

Short-Term Financial Time Series Forecasting Integrating Principal Component Analysis and Independent Component Analysis with Support Vector Regression

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Abstract

Financial time series forecasting could be beneficial for individual as well as institutional investors. But, the high noise and complexity residing in the financial data make this job extremely challenging. Over the years, many researchers have used support vector regression (SVR) quite successfully to conquer this challenge. In this paper, an SVR based forecasting model is proposed which first uses the principal component analysis (PCA) to extract the low-dimensional and efficient feature information, and then uses the independent component analysis (ICA) to preprocess the extracted features to nullify the influence of noise in the features. Experiments were carried out based on 16 years' historical data of three prominent stocks from three different sectors listed in Dhaka Stock Exchange (DSE), Bangladesh. The predictions were made for 1 to 4 days in advance targeting the short term prediction. For comparison, the integration of PCA with SVR (PCA-SVR), ICA with SVR (ICA-SVR) and single SVR approaches were applied to evaluate the prediction accuracy of the proposed approach. Experimental results show that the proposed model (PCA-ICA-SVR) outperforms the PCA-SVR, ICA-SVR and single SVR methods.

Keywords

Financial Time Series, Forecasting, Support Vector Regression, Principal Component Analysis, Independent Component Analysis, Dhaka Stock Exchange

1. Introduction

The endeavor of financial time series forecasting has gained extreme attention

from both the individual and institutional investors because the accurate forecasting can influence the decision behind investment. This field is characterized by data intensity, noise, non-stationary, unstructured nature, high degree of uncertainty, and hidden relationships [1]. Capital market trend depends on many factors including political events, general economic conditions, news related to the stocks and traders' expectations. Moreover, according to academic investigations, movements in market prices are not random. Rather, they behave in a highly non-linear, dynamic manner [2]. Therefore, predicting stock market price is a quite challenging task.

Technical analysis is a popular approach to study the capital market patterns and movement. The results of technical analysis may be a short or long-term forecast based on recurring patterns; however, this approach assumes that stock prices move in trends, and that the information which affects prices enters the market over a finite period of time, not instantaneously [3]. Technical indicators used in this analysis are calculated from the historical trading data. Researchers use various machine learning and artificial intelligent approaches to analyze these technical indicators to predict future trends or prices. The traditional statistical models include Box Jenkins ARIMA [4]. Continuous research has introduced plentiful approaches including Artificial Neural Networks (ANN), genetic algorithm, rough set (RS) theory, fuzzy logic and others [5] [6]. Most of these approaches suffer from different problems like over-fitting or under-fitting, initializing large number of control parameters, finding the optimum solutions etc. To resolve most of these shortcomings, support vector regression (SVR) has been widely used in various nonlinear regression tasks. This is largely because; SVR uses the structural risk minimization principal for function estimation while the traditional methods implement empirical risk minimization principal. The successful application of SVR in various time series problems [7] [8] [9] has encouraged its adaptation in financial time series forecasting [10] [11] [12] [13].

The first important step in developing an SVR based forecasting model is feature extraction (transforming the original features into new ones) and feature selection (choosing the most influential set of features). Principal component analysis (PCA) is a widely applied feature extraction method in the framework of SVR [14] [15]. PCA transforms high-dimensional input vectors into uncorrelated principal components (PCs) by calculating the eigenvectors of the covariance matrix of original inputs. Again, the latent noise residing in financial time series data often leads to over-fitting or under-fitting and hence impairs the performance of the forecasting system. Lu *et al.* has proposed the use of independent component analysis (ICA) (both linear and non-linear) with SVR to negate the influence of such noise in data in order to improve the forecasting accuracy [16] [17]. In both approaches, at first ICA was used to extract the most influential components from the technical indicators and then were fed to SVR for better prediction purpose. ICA is a signal processing technique that was originally developed for blind source separation. It attempts to achieve statisti-

cally independent components (ICs) from the transformed vectors. Cao *et al.* has shown that both PCA and ICA can improve the performance of SVR in time series forecasting [18] which motivated this research work to adopt PCA and ICA with SVR for predicting future stock prices.

In this paper, an SVR based forecasting model is developed integrating both PCA and ICA to elevate the prediction accuracy for stock prices because even a small improvement of this performance can have a significant influence on investment decisions. Considering the fact that, technical analysis plays a vital role in the forecasting, it has been conducted to calculate technical indicators as the input features. Then PCA is used to extract the influential components from input features which are then filtered to transform the high-dimensional input into low-dimension features. After that, ICA is applied to convert the reduced features into independent components. The SVR then finally uses the filtered and transformed low-dimensional input variables to construct the forecasting model and predict stock prices for 1 to 4 days in advance. The predictive performance of the proposed approach is compared with three traditional approaches: the integration of PCA with SVR (PCA-SVR), ICA with SVR (ICA-SVR) and single SVR.

The remainder of this paper is organized into 6 sections. Section 2 provides a brief overview of the methodologies used in this study which includes PCA, ICA and SRV. Section 3 introduces the proposed method. Section 4 describes the research data. Section 5 reports the experimental results obtained from the study. Finally Section 6 contains the concluding remarks.

2. Methodology

2.1. Principal Component Analysis (PCA)

Principal component analysis (PCA), invented by Karl Pearson [19], is a well-known statistical procedure for feature extraction. It finds smaller number of uncorrelated components from high dimensional original inputs by calculating the eigenvectors of the covariance matrix. Given a set of m dimensional input vectors $\mathbf{x}_i = (x_i(1), x_i(2), \dots, x_i(m))^T$ where $i = 1, 2, \dots, n$. PCA is a transformation of \mathbf{x}_i into a new vector \mathbf{y}_i by:

$$\mathbf{y}_i = U^T \mathbf{x}_i \quad (1)$$

where U is the $m \times m$ orthogonal matrix whose j th column u_j is the j th eigenvector of the sample covariance matrix $C = \frac{1}{n} \sum_{i=1}^n x_i x_i^T$. In other words, PCA solves the eigenvalue problem of Equation (2).

$$\lambda_j u_j = C u_j, \quad j = 1, 2, \dots, m \quad (2)$$

where λ_j is one of the eigenvalues of C . u_j is the corresponding eigenvector. Based on the estimated u_j , the components of \mathbf{y}_i are calculated as the orthogonal transformation of \mathbf{x}_i :

$$\mathbf{y}_i(j) = \mathbf{u}_j^T \mathbf{x}_i, \quad j = 1, 2, \dots, m \quad (3)$$

The new components are called principal components. By using only the first several eigenvectors sorted in descending order of the eigenvalues, the number of principal components in \mathbf{y}_i can be reduced [20]. Thus, PCA can be used to reduce dimensions where the principal components are uncorrelated and have sequentially maximum variances.

2.2. Independent Component Analysis (ICA)

ICA is basically a signal processing technique that regains mutually independent but unknown source signals from their mixture without having any prior knowledge of the mixing mechanism. Let $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_m]^T$ be an $m \times n$ matrix which is a mixture of m source signals \mathbf{x}_i of size $1 \times n$, $i = 1, 2, \dots, m$. In basic ICA the above mixing model can be rewritten as [21]:

$$\mathbf{X} = \mathbf{A}\mathbf{S} = \sum_{i=1}^m \mathbf{a}_i \mathbf{s}_i \quad (4)$$

where \mathbf{a}_i is the i^{th} column of the $m \times m$ unknown mixing matrix \mathbf{A} and \mathbf{s}_i is the i^{th} row of the $m \times n$ source matrix \mathbf{S} . The goal of the ICA is to estimate the un-mixing matrix \mathbf{W} of size $m \times m$ that is used to transform the observed mixture signals \mathbf{X} to yield the independent signals \mathbf{Y} such that

$$\mathbf{Y} = [\mathbf{y}_i] = \mathbf{W}\mathbf{X} \quad (5)$$

where \mathbf{y}_i is the i^{th} row of the matrix \mathbf{Y} , $i = 1, 2, \dots, m$. The rows of \mathbf{Y} are called the independent components (ICs) and are required to be statistically as independent as possible. Here, statistically independence means that the joint probability density of the components of \mathbf{Y} is equal to the product of the marginal densities of the individual components. If the un-mixing matrix \mathbf{W} is the inverse of the original mixing matrix \mathbf{A} *i.e.* $\mathbf{W} = \mathbf{A}^{-1}$, the latent source signals (\mathbf{s}_i) can be estimated using the ICs (\mathbf{y}_i). For the identification of Equation (5), one fundamental requirement is that all the ICs, with the possible exception of one component, must be non-Gaussian.

Several algorithms have been developed to perform ICA modeling [22] [23] [24] [25] [26]. The FastICA algorithm proposed by [27] is adopted in this research work where the mutual information is used as criteria to estimate \mathbf{Y} . Minimizing mutual information between components implies maximizing their negentropy. The negentropy is always non-negative and is zero if and only if \mathbf{y} has a Gaussian distribution. In the FastICA algorithm, the approximation of the negentropy is using the following contrast function:

$$J_G(y) \approx [E\{G(y)\} - E\{G(v)\}]^2 \quad (6)$$

where v is a standardized Gaussian variable and G is a non-quadratic function. G is given by $G(y) = \exp(-y^2/2)$ in this study.

Two preprocessing steps are applied to the input matrix \mathbf{x} to simplify the FastICA algorithm, centering and whitening [27]. First, \mathbf{x} is made zero mean by subtracting its mean *i.e.* $\mathbf{x}_i \leftarrow (\mathbf{x}_i - E(\mathbf{x}_i))$. The second step is to whiten \mathbf{x} by

passing it through a whitening matrix V , i.e., $Z = VX$. The rows of the whitened variable Z , denoted by z , are uncorrelated and have unit variance, i.e., $E\{zz^T\} = I$.

2.3. Support Vector Regression (SVR)

The SVR extends the basic principles of Vapnik's support vector machines (SVM) [28] for classification by setting a margin of tolerance in approximation and up until the threshold ε , 0 error is considered. Given a training set $(x_i, y_i), i = 1, 2, \dots, n$, where the $x_i \in \mathbf{R}^m$ is the m -dimensional input vector and $y_i \in \mathbf{R}$ is the response variable. SVR generates the linear regression function in the form:

$$f(x, w) = w^T x + b \quad (7)$$

Vapnik's linear ε -Insensitivity loss (error) function is:

$$|y - f(x, w)|_\varepsilon = \begin{cases} 0, & \text{if } |y - f(x, w)| \leq \varepsilon \\ |y - f(x, w)| - \varepsilon, & \text{otherwise} \end{cases} \quad (8)$$

Based on this, linear regression $f(x, w)$ is estimated by simultaneously minimizing $\|w\|^2$ and the sum of the linear ε -Insensitivity losses as shown in Equation (10). The constant c controls a trade-off between an approximation error and the weight vector norm $\|w\|$, is a design parameter chosen by the user.

$$R = \frac{1}{2} \|w\|^2 + c \left(\sum_{i=1}^n |y - f(x, w)|_\varepsilon \right) \quad (9)$$

Minimizing the risk R is equivalent to minimizing the following risk under the constraints mentioned in Equations (11)-(13).

$$R = \frac{1}{2} \|w\|^2 + c \sum_{i=1}^n (\xi + \xi^*) \quad (10)$$

$$(w^T x_i + b) - y_i \leq \varepsilon + \xi_i \quad (11)$$

$$y_i - (w^T x_i + b) \leq \varepsilon + \xi_i^* \quad (12)$$

$$\xi_i, \xi_i^* \geq 0, i = 1, 2, \dots, m \quad (13)$$

Here, ξ_i and ξ_i^* are slack variables, one for exceeding the target value by more than ε and other for being more than ε below the target. As used in SVM, the above constrained optimization problem is solved using Lagrangian theory and the Karush-Kuhn-Tucker conditions to obtain the desired weight vector of the regression function.

SVR maps the input vectors $x_i \in \mathbf{R}^m$ into a high dimensional feature space $\phi(x_i) \in H$. A kernel function $K(x_i, x_j)$ performs the mapping $\phi(\cdot)$. The most popular kernel function that is used in this study is Radial Basis Function (RBF) as shown in Equation (14).

$$K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right) \quad (14)$$

where γ is the constant of the kernel function. The RBF kernel function parameter γ and regularization constant C are the design parameters of SVR.

3. Proposed PCA-ICA-SVR Forecasting Model

The three stage methodology named PCA-ICA-SVR proposed in this research scheme is depicted in **Figure 1**. In the first stage we used PCA to the input data to extract features which were then reduced into a low-dimensional feature space. Then ICA was applied to these reduced feature space to extract independent components. Finally, these independent components were used in the SVR for constructing the forecasting model.

First of all, technical analysis is conducted on the dataset and 29 technical indicators (TIs) are calculated that are being used by financial experts [3]. Some important technical indicators and their formulas are shown in **Table 1**. All values of these constructed features are scaled into the range of [0, 1] to eliminate the biasness towards larger value attributes. Then PCA is applied to the normalized data to extract the PCs containing the most influential information. These PCs are filtered according to the corresponding variance and thus the irrelevant features are discarded to construct a reduced feature space. The ICA model is then used in the low-dimensional data to estimate ICs containing the hidden and effective information of the prediction variables. Finally, the ICs are used as input variables to construct the SVR stock price forecasting model.

As mention in Section 2.3, the RBF kernel function is incorporated in this study because it is the most widely used and well performing kernel function for forecasting purpose. But the performance of SVR is highly influenced by the selection of the parameters: γ and C . A very popular method to select the best values of these parameters is the grid search approach with cross-validation [29]. This is a straightforward method of trying geometric sequences for the best (C ,

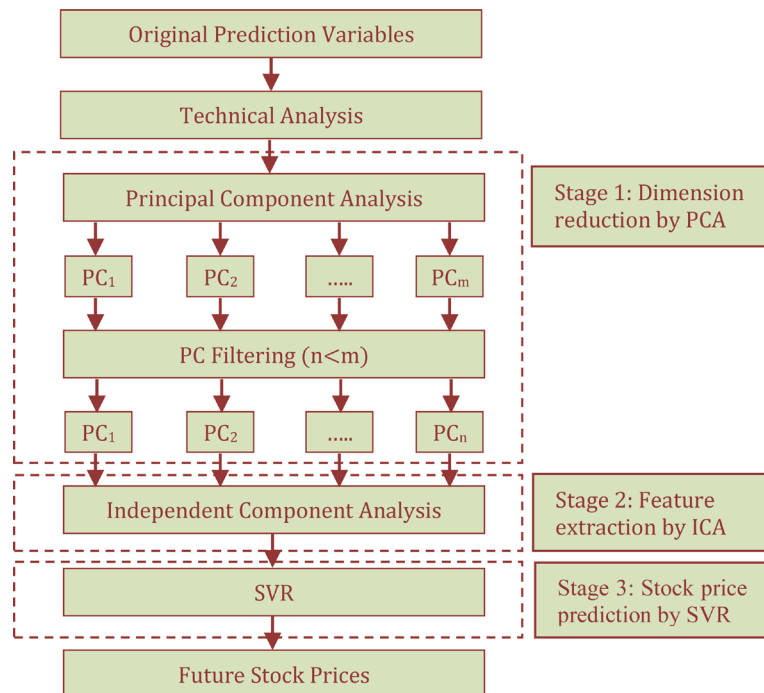


Figure 1. Proposed prediction framework.

Table 1. Important technical indicators and their formulas.

Feature	Description	Calculation Formula
10-day SMA	Simple 10-day moving average	$\left(\frac{1}{n}\right) \sum_{i=t-n+1}^t C_i$, where C_t is the closing price.
10-day EMA	Exponential 10-day moving average	$EMA(n)_{t-1} + \alpha \times (C_t - EMA(n)_{t-1})$, where α is a smoothing factor and $\alpha = \frac{2}{n+1}$
10-day WMA	Weighted 10-day moving average	$\frac{(n)C_t + (n-1)C_{t-1} + \dots + C_{t-n+1}}{n + (n-1) + \dots + 1}$
A/D Oscillator	Accumulation/distribution oscillator. It is a momentum indicator that relates changes in price.	$\frac{H_t - C_{t-1}}{H_t - L_t}$, where L_t is the low price and H_t is the high price at time t .
MACD	Moving Average Convergence/Divergence.	$MACD(n)_{t-1} + \frac{2}{n+1} \times (DIFF_t - MACD(n)_{t-1})$, where $DIFF_t = EMA(12)_t - EMA(26)_t$
Stochastic K%	Stochastic %K. It compares where a security's price closed relative to its price range over a given period.	$\frac{C_t - LL_{t-(n-1)}}{HH_{t-(n-1)} - LL_{t-(n-1)}} \times 100$, where LL_t and HH_t mean lowest low and highest high in the last t days, respectively
Stochastic D%	Stochastic %D. Moving average of %K.	$\frac{\sum_{i=0}^{n-1} K\%_{t-i}}{10}$
Momentum (close price)	It measures the amount that a security's price has changed over a given time span.	$C_t - C_{t-9}$
Larry William's R%	Larry William's R%. It is a momentum indicator that measures overbought/oversold levels.	$\frac{H_n - C_t}{H_n - L_n} \times 100$
Relative Strength Index (RSI)	Relative Strength Index. It is a price following an oscillator that ranges from 0 to 100.	$100 - \frac{100}{1 + \left(\frac{\sum_{i=0}^{n-1} Up_{t-i}/n}{\sum_{i=0}^{n-1} Dw_{t-i}/n}\right)}$, where Up_t means upward-price-change and Dw_t means downward-price-change at time t .
Close price ROC	Price rate-of-change. It is the difference between the current price and the price of n days ago.	$\frac{C_t - C_{t-n}}{C_{t-n}} \times 100$
CCI	Commodity Channel Index. It measures the variation of a security's price.	$\frac{(M_t - SM_t)}{(0.015D_t)}$, where $M_t = (H_t + L_t + C_t)/3$, $SM_t = \frac{\sum_{i=1}^n M_{t-i+1}}{n}$ and $D_t = \frac{\sum_{i=1}^n M_{t-i+1} - SM_t }{n}$
Disparity 5	5-day disparity. It is the distance of current two moving averages of a stock's price.	$\frac{C_t}{MA_5} \times 100$
Disparity 10	10-day disparity.	$\frac{C_t}{MA_{10}} \times 100$
OSCP	Price oscillator. It is the difference between two moving average of a stock's price.	$\frac{MA_5 - MA_{10}}{MA_5}$

γ) value pair. The (C, γ) value pair generating the minimum mean absolute percentage error (MAPE) is considered the best values for the parameters. The complete grid search is a time-consuming task. That's why a coarse grid is used at first which identifies a better region on the grid. Then a finer grid search is conducted on that region.

Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), relative Root Mean Squared Error (rRMSE) and Mean Squared Error (MSE) are used to evaluate the performance of the proposed model. Formulas of these evaluation measures are shown in Equations (15)-(18) [30]. These are the measures of deviation between actual and predicted prices. The smaller the values of these measures, the closer the predicted prices are to actual prices. They can be used to evaluate the predictive performance of any forecasting model.

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^n \frac{|A_t - F_t|}{|A_t|} \times 100 \quad (15)$$

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^n \frac{|A_t - F_t|}{|A_t|} \quad (16)$$

$$\text{rRMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^n \left(\frac{A_t - F_t}{A_t} \right)^2} \times 100 \quad (17)$$

$$\text{MSE} = \frac{1}{n} \sum_{t=1}^n (A_t - F_t)^2 \quad (18)$$

where A_t is the actual value, F_t represent the predicted value and n is the total number of data points.

4. Research Data

To conduct the study and evaluate the performance of the proposed approach, the 16 years' historical data of daily transaction for the time period from January 2000 to December 2015 are collected from Dhaka Stock Exchange, Bangladesh (<http://www.dsebd.org/>). This data covers 3600 trading days and each data comprises five attributes: open price, high price, low price, close price and trade volume. We have considered three companies from three different sectors: *Square Pharmaceuticals Limited*, *AB Bank Limited* and *Bangladesh Lamps Limited* as these are the most prominent stocks in DSE. The daily closing prices of these companies are shown in **Figures 2-4** respectively. The first one is a leading company in pharmaceuticals sector, the second leads the banking sector and the last one belongs to the engineering sector. 70% of the total sample points (around 2520 trading days) are used as the training sample and the remaining 30% of the total sample points (around 1080 trading days) are holdout to be used as the testing sample.

5. Experimental Results

The principal component analysis on the original data shows that the first 10

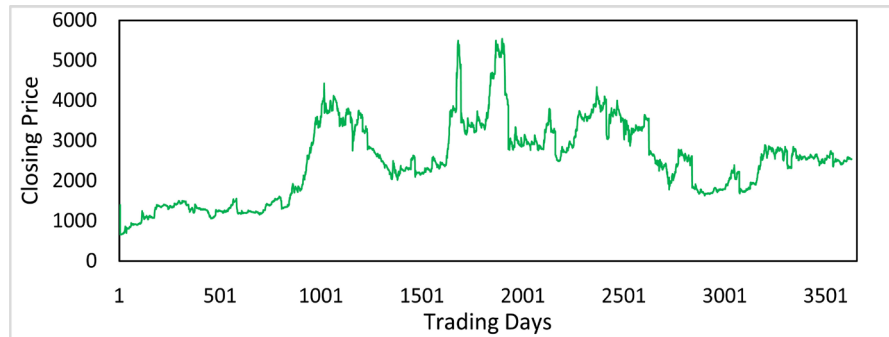


Figure 2. Closing prices of square pharmaceuticals limited.

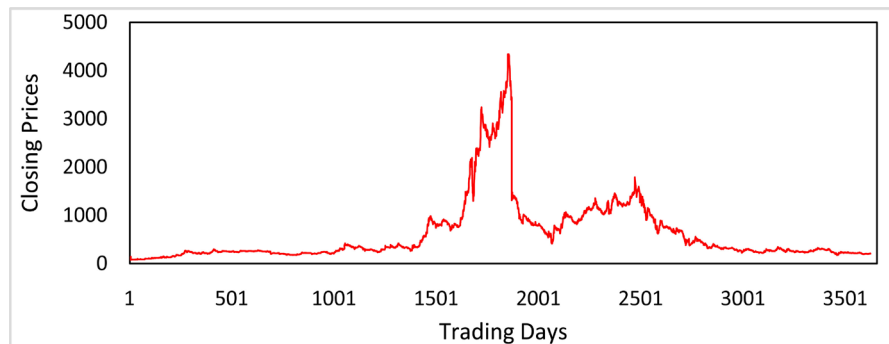


Figure 3. Closing prices of AB bank limited.

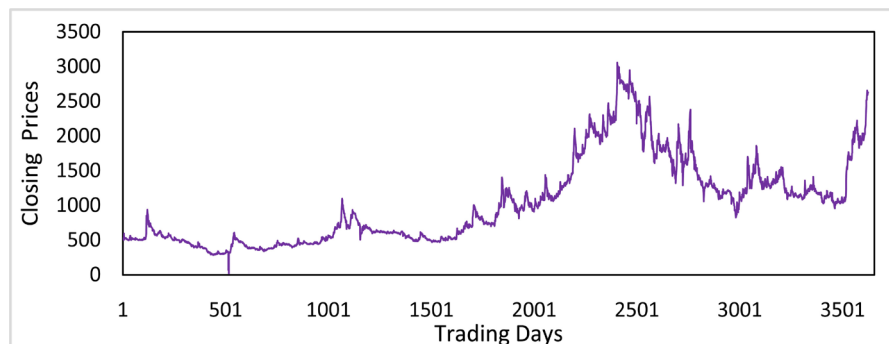


Figure 4. Closing prices of Bangladesh lamps limited.

components contribute over 98% cumulative covariance providing most information. **Figure 5** shows the cumulative covariance contribution of principal components for *AB Bank Limited* and the same results are obtained for other cases (not shown here). Hence the first 10 PCs are selected to form the low-dimensional input variables for all the three companies. Then ICA is applied on these 10 PCs and the estimated corresponding ICs are considered as the final input variables for SVR.

In this study, the radial basis function (RBF) is used as the kernel function of SVR. To find the best C and γ value pair we have considered e^{-5} to e^{10} for both parameters as our research space. For the data of *Square Pharmaceuticals Limited*, the coarse grid discovered the best (C, γ) as (e^9, e^3) with the 5-fold cross validation MAPE 2.23%. Then a finer grid search on the neighborhood of (e^9, e^3)

produced a better cross-validation MAPE of 1.66% at ($e^9, e^{2.8}$). After the best (C, γ) is found the whole training set is trained again to generate the final SVR model. The best value pairs for C and γ for every prediction task where minimum prediction error is exhibited by the grid search approach are shown in **Table 2**.

The forecasting results of the proposed PCA-ICA-SVR model are compared with single SVR model that uses all the original input variables, the PCA-SVR model where the filtered PCs are used as input variables by the SVR model and finally the ICA-SVR model where non-filtered ICs calculated from the original variables are used by the SVR model.

In all the cases, closing prices of the target stock are predicted for 1, 2, 3, and 4 days in advance. Prediction results for *Square Pharmaceuticals Limited* are listed in **Tables 3-6**. **Tables 7-10** illustrate the comparative results of price forecasting for *AB Bank Limited*. **Tables 11-14** compare the performance of price forecasting for *Bangladesh Lamps Limited*.

It is evident from all the results that, the proposed PCA-ICA-SVR model has produced lower MAPE (%), MAE, MSE and rRMSE (%) for all three target stocks. The integration of PCA and ICA improves the performance of SVR in most of the cases but the proposed PCA-ICA-SVR model outperforms other

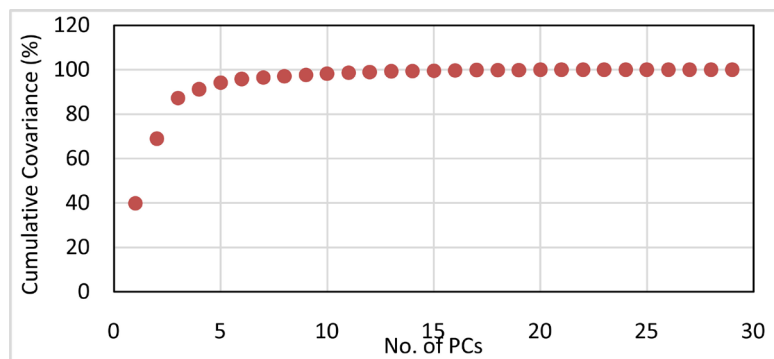


Figure 5. Cumulative covariance of PCs for AB bank limited.

Table 2. Grid search results for RBF kernel parameters.

Parameter	Square Pharmaceuticals Ltd.	AB Bank Ltd.	Bangladesh Lamps Limited.
C	$e^{9.0}$	$e^{8.4}$	$e^{5.8}$
γ	$e^{2.8}$	$e^{2.0}$	$e^{2.4}$

Table 3. Prediction performance for 1 day ahead of Square Pharmaceuticals Limited.

Prediction models	Performance measures			
	MAPE (%)	MAE	MSE	rRMSE (%)
PCA-ICA-SVR	1.70	0.0170	3573.58	14.70
PCA-SVR	1.95	0.0195	3947.96	23.11
ICA-SVR	2.23	0.0223	5801.64	28.98
Single SVR	1.98	0.0198	3864.83	33.97

Table 4. Prediction performance for 2 days ahead of Square Pharmaceuticals Limited.

Prediction models	Performance measures			
	MAPE (%)	MAE	MSE	rRMSE (%)
PCA-ICA-SVR	2.12	0.0212	6865.01	18.04
PCA-SVR	2.34	0.0234	7436.84	30.78
ICA-SVR	2.68	0.0268	8479.62	37.70
Single SVR	2.46	0.0246	7388.21	41.60

Table 5. Prediction performance for 3 days ahead of Square Pharmaceuticals Limited.

Prediction models	Performance measures			
	MAPE (%)	MAE	MSE	rRMSE (%)
PCA-ICA-SVR	2.55	0.0255	11,435.36	19.42
PCA-SVR	2.81	0.0281	12,358.35	36.03
ICA-SVR	3.04	0.0304	13,575.35	35.82
Single SVR	2.95	0.0295	12,331.95	47.27

Table 6. Prediction performance for 4 days ahead of Square Pharmaceuticals Limited.

Prediction models	Performance measures			
	MAPE (%)	MAE	MSE	rRMSE (%)
PCA-ICA-SVR	3.05	0.0305	16,161.23	23.63
PCA-SVR	3.28	0.0328	17,345.36	38.74
ICA-SVR	3.36	0.0336	17,246.75	24.18
Single SVR	3.32	0.0332	17,097.40	43.15

Table 7. Prediction performance for 1 day ahead of AB Bank Limited.

Prediction models	Performance measures			
	MAPE (%)	MAE	MSE	rRMSE (%)
PCA-ICA-SVR	4.66	0.0466	900.50	20.16
PCA-SVR	6.22	0.0622	1737.34	58.53
ICA-SVR	5.46	0.0546	1530.14	74.01
Single SVR	5.67	0.0567	1474.24	64.36

Table 8. Prediction performance for 2 days ahead of AB Bank Limited.

Prediction models	Performance measures			
	MAPE (%)	MAE	MSE	rRMSE (%)
PCA-ICA-SVR	5.30	0.0530	1822.75	11.66
PCA-SVR	6.65	0.0665	2740.14	21.76
ICA-SVR	6.26	0.0626	2403.27	59.42
Single SVR	6.19	0.0619	1474.24	64.36

Table 9. Prediction performance for 3 days ahead of AB Bank Limited.

Prediction models	Performance measures			
	MAPE (%)	MAE	MSE	rRMSE (%)
PCA-ICA-SVR	5.84	0.0584	5638.42	22.06
PCA-SVR	7.57	0.0757	7666.62	76.42
ICA-SVR	6.32	0.0632	6302.39	87.78
Single SVR	6.91	0.0691	7177.64	67.57

Table 10. Prediction performance for 4 days ahead of AB Bank Limited.

Prediction models	Performance measures			
	MAPE (%)	MAE	MSE	rRMSE (%)
PCA-ICA-SVR	6.10	0.0610	8907.89	17.50
PCA-SVR	8.00	0.0800	12,200.47	56.22
ICA-SVR	6.67	0.0667	9155.54	78.69
Single SVR	7.44	0.0744	11,675.15	52.66

Table 11. Prediction performance for 1 day ahead of Bangladesh Lamps Limited.

Prediction models	Performance measures			
	MAPE (%)	MAE	MSE	rRMSE (%)
PCA-ICA-SVR	3.35	0.0335	1680.07	43.68
PCA-SVR	3.69	0.0369	2055.00	57.15
ICA-SVR	4.05	0.0405	1922.19	83.90
Single SVR	3.70	0.0370	2043.94	61.46

Table 12. Prediction performance for 2 days ahead of Bangladesh Lamps Limited.

Prediction models	Performance measures			
	MAPE (%)	MAE	MSE	rRMSE (%)
PCA-ICA-SVR	4.52	0.0452	3284.34	62.25
PCA-SVR	4.68	0.0468	3803.27	71.93
ICA-SVR	5.06	0.0506	3319.44	93.45
Single SVR	4.81	0.0481	3859.30	81.16

Table 13. Prediction performance for 3 days ahead of Bangladesh Lamps Limited.

Prediction models	Performance measures			
	MAPE (%)	MAE	MSE	rRMSE (%)
PCA-ICA-SVR	4.66	0.0466	5033.45	46.49
PCA-SVR	4.91	0.0491	5707.75	58.84
ICA-SVR	5.05	0.0505	5006.75	67.41
Single SVR	4.94	0.0494	5668.56	61.32

Table 14. Prediction performance for 4 days ahead of Bangladesh Lamps Limited.

Prediction models	Performance measures			
	MAPE (%)	MAE	MSE	rRMSE (%)
PCA-ICA-SVR	6.77	0.0677	6596.20	96.67
PCA-SVR	6.89	0.0689	7712.17	108.01
ICA-SVR	7.16	0.0716	6852.73	117.38
Single SVR	6.89	0.0689	7619.66	110.77

three compared methods. This corroborates that the proposed PCA-ICA-SVR approach can generate lower prediction errors than other three compared approaches. Again, it could be noticed from the results that, the forecasting performance of all the approaches decreases as the predictions are made for more and more number of days in advance, which may be obvious for any prediction system.

The robustness of the proposed PCA-ICA-SVR method is evaluated by comparing its performance with PCA-SVR, ICA-SVR and single SVR methods using different ratios of training and testing sample sizes. The performance is compared in terms of MAPE (%) and rRMSE (%) with four relative ratios, 60%, 70%, 80%, and 90% of training sample size with respect to the complete dataset size. Predictions are made for the closing price of the target stock for next trading day. **Table 15** summarizes the prediction results for *Square Pharmaceuticals Limited*, *AB Bank Limited* and *Bangladesh Lamps Limited*. Based on the findings in **Table 15**, we can discover that the proposed PCA-ICA-SVR method outperforms other three methods under all four different relative ratios for all three target stocks. It therefore concludes that PCA-ICA-SVR approach clearly produces less forecasting error than other three approaches. This demonstrates the effectiveness of our proposal.

6. Conclusions

This paper proposes a price forecasting model integrating PCA and ICA with SVR for financial time series. This PCA-ICA-SVR model first uses the PCA to extract the most influential components from the input features in order to overcome the over-fitting or under-fitting challenge caused by the noisy nature of financial time series data. The filtered PCs are then processed by ICA to estimate ICs which are finally used in SVR with RBF kernel function as input variables. The grid search for the best kernel parameters is conducted to improve SVR's performance. The experiments have evaluated 16 years' data for three commencing stocks from Dhaka Stock Exchange, Bangladesh. The performance of proposed model is compared with PCA-SVR, ICA-SVR and single SVR for short time durations (1 to 4 days) in terms of prediction error. Experiment results show that the proposed PCA-ICA-SVR model outperforms all three other methods by generating less predictive errors. The empirical results can conclude that the PCA and ICA, working together, can successfully unfold the influential

Table 15. Robustness evaluation of PCA-ICA-SVR, ICA-SVR, PCA-SVR and single SVR with different relative ratios for Square Pharmaceuticals Limited, AB Bank Limited and Bangladesh Lamps Limited.

Relative Ratio (%)	Models	<i>Square Pharmaceuticals Limited</i>		<i>AB Bank Limited</i>		<i>Bangladesh Lamps Limited</i>	
		Testing MAPE (%)	Testing rRMSE (%)	Testing MAPE (%)	Testing rRMSE (%)	Testing MAPE (%)	Testing rRMSE (%)
60	PCA-ICA-SVR	1.85	18.82	4.89	6.37	3.40	18.61
	ICA-SVR	2.47	30.11	6.03	98.82	3.80	80.78
	PCA-SVR	2.18	40.26	6.31	19.08	3.84	47.00
	Single SVR	2.16	43.84	5.98	43.85	3.86	70.36
70	PCA-ICA-SVR	1.70	14.70	4.66	20.16	3.35	43.68
	ICA-SVR	2.23	28.98	5.46	74.01	4.05	83.90
	PCA-SVR	1.95	23.11	6.22	58.53	3.69	57.15
	Single SVR	1.98	33.97	5.67	64.36	3.70	61.46
80	PCA-ICA-SVR	1.71	12.39	4.91	8.09	3.40	3.15
	ICA-SVR	2.24	20.47	5.31	59.13	3.74	60.91
	PCA-SVR	1.99	20.59	6.40	10.37	3.75	22.60
	Single SVR	2.07	31.60	5.31	27.02	3.59	34.10
90	PCA-ICA-SVR	2.04	5.08	5.17	1.59	3.28	8.88
	ICA-SVR	2.62	16.39	5.96	50.03	3.56	42.74
	PCA-SVR	2.13	12.25	6.57	4.59	3.71	17.08
	Single SVR	2.19	19.31	5.77	26.61	3.70	35.25

information from the original data and uplift the performance of SVR in stock price forecasting. As the proposed model helps to predict stock prices with less error, investors can use this to gain more profit or obtain less loss in stock market. Again, this proposed approach can also be used in other domains like weather forecasting, energy consumption forecasting or GDP forecasting.

Future research may integrate Kernel PCA, non-linear ICA and other signal processing techniques like wavelet transformation with SVR to further enhance the forecasting performance. This study mainly focuses on short-term price prediction. Its applicability might be investigated for long-term forecasting in future and appropriate methods could be integrated to enhance performance in future. However, only the price related historical data is used here to predict future prices. But, it is well known that various other aspects like general economic conditions, government policies, company performance, investor's interest etc. also play vital roles in stock market. In future, these aspects can also be incorporated as input features for prediction which may buttress the accurate prediction.

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Nomenclature

ANN	Artificial neural networks
ARIMA	Autoregressive integrated moving average
CCI	Commodity channel index
DSE	Dhaka stock exchange
EMA	Exponential moving average
GDP	Gross domestic product
ICA	Independent component analysis
IC	Independent component
MACD	Moving average convergence/divergence
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MSE	Mean squared error
PCA	Principal component analysis
PC	Principal component
RBF	Radial basis function
ROC	Rate-of-change
rRMSE	Relative root mean squared error
RS	Rough set
RSI	Relative strength index
SMA	Simple moving average
SVM	Support vector machine
SVR	Support vector regression
WMA	Weighted moving average