algorithm doesn't identified the predicted price.
Nayak et al. (2015) [7]	Proposes a hybridized framework of Support Vector Machine (SVM)	Better prediction capability

	with K-Nearest Neighbor approach	
Chiang et al. (2016) [8]	Decision support system is used for prediction	Generate higher returns
Podsiadlo et al. (2016) [10]	Rough set analysis is used for prediction	Trading signals was further improved
Zhong et al. (2017) [11]	Principal component analysis (PCA), fuzzy robust principal component analysis (FRPCA), and kernel-based principal component analysis (KPCA) are applied	Gain significantly, higher risk-adjusted profits
Pankaj et al. (2017) [12]	Used swarm intelligence and ANN produce more accurate and optimized results	Make optimized results
Zhixi et al (2017) [13]	Long short-term memory (LSTM), and support vector machines (SVM) is used for forecasting	Including the principal component analysis are utilized to enhance their overall performance
Hasan et al. (2017) [14]	Machine learning algorithms to predict the future stock price of Dhaka Stock Exchange	The combination of technical indicators with the machine learning algorithms can often provide better results
Lei et al (2018) [15]	Wavelet Neural Network Prediction Method for prediction of financial time series	Prediction results are better than those obtained by other neural networks, SVM, WNN and RS-WNN, which verifies the feasibility and effectiveness
Manas et al (2018) [16]	Used stock market price prediction using hybridization of Adaline Neural Network (ANN) and modified Particle Swarm Optimization (PSO)	Enhances the performance with respect to mean absolute percentage error

III. METHODLOGY

A. Data Collection

In order to perform modeling of stock market analysis, this paper collected historical datasheet for Technical feature extraction which is taken for different companies during year 2014-2018. Historical Dataset is taken from Yahoo finance website. For this simulation analysis 10 different companies historical dataset is created for three years i.e. from 2014 upto 2018. The dataset is acquired in order to predict the direction of any share or stock whether it will go high or low. All the available data is trained by supervised machine learning algorithm using adaptive resonance theory (ART) and support vector regression (SVR).

B. Technical Feature Extraction

Technical indicator is composed of data derived from the application of a certain formula to the past prices of a stock. In this research work 10 features are extracted for further analysis of proposed algorithm which is discussed in detail in previous section.

Moving Average Convergence Divergence (MACD)

Moving average convergence divergence (MACD) is used as an indicator that shows relationship between moving averages of stock prices. It is calculated as :

$$\text{MACD} = 26 - \text{day EMA} - 12 - \text{day EMA} \qquad (1)$$

A signal line is plotted for nine-day EMA of the MACD functioning as a trigger for buy and sell signals.9-day MACD is allocated as a signal line which is used to buy and sell signal for any stock price.A sell (short) signal occurs when the MACD line crosses below the Signal line.A buy signal occurs when the MACD line crosses above the Signal line.

Relative Strength Index (RSI)

The Relative Strength Index (RSI) is a comparison indicator between losses and recent gains and determines an overbought or oversold market. At time t, it has the form of

Eq. 3.2. Typically, RSI is calculated over a 14 Day Period. The basic formula is:

$$\mathrm{RSI} = 100 - 100/\,(1 + \mathrm{RS}) \tag{2}$$

where, RS = (Average Gains) / (Average Losses)

For predicting stock position there are two lines i.e. 70 and 30.If the indicator is below 30, then the price action is considered weak and possibly oversold i.e. Buy condition.If it is reading above 70, then the asset is after a strong uptrend and could be overbought i.e. sell condition.

Momentum

One of the simplest oscillator is Momentum which is used to measure the frequency or intensity of price changes. For example, in ordet to construct a 10-day momentum line, simply subtract the closing price 10 days ago from the last closing price. The formula for momentum is:

$$M = V - Vx \tag{3}$$

Where V is the latest price, Vx is the closing price x number of days ago.

There is signal line plotted at 100 or zero line cross.If a stock is trending higher, only buy when the indicator falls below zero/100 line cross.

Simple Moving Average (SMA)

SMA is used to calculate the average price of stock over a period of time. The Simple Moving Average (SMA) is the arithmetic mean of T past prices C_i.

$$SMA = \frac{1}{t}\sum_{i=1}^{T} C_i \tag{4}$$

There are two basic signals in relation to the 200-day moving average. If the price is above the 200-day SMA this is a buy condition or long signal.If the price is below the 200-day SMA this is a sell condition or short signal.

Commodity Channel Index (CCI)

The CCI is used to compares the current mean price with the average mean price over a typical window of time periods.

CCI = (Typical Price- t-period SMA of TP) / (.015 x Mean Deviation) (5)

Where, Typical Price (TP) = (High + Low + Close)/3

Constant = .015

The indicator fluctuates between -200 and +200.If the indicator is below -200, then the price action is considered weak and possibly oversold i.e. Buy condition.If it is reading above +200, then the asset is after a strong uptrend and could be overbought i.e. sell condition.

Linear Regression Indicator (LRI)

The Linear Regression Indicator is used for trend identification and trend following, similar to a moving average. A trend line drawn with the linear regress always finishes with the LRI indicator point.

If/when the price closely approached the upper limit (max Value of LRI), then sell condition.If it is at the very bottom of the channel then buy condition.

Double Exponential Moving Average (DEMA)

The name double comes from the fact that the value of an EMA (Exponential Moving Average) is doubled. To keep it in line with the actual data and to remove the lag the value "EMA of EMA" is subtracted from the previously doubled ema. Double exponential moving average calculated as:

$$\text{DEMA} = 2{*}\text{EMA}-\text{EMA(EMA)} \tag{6}$$

In DEMA two signal lines are plotted with time period 12 and 24.If output DEMA value is greater than both signal line then buy condition is established.Whereas DEMA value is lower than both signal line then sell condition is established.

Weighted Moving Average (WMA)

A Weighted Moving Average is calculated by multiplying each bar's price by a weighting factor. WMA is calculated as in equation 3.7.

$$WMA = \frac{PC_i + (P-1)C_{i-1} + \cdots + C_{i-P}}{P + (P-1) + \cdots + 1} \tag{7}$$

Where, P= Time period

C_i as either daily closing or up-to-the-minute prices

There are two basic signals in relation to the 200-day WMA. If the price is above the 200-day WMA this is a buy condition or long signal.If the price is below the 200-day WMA this is a sell condition or short signal.

Detrended Price Oscillator (DPO)

DPO is a technical indicator that uses displaced moving average in order to eliminate the long-term trends. This indicator is used to check the level of overbought and oversold efficiently.

$$\text{DPO} = (\text{Price of } (n/2\ +\ 1) \text{ periods ago}) - (\text{n Period SMA}) \tag{8}$$

Where, n = time period

Peaks in price are occurring look for sell/shorting signals that align with the stock price cycle.

Envelopes Trading Bands (ETB)

ETB is an indicator that is based on a simple or exponential moving average, and sets bands based on a set percentage deviation, thus creating envelopes. Envelopes define the upper and lower boundaries of a security's normal trading range. A sell signal is generated when the security reaches the upper band whereas a buy signal is generated at the lower band.

There are two signal lines termed as ETB lower line and ETB upper line.

ETB upper =Average of SMA+[Average of SMA *0.025].

ETB lower = Average of SMA-[Average of SMA *0.025].

If the indicator is below ETB lower, then the price action is considered weak and possibly oversold i.e. Buy condition.If it is reading above ETB upper , then the asset is after a strong uptrend and could be overbought i.e. sell condition.

C. *Proposed Architecture*

The objective of this paper is to introduce a combined machine learning approach with technical indicators to predict future price of particular stocks.

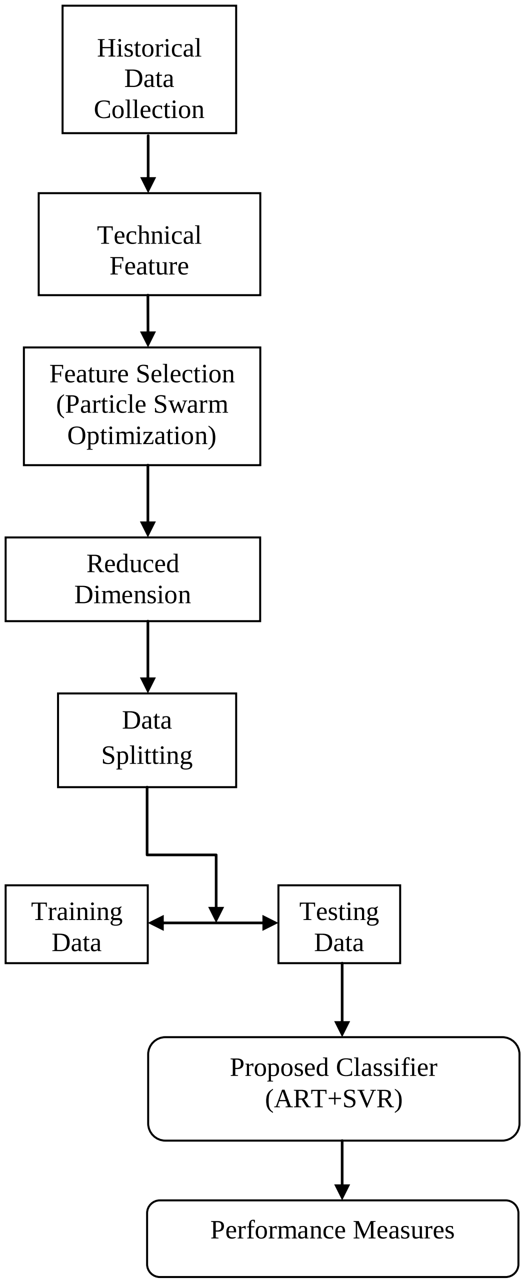

Figure 1: Proposed Architecture

The proposed methodology is performed as following:

Extraction of historical data from website

Finding 10 technical indicators

Feature Selection

Classification of data into three class i.e. buying type data, holding type data as well as selling type data

Finding performance parameters for variable features

Figure 1 illustrates the flow chart of proposed algorithm for prediction of buying and selling status of any companies' stock. Each stage is discussed below in details.

D. Proposed Algorithm

Input: D {Historical Stock Data};

Output: predicted Stock price for 30 days, 60 days, 120 days, 365 days and 730 days

Step1: Pre-processing

Step2: For each entity in D, do

Find feature vector (V) from D

Step 3: For each V do

Predict using ART-SVM

Step 4: Determine the error

Find Performance Parameters i.e. MSE, RMSE, MAE, MAPE

end for

E. Proposed Methodology

Data Extraction

In order to perform modeling of stock market analysis, this paper collected historical datasheet for Technical feature extraction which is taken for different companies during year 2014-2018.

Technical Feature Extraction

Technical indicator is composed of data derived from the application of a certain formula to the past prices of a stock which is discussed in above section.

Feature Selection

The aim Feature selection phase is to further select only those features from the database which are relevant for proper classification of the dataset and consequently reduces the feature space dimension so as to reduce complexity by removing irrelevant data. This task is accomplished by using the Particle Swarm Optimization (PSO).

The basic process of the PSO algorithm is given by:

Step 1: (Initialization) Create random initial particles. For the PSO algorithm, the complete set of entities is represented by a string of length N.

Step 2: (Fitness) Measure the fitness of each particle in the population. This fitness value is used to optimize the result. In this algorithm global minimum to determine fitness function for the accuracy of detection.

Step 3: (Update) Calculates the speed of each particle.

Step 4: (Construction) For each particle, move to the next position.

Step 5: (Termination) Stop the algorithm if the termination criterion is satisfied; return to Step 2 otherwise.

PSO Algorithm

For every particle or jobs

Initialize jobs

end

Do

For each job

Calculate fitness value

If the fitness value is greater than the best fitness value (pBest) in history

Then set current fitness value as the new pBest

End

Choose the job with the best fitness value of all the particles as the gBest

For each job

Calculate particle velocity

Update job position in queue

End

While maximum iterations or minimum error criteria is not attained.

Calculation of fitness function

Each Particle's fitness function is calculated using pbest as well as gbest which is best position among entire group of particles.

In each generation velocity and position of each particle is updated using following equation

$$v_{new} = v_{old} + c1 * r1 * (pbest - present\_position) + c2 * r2 * (gbest - present\_position) \quad (9)$$

$$present\_position = present\ position + v_{old}$$

Where, v is the particle velocity

Present_position is the current particle (solution)

Pbest and gbest are defined as stated before.

r1 and r2 is a random number between (0,1).

c1, c2 are learning factors. usually c1 = c2 = 2.

Data Classification

Data classification is the process of sorting and categorizing data into various types, forms or any other distinct class [17],[18],[19],[20],[21]. Data classification enables the separation and classification of data according to data set requirements for various objectives. ART-SVR has been used in simulation experiments.

For each classifier, a preliminary detector was initially formed using a small sub-sample of features extracted from the training data set.

The main operation of the ART classification can be divided into several phases:

Recognition phase: The input vector is compared to the classification displayed on each node of the output level. The output of the neuron becomes "1" if it corresponds better to the applied classification, otherwise it becomes "0".

Comparison phase: In this phase a comparison of the input vector is performed with the comparison level vector. The condition for restoration is that the degree of similarity would be lower than the supervisory parameter.

Search phase: In this phase, the network is looking for both silence and agreement in the previous phases. So if there is no reset and the match is good enough, the ranking is over. Otherwise, the process would be repeated and the other stored model sent to find the correct match.

Reset Mechanism: The work of this mechanism is based on the similarity between the descending weight and the input vector. Now, if the degree of this resemblance is lower than the supervisory parameter, the input vector should not learn the model.

Adaptive Resonance Theory (ART) Algorithm

Following parameters are used :

n − Number of components in the input vector

wij − Weight from F1(b) to F2 layer

α - choice parameter $\alpha > 0$

β - a learning rate parameter ,$\beta\varepsilon[0,1]$

ρ − Vigilance parameter

Step 1 − Initialize the learning rate, the vigilance parameter, and the weights as follows:

α>1and 0<ρ≤1

for each input, ij

choice function(CF) = sum(min(input_valij, wij}))/ (αij+ wi);

end

These values of CFj in F2 undergo a competitive process. Only one value of CFj will win. The category choice, where

CF = max{CFi: i = 1 ... N }.

If more than one CFi is maximal, the smallest index is chosen.

When ART receives an input pattern I, I is copied immediately over into x. The next step is to pass the information in layer F1 up to F2, with the Match function, Tj, is defined as

Match Function:

Tj = sum(min(Iij, wij))/total Input vectors;

Step 2 − For every training input.

Resonance or ρ : Resonance occurs if the match function, of the chosen category meets the vigilance criterion.

if match>= Resonance(ρ)

% Check labels

if input_label= = labels(i)

% update the prototype

wij = β *(min(input,wij)) + (1- β)*wij;

network_changed = true;

create_new_prototype = false;

break;

else

% Increase vigilance, ρ

Resonance(ρ) = sum(min(input, wij }))/total input vector + epsilon;

End if End if

Support Vector Regression Algorithm

Considering a set of training data $\{(x_1, y_1),....,(x_\ell, y_\ell)\}$, where each $x_i \subset R^n$ denotes the input space of the sample and has a corresponding target value $y_i \subset R$ for i=1,…, l where l corresponds to the size of the training data. The idea of the regression problem is to determine a function that can approximate future values accurately.

The generic SVR estimating function takes the form:

$$f(x) = (w \cdot \Phi(x)) + b \tag{10}$$

where $w \subset R^n$, $b \subset R$ and Φ denotes a non-linear transformation from R^n to high dimensional space. Our goal is to find the value of w and b such that values of x can be determined by minimizing the regression risk:

$$R_{reg}(f) = C\sum_{i=0}^{\ell}\Gamma(f(xi) - yi) + \frac{1}{2}\|w\|^2 \tag{11}$$

where $\Gamma(\cdot)$ is a cost function, C is a constant and vector w can be written in terms of data points as:

$$w = \sum_{i=1}^{\ell}(\alpha_i - \alpha_i^*)\Phi(x_i) \tag{12}$$

By substituting equation (3.12) into equation (3.10), the generic equation can be rewritten as:

$$\begin{aligned} f(x) &= \sum_{i=1}^{\ell}(\alpha_i - \alpha_i^*)(\Phi(x_i)\cdot\Phi(x)) + b \\ &= \sum_{i=1}^{\ell}(\alpha_i - \alpha_i^*)k(x_i, x) + b \end{aligned} \tag{13}$$

In equation (3.13) the dot product can be replaced with function $k(x_i, x)$, the kernel functions allow you to run a scalar product in a large space using a data entry with reduced space, without knowing the transformation. All kernel functions must meet the Mercer requirement, which is the internal product of a feature space.

The radial base function (RBF) is commonly used as a regression kernel:

$$k(x_i, x) = \exp\left\{-\gamma |x - x_i|^2\right\} \quad (14)$$

Some common kernels are shown in Table 2. In our studies we have experimented with these three kernels.

Table 2: Common Kernel Functions

Kernels	Functions
Linear	$x \cdot y$
Polynomial	$[(x * x_i) + 1]^d$
RBF	$\exp\left\{-\gamma \|x - x_i\|^2\right\}$

The ε -insensitive loss function is the most widely used cost function. The function is in the form:

$$\Gamma(f(x) - y) = \begin{cases} |f(x) - y| - \varepsilon, & for \quad |f(x) - y| \geq \varepsilon \\ 0 & otherwise \end{cases} \quad (15)$$

By solving the quadratic optimization problem in (7), the regression risk in equation (2) and the ε -insensitive loss function (6) can be minimized:

$$\frac{1}{2}\sum_{i,j=1}^{\ell}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)k(x_i, x_j) - \sum_{i=1}^{\ell}\alpha_i^*(y_i - \varepsilon) - \alpha_i(y_i + \varepsilon) \quad (16)$$

subject to

$$\sum_{i=1}^{\ell}\alpha_i - \alpha_i^* = 0, \quad \alpha_i, \alpha_i^* \in [0, C] \quad (17)$$

The Lagrange multipliers, $\alpha_i \; and \alpha_i^*$, represent solutions to the above quadratic problem that act as forces pushing predictions towards target value y_i. Only Lagrangian multipliers not null in the equation (3.17) are useful for predicting the regression line and are called support vectors. For all points on the tube, Lagrange multipliers, which are zero, do not contribute to the regression function. Only if the requirement $|f(x) - y| \geq \varepsilon$ is satisfied, Lagrange multipliers can be non-zero values and used as support vectors.

The constant C introduced determines the penalties for estimation errors. A large C assigns higher errors to errors, so that the regression is trained to minimize errors with less generalization, while a small C assigns less penalty to errors; This allows to minimize the margin of error and therefore a greater capacity for generalization. If C becomes infinitely large, the RVS would not allow any error and would lead to a complex model, whereas if C goes to zero, the result would tolerate a large amount of errors and the model would be less complex [23],[24].

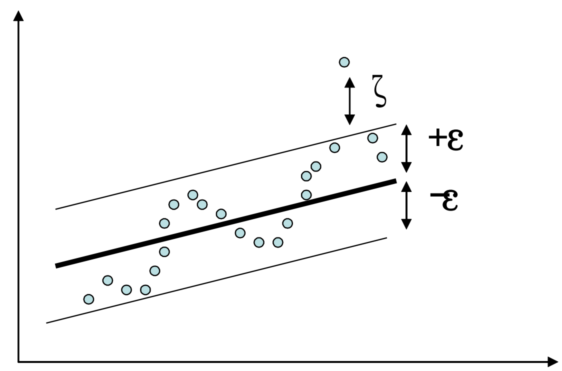

Figure 2: Support Vector Regression

We have now solved the value of Lagrange multipliers. For the variable, it can be calculated using the Karush-Kuhn-Tucker (KKT) conditions, which implies that the product of Lagrange multipliers and constraints must be zero:

$$\begin{aligned} \alpha_i(\varepsilon + \zeta_i - y_i + (w, x_i) + b) &= 0 \\ \alpha_i^*(\varepsilon + \zeta_i^* + y_i - (w, x_i) - b) &= 0 \end{aligned} \quad (18)$$

$$\begin{aligned} (C - \alpha_i)\zeta_i &= 0 \\ (C - \alpha_i^*)\zeta_i^* &= 0 \end{aligned} \quad (19)$$

where ζ_i and ζ_i^* are slack variables used to measure errors outside the ε -tube. Since $\alpha_i, \alpha_i^* = 0$ and $\zeta_i^* = 0$ for $\alpha_i^* \in (0, C), b$ can be computed as follows:

$$\begin{aligned} b &= y_i - (w, x_i) - \varepsilon \quad for \;\; \alpha_i \in (0, C) \\ b &= y_i - (w, x_i) + \varepsilon \quad for \;\; \alpha_i^* \in (0, C) \end{aligned} \quad (20)$$

Putting it all together, we can use SVM and SVR without knowing the transformation.

IV. RESULT AND DISCUSSION

This section shows the experimental results. The historical dataset is prepared from Yahoo finance website. In order to evaluate the performance of proposed algorithm scheme, the proposed algorithm is simulated in following configuration:

Pentium Core I5-2430M CPU @ 2.40 GHz

4GB RAM

64-bit Operating System

MATLAB Platform

In order to perform modeling of stock market analysis, this paper collected historical datasheet for Technical feature extraction which is taken for different companies during year 2014-2018. Historical Dataset is taken from Yahoo finance website. For this simulation analysis different companies historical dataset is created for four years i.e. from 2014 upto 2018. The dataset is acquired in order to predict the direction of any share or stock whether it will go high or low. List of companies that are used for analysis are :

- Adani Powers
- Reliance Industries
- BHEL
- State bank of India
- Infosys

A. Performance Parameters

Mean Square Error (MSE)

MSE of any estimator (classifier) measures the average squares of errors or deviations, i,e. the difference between the estimator and what is estimated. MSE is a risk function corresponding to the expected value of the squared error loss.

$$MSE = \frac{1}{N}(Target_{value} - Obtained_{value}) \tag{21}$$

Root Mean Square Error (RMSE)

RMSE is a parameter that determines the difference in squares between the output and the input.

$$RMSE = \sqrt{MSE} \tag{22}$$

Mean Absolute Error (MAE)

MAE measures the average size of errors in a series of forecasts regardless of their direction. This is the average of absolute differences between prediction and actual observation, in which all individual differences are also weighted.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} y_i - \hat{y}_i \tag{23}$$

Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error (MAPE) is a measure of the predictive accuracy of a forecasting method in statistics, for example in estimating the trend. It usually expresses the precision in percentage and is defined by the formula:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{Target_{value} - Obtained_{value}}{Target_{value}} \tag{24}$$

A. Technical Parameter Prediction

In this section some of the technical features values are forecasted for and their respective graphs are shown below.

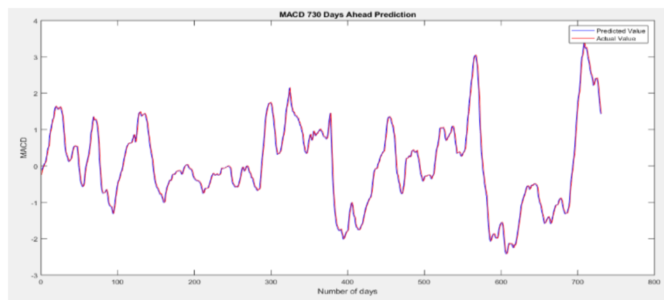

Figure 3: 730 days Ahead Prediction of MACD

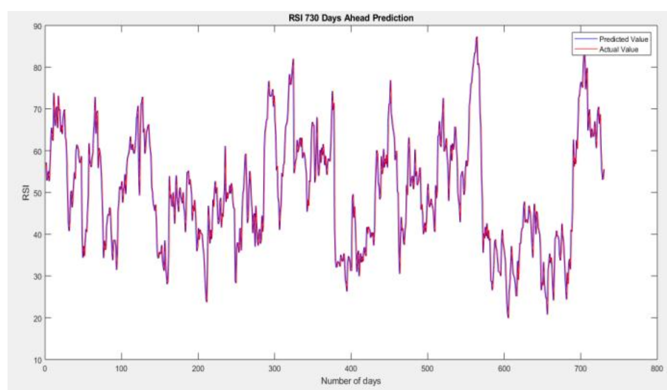

Figure 4: 730 days Ahead Prediction of RSI

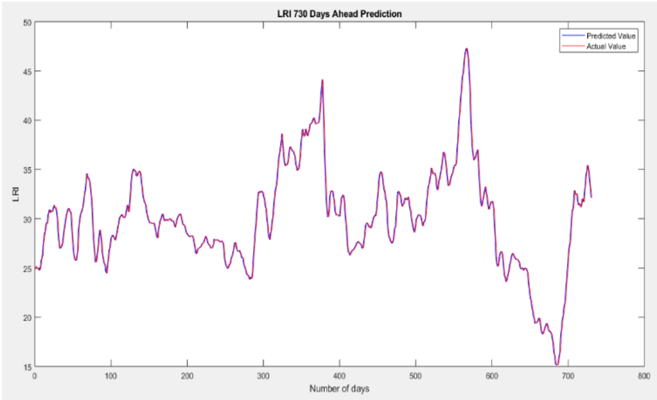

Figure 5: 730 days Ahead Prediction of LRI

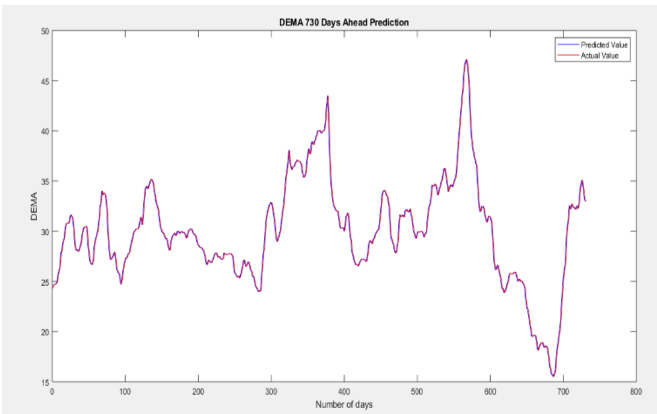

Figure 6: 730 days Ahead Prediction of DEMA

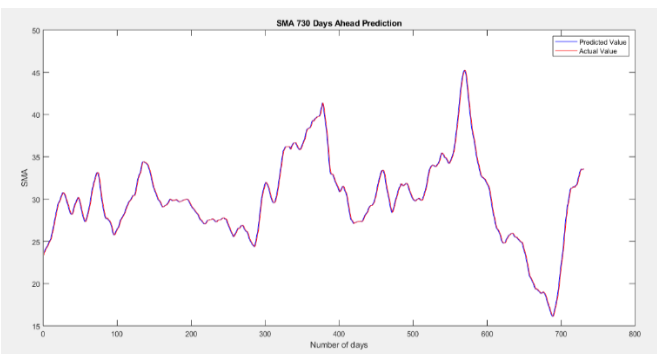

Figure 7: 730 days Ahead Prediction of SMA

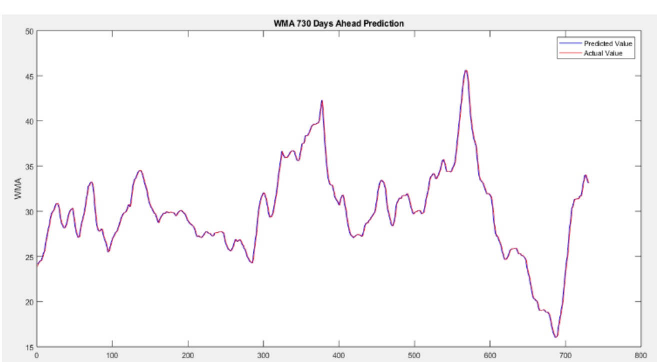

Figure 8: 730 days Ahead Prediction of WMA

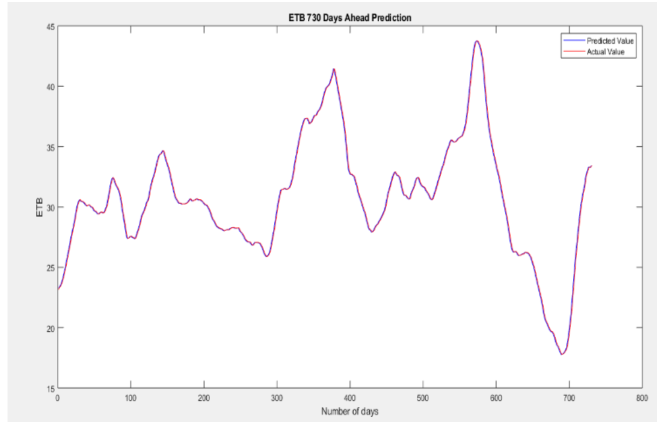

Figure 9: 730 days Ahead Prediction of ETB

B. Closing Price Prediction

In this section stock closing price are forecasted for 730 days ahead.

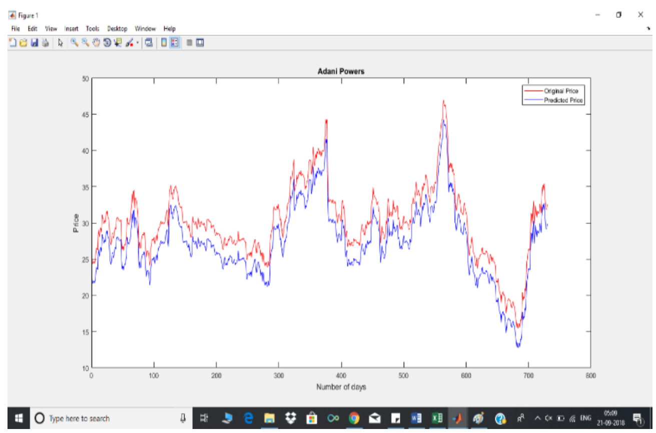

Figure 10: 730 days Ahead Price Prediction of Adani Powers

From figure 3-12 technical features are predicted on the basis of proposed algorithm for 30 days ahead, 60 days ahead, 180 days ahead and 365 days ahead respectively. Whereas figure 13 shows the closing price prediction of the Adani Powers using proposed algorithm and from result analysis it is shown that the proposed algorithm outperforms better.

C. Comparative Performance Evaluation

In this section, to make the performance of the proposed model more persuasive, the proposed forecasting model is analyzed for 730 days ahead and repeat the comparative experiments between ART-SVR and ART.

In table 3 Stock behavior is analyzed using 5 features selected by PSO algorithm. The table shows that 5 features selected was MACD, RSI, Momentum, CCI and DPO. These all features actually recommend to buy a stock. Similarly, ART-SVR algorithm predicts stock position to buy. Whereas only ART algorithm predicts sell position of the stock. This analysis concluded that ART-SVR algorithm correctly predicts the stock position.

Table 3: Stock Behavior using 5 Features

No. of Features					5 Features				
ACTUAL VALUE									
MACD	RSI	Momentum	CCI	LRI	DEMA	SMA	WMA	DPO	ETB
sell	buy	buy	buy	N/A	N/A	N/A	N/A	sell	N/A
ART-SVR VALUE									
MACD	RSI	Momentum	CCI	LRI	DEMA	SMA	WMA	DPO	ETB
sell	buy	buy	buy	N/A	N/A	N/A	N/A	sell	N/A
ART VALUE									
MACD	RSI	Momentum	CCI	LRI	DEMA	SMA	WMA	DPO	ETB
sell	buy	sell	sell	N/A	N/A	N/A	N/A	buy	N/A
Overall Actual Condition			ART-SVR Condition			ART Condition			
BUY			BUY			SELL			

Table 4: Stock Behavior using 7 Features

No. of Features					5 Features				
ACTUAL VALUE									
MACD	RSI	Momentum	CCI	LRI	DEMA	SMA	WMA	DPO	ETB
buy	sell	buy	sell	n/a	n/a	sell	sell	sell	n/a
ART-SVR VALUE									
MACD	RSI	Momentum	CCI	LRI	DEMA	SMA	WMA	DPO	ETB
Buy	Sell	Buy	Sell	N/A	N/A	Sell	Sell	Sell	N/A
ART VALUE									
MACD	RSI	Momentum	CCI	LRI	DEMA	SMA	WMA	DPO	ETB
Sell	Buy	Sell	Buy	N/A	N/A	Sell	Sell	buy	N/A
Overall Actual Condition			ART-SVR Condition			ART Condition			
SELL			SELL			SELL			

In table 4 Stock behavior is analyzed using 7 features selected by PSO algorithm. The table shows that 7 features selected was MACD, RSI, Momentum, CCI, SMA, WMA and DPO. These all features recommend the overall condition to be sell. Similarly, ART-SVR algorithm predicts stock position to sell. Whereas only ART algorithm predicts sell position of the stock but individual indicator predicts different stock position as actual condition. This analysis concluded that ART-SVR algorithm correctly predicts the stock position.

Table 5: Stock Behavior using 10 Features

No. of Features					5 Features				
ACTUAL VALUE									
MACD	RSI	Momentum	CCI	LRI	DEMA	SMA	WMA	DPO	ETB
buy	sell	buy	sell	sell	sell	sell	sell	sell	buy
ART-SVR VALUE									
MACD	RSI	Momentum	CCI	LRI	DEMA	SMA	WMA	DPO	ETB
buy	sell	buy	sell	sell	sell	sell	sell	sell	buy
ART VALUE									
MACD	RSI	Momentum	CCI	LRI	DEMA	SMA	WMA	DPO	ETB
sell	buy	sell	sell	sell	sell	sell	sell	buy	buy
Overall Actual Condition			ART-SVR Condition			ART Condition			
SELL			SELL			SELL			

In table 5 Stock behavior is analyzed using 10 features selected by PSO algorithm. The table shows that all 10 features selected was MACD, RSI, Momentum, CCI, LRI, DEMA, SMA, WMA,DPO and ETB. These all features recommend the overall condition to be sell. Similarly, ART-SVR algorithm predicts stock position to sell. Whereas only ART algorithm predicts sell position of the stock but individual indicator predicts different stock position as actual condition. This analysis concluded that ART-SVR algorithm correctly predicts the stock position.

V. CONCLUSION AND FUTURE SCOPE

As a result, in this study, the influence of various technical indicators on the prediction of share prices was assessed. From the machine learning point of view, each technical indicator was used by ART-SVR to forecast the daily closing prices of five highly represented companies.

This study examines the forecasts on equity price, which represent an interesting and important research in the fields of investment and application, as they can generate greater profits and lower returns through effective trading strategies. To make an accurate prediction, several methods have been tried, according to which the soft computing methods have attracted attention and have been developed.

In this research work, a hybridized framework composed of PSO, ART and SVR is proposed and applied this framework to forecast stock market price. An important characteristic of this method is that the ten technical indicators are selected and using PSO relevant features among them is taken intoaccount in the classification using ART and SVM. This method has been compared with SVR and NN.

The results have led to following main conclusions:

- Technical indicators such as Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), when used as isolated inputs of the ART-SVR, can improve the accuracy of the stock forecast as compared to classical SVR method or ART Algorithm.
- On the basis of price forecasting the proposed algorithm can suggest whether to buy or sell any stock.

The results obtained in this paper may contribute to users and applications that use stock closing prices forecasting in different ways: from users that combine such information with other parameters to define their strategy in the Financial Market to Decision Support Systems (DSS) that automatically generate recommendations to buy or sell stocks. These results may contribute to the development of more robust forecasting techniques for stock prices in the future. For future work, other correlation weighted methods are to be considered.

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