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Presenting an Intelligent Stock Price Prediction Model based on Deep Learning in Tehran Stock Exchange Market*

Shohreh Zokaei[1], Mohammad reza Sanaei[2†], Akbar Mirzapour Babajan[3]

[1]PhD student of Information Technology Management, Department of Information Technology Management, Faculty of Management and Accounting, Qazvin Branch, Islamic Azad University, Qazvin, Iran

[2]Assistant professor,Department of Information Technology Management, Faculty of Management and Accounting, Qazvin Branch, Islamic Azad University, Qazvin, Iran

[3]Assistant professor,Department Economics, Faculty of Management and Accounting, Qazvin Branch, Islamic Azad University, Qazvin, Iran

Abstract

Forecasting stock prices and returns is one of the most complicated and controversial topics in financial markets. Stock market is constantly influenced by the state of the national economy, investors' perceptions, and political events. Furthermore, the price series is highly non-linear and unstable. Ongoing research and updates in economic and stock market theories have gradually revealed the components necessary for predicting stock price indices, making accurate predictions possible. This research aims to develop an intelligent stock price prediction model based on deep learning for the Tehran Stock Exchange market. This model incorporates dimensionality reduction techniques to manage the capital portfolio, thereby increasing returns and reducing investment risks. The data from 2020 to 2023 were sourced from the Kodal system and were coded and analyzed using the RISP method and the Python programming language. A combination of LSTM, PCA, GRP, and SVD algorithms was used for the proposed model. A comparison of dimensionality reduction methods with artificial intelligence techniques shows that the PCA dimensionality reduction method can enhance the performance of deep learning compared to other data dimensionality reduction methods.

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† Corresponding author
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1.Introduction

Stock market represents a collective approach to buying and selling various instruments, either publicly or privately (Thakkar, 2021). The primary motivation for investing in the stock market is to realize profits, which requires accurate information about market changes and stock trends. Consequently, investors need powerful and reliable tools for predicting stock prices (Jiang, 2021). Financial market forecasting is critical for stock market investment and risk management. Many academic efforts have been devoted to discovering new methods and predictive indicators to enhance performance (Chenyao Ma, 2022). Capital market activists and researchers employ various methods to predict prices and are continually seeking new models and algorithms that can be used more reliably by addressing the shortcomings of previous models (Kehinde et al., 2023).

In recent years, intelligent financial forecasting has emerged as a promising direction for financial industry development, significantly enhancing the efficiency of financial risk management and related decision analysis (Niu et al., 2020). However, the randomness and volatility of the stock market complicate the understanding of price changes, making effective and timely regulation by the government challenging (Liu & Long, 2020). Financial stock markets generate vast amounts of daily stock price data, prompting scholars and stakeholders to focus on using existing datasets to learn and master the rules of stock price prediction (Kanwal, 2022). It is crucial to consider the variety of variables that can be used for prediction. Raw price data, technical indicators derived from historical data, other markets related to the target market, exchange rates, oil prices, and many other variables can aid market forecasting. Unfortunately, aggregating such diverse information for use by an automated market prediction algorithm is not straightforward, and given the complex, non-linear, and noisy behavior of stock markets, extracting meaningful and deep predictive features is a significant challenge.

Deep learning appears to be a promising approach in this regard (Hoseinzadeh, 2019). Although classical machine learning methods have shown positive performance in stock price prediction, their ability to process information at a deeper general level needs further improvement (Niu et al., 2020). Recent studies have demonstrated that deep learning predictive models produce more accurate results compared to traditional machine learning models in the financial market. Deep learning involves a series of algorithms that process multiple layers of information, especially non-linear information, to extract the most suitable features from raw input. Moreover, the stock market is a very complex, non-linear, and chaotic system influenced by political, economic, and psychological conditions. For this reason, analyzing such a system appears daunting, and over time, researchers have recognized that traditional methods cannot adequately analyze a dynamic and complex system, leading them to adopt intelligent methods. A high number of input variables usually increases complexity and consequently reduces the model's efficiency. Therefore, employing input dimensionality reduction techniques may help increase the algorithm's accuracy. The problem of unwanted increase in dimensions—caused by measurement stabilization and data recording—has existed historically but has recently gained prominence with the data surge. Addressing all factors not only causes technical issues, but also adds to model complexity and increases statistical errors. Hence, it is preferable to employ different dimension reduction techniques to mitigate these errors and achieve better outcomes.

In this research, we aim to evaluate the accuracy of each combination and ultimately determine the most accurate combination of deep learning algorithms and dimension reduction methods to achieve the highest level of accuracy in predicting stock prices on a future day.

2.Literature Review

Forecasting is a vital issue in global stock market. Typically, stock market forecasting involves accurate predictions of stock trends and prices to increase trading profits. Due to the non-linearity and volatility of the stock market, achieving accurate forecasts is a challenging process (John and Lata, 2023). Over time, researchers have realized that traditional methods cannot adequately analyze dynamic and complex systems, thus shifting towards the use of intelligent methods (Sharif Far et al., 2001). Some theorists assert that future stock prices can be predicted based on historical data (Malkiel and Fama, 1970). However, accurately predicting time series, especially multivariate financial time series, remains challenging due to factors such as the inherent randomness of time series (New et al., 2020). In one study (Sharif Far et al., 1401), a combination of CNN and LSTM deep learning algorithms was used. Only was the PCA dimensionality reduction technique employed. The results of this study show that this combined algorithm performs better than the RNN algorithm.

Another study (Beheshti et al., 1401) presented a method for forecasting future stock prices using a deep neural network structure, incorporating price data, a set of technical indicators, and news headlines as inputs. Three networks—SVM, MLP, and RNN—were used to evaluate the model. The results indicate that the LSTM model, using news and financial data, achieved the highest forecasting accuracy and outperformed SVM, MLP, and RNN neural networks. In the research (Khalili et al., 1400), the architectural ability of the Short-term Persistent Memory (LSTM) algorithm was examined for stock price prediction. Additionally, real and legal shareholder transactions were identified and studied as influencing factors on stock prices. The research utilized data from three groups—prices, technical indicators, and transactions of real and legal shareholders. The results show superior performance of the LSTM architecture with Dropout compared to its simpler model and the RNN model. This study also noted the absence of dimension reduction techniques. Babajani et al. (2018) utilized a hybrid approach with a recurrent neural network based on the artificial bee colony algorithm (ABC-RNN) to predict stock prices in Tehran Stock Exchange. By using data from stocks traded from 2013 to the end of 2014 and applying a step-by-step regression-correlation process (SRCS), key components influencing stock prices were identified and used as model inputs. The ABC algorithm was then applied in a parametric design space to optimize the network's weights and biases. The results show that the optimized neural network with the artificial bee colony algorithm achieved considerable accuracy compared to other forecasting methods. Dimension reduction techniques were not used in this research either. Shushterian et al. (2017) designed and applied a model to accurately predict the price of precious metals over time. Both LSTM and RNN methods were used. Various modelings were done on the data, and the results were examined under different conditions and time series in Python. The research showed that the RNN method performed better than the LSTM method. Dimension reduction techniques were not used in this study.

Song et al. (2023) concluded that the accuracy of the predictor is closely linked to the reduction of its dimensions. Zheng et al. (2021) presented a hybrid forecasting model combining principal component analysis (PCA) and recurrent neural networks (RNN), where the stock prices of two types of aerospace industry (manufacturer and operator) were examined. The results show that PCA can improve the accuracy and efficiency of prediction. Other reviewed studies are summarized below in table 1:

Table 1: summary of the articles reviewed

Authors	Methods	Results
Zhang, L., Ding, X., Hou, R., Tao, Y. (2019)	Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN)	30% increase in generalizability of results (decreased error standard deviation)
Merello, S., Ratto, A. P., Oneto, L., Cambria, E. (2019)	Genetic Algorithm, Deep Neural Networks (LSTM)	Improved performance of the prediction model through parameter optimization
Miao, R., Zhang, X., Yan, H., Chen, C. (2019)	Transfer Learning Algorithm	Enhanced market psychology learning through the transfer learning algorithm
Nguyen, T. T., &Yoon, S. (2019)	Short-term and Long-term Neural Networks, CNN, Adversarial Competition	The deep hybrid model shows lower error rates than basic machine learning models
Wu, J. L., Yang, C. S. Liu, K. H.., Huang, M. T. (2019	CNN, RNN, LSTM	Successful development of a recommender system using deep learning and hybrid models
Sinaga, F. M., Jonas, M., Felix, Halim, A. (2019)	Principal Component Analysis (PCA), Support Vector Machine (SVM) Regression, Particle Swarm Metaheuristic Algorithm	Hybrid model achieved a prediction error of 0.65%, significantly low in stock price prediction
Long, W., Lu, Z., & Cui, L. (2019)	Kernel-based PCA, SVM Regression	Absolute superiority of the kernel-based component analysis in feature engineering for stock prices

Chandar, (2019)	ARIMA, Mushroom (non-linear time series models)	Hybrid model performs better than individual models separately
Singh, S., Ahmad, M., Bhattacharya, A., Azhagiri, M. (2019)	SVM Regression, Metaheuristic Firefly Model	Optimization of model parameters leads to increased accuracy
Xu, Y., Yang, C., Peng, S., & Nojima, Y. (2020)	Balanced Search Algorithm, Bayesian Deep Belief Networks	Hybrid model demonstrates superiority over reference models
Liu, H., & Long, Z. (2020)	Transfer Learning Algorithm	Transfer learning with algorithm-based weighting logic reduces risks in stock trading decisions
Chen, X., Rajan, D., Quek, C. (2020)	Reinforcement Learning, Graph Theory, Transfer Learning	This hybrid model provides a framework for building a recommendation system
Zhang, Y., Yan, B., Aasma, M. (2020)	Transfer Learning, LSTM	Significant improvement in forecasting accuracy for stocks with irregular behavior
Pang, X., Zhou, Y., Wang, P., Lin, W., & Chang, V. (2020)	Hierarchical Attention Networks	Algorithm leads to accurate predictions, increasing emotional responsiveness
Chung, H., & Shik Shin, K. (2020)	Hybrid Model: SVM, Nearest Neighbor Algorithm, Self-Organized Maps	High accuracy in identifying stock trends (rising or falling)
Cardoso, T. N. C., Silva, R. M., Canuto, S., Moro, M. M., Gonçalves, M. A. (2017)	MFNN Deep Algorithm, LSTM	Feature engineering approach increased value of shares in transactions
Gal, Y., & Ghahramani, Z. (2016)	Chi-means Clustering, SVM, Random Forests	Hybrid approach shows less error compared to similar and reference models
Hazewinkel, M. (2013)	Wavelet Transforms, Deep Learning (LSTM)	Improved model performance in outlier detection enhances generalizability in stock price forecasting
He, G., Li, Y., & Zhao, W. (2017)	Humbershein-Wiener Fuzzy Network	Hybrid model effectively predicts and models dynamic shifts in data
Bauckhage,C., Kersting, K., Hadiji, F. (2013)	Deep Convolutional Neural Networks, LSTM	Model identifies similar behaviors over time, predicting stock price turning points
Hensman, P., Masko, D., He, K., Zhang, X., Ren, Sh., Sun, J. (2015/2016)	PCA, Time Series Decomposition with CEEMD Algorithm	Increased accuracy in forecasting by decomposing time series into seasonal, trend, and random factors
Käding, C., Rodner, E., Freytag, A., Denzler, J. (2016)	Genetic Algorithm, Deep Convolutional Neural Networks	High accuracy in deep algorithms contingent on effective parameter optimization
Sheeba, L., Gupta, S., Ragavender, N., Anirudh R. M., Divya, D. (2021)	Prophet Approach	Requires time-based data for accurate forecasting

3.Research Methodology

The type of study in this research is descriptive and involves modeling. In the modeling phase, the approach used is the CRISP-DM approach, which includes the following steps:

Step 1: Understanding the Business Nature. This step involves gaining an understanding of the stock's nature, behaviors, and interactions between different market participants. Step 2: Data Recognition. After selecting the desired stock market, the data is examined from various perspectives such as cleanliness, presence of outliers, common behaviors, and existing primary patterns. Step 3: Data Preparation. Most of the selected raw data are not suitable for analysis, so some missing data should be filled using an appropriate strategy. Transformations and normalization are performed as needed, and new features, such as holidays, may be added. This step is crucial for achieving high precision in the results. Step 4: Modeling. At this stage, the initial modeling of the deep learning hybrid model is designed and implemented alongside the transfer learning model. Step 5: Evaluation. Models are evaluated based on metrics such as accuracy and generalizability to select the best model. Step 6: Deployment. After selecting the best model, it is embedded into a system as an automated structure for regular prediction processes. This system is presented in the form of a recommender system.

In addition to library research, the data for modeling was obtained through embedded electronic portals. Existing databases from stock exchange data portals (both domestic and international) are utilized for data collection. Python programming software is used for data analysis, model creation, and building the recommender system.

Mathematical Model of Research: This research aims to use a combination of deep learning algorithms suitable for financial time series, such as LSTM, with dimensionality reduction techniques including PCA, SVD, and GRP, to provide a stock price prediction model. Dimensionality reduction techniques are employed to eliminate irrelevant and redundant features from the dataset, significantly enhancing the efficiency of deep learning models.

Statistical Population, Sampling Method, and Sample Size: The study seeks to develop an intelligent model for predicting stock prices in Tehran Stock Exchange, utilizing dimensionality reduction techniques for portfolio management. The statistical population includes the daily time series of stock prices accepted on the exchange, with data collected from the beginning of 2018 to the first half of 2021 through the website of the Tehran Stock Exchange Technology Management Company.

4.Descriptive Statistics

Data collection includes initial price, final price, highest price, lowest price, rate of change, and percentage change of the total price index of Tehran Stock Exchange from the year 2018 until February 2023. This data was collected daily and cumulatively comprising 1,110 observations over approximately 1,800 days. Data for 36 days related to the percentage change variable were removed from the sample due to inconsistencies.

Table 2 presents a summary of the daily data conditions. Additionally, Figure 1 displays a chart showing the price changes over the specified period.

Table 2: Data Collection Specifications

Statistic	Starting Price	Final Price	Highest Price	Lowest Price	Rate of Change	Percentage Change
Average	1,242,474	1,236,630	1,249,643	1,243,475	13,384	0%
Standard Deviation	594,797	591,893	597,444	594,426	16,029	0%
First Quartile	938,709	929,230	949,607	943,122	2,521	0%
Median	1,355,466	1,344,945	1,361,572	1,355,296	7,619	0%
Third Quartile	1,547,076	1,540,182	1,552,784	1,545,974	18,395	0%
Maximum	2,535,237	2,527,546	2,548,227	2,535,237	132,908	0%
Minimum	178,788	178,743	179,194	179,194	0	0%
Skewness	-0.308655	-0.308039	-0.311898	-0.311044	2.303427	1.303537
Kurtosis	-0.672152	-0.671825	-0.671240	-0.670765	7.786422	1.345245
Number of Data Points	1110	1110	1110	1110	1110	1110

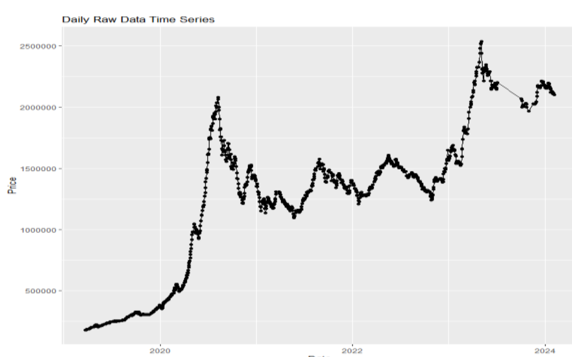


Figure 1: Daily chart of the time series price of the price index of the Tehran Stock Exchange

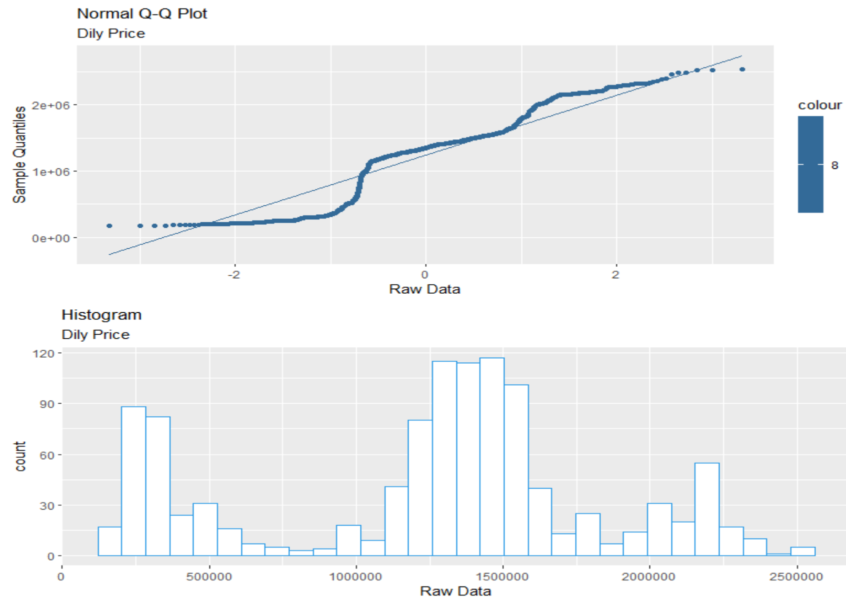


Figure 2: Normality QQ chart and average daily price histogram

5.Results

In this part, we will present the results of the forecasting models and evaluate the accuracy of each model. We employed three-dimension reduction methods—PCA, SVD, and GRP—along with LSTM deep learning neural networks. The optimization of hyperparameters for each model was conducted using training data, and the final validation was performed on test data to assess the accuracy of each model against the benchmark algorithms.

Analysis of Dimension Reduction Results

Principal Component Analysis (PCA)

There may be a correlation between various technical indicators that influence stock prices. In this study, the Python programming language is utilized to perform principal component analysis on six technical indicators: opening price, high price, low price, final price, rate of change, and percentage change. The results of the breakdown and analysis are displayed in Table 3. According to the estimates, approximately 69.44 percent of the data variability is accounted for by the first component. Additionally, about 29.3% of the variability is explained by the second component. Therefore, roughly 98.67% of the data dispersion is captured by the first two components. The number of principal components selected was based on achieving a cumulative explained variance of at least 85%, leading to the extraction and utilization of two main components for stock price prediction. Figure 3 illustrates the principal component analysis of the dataset.

Table 3: Results of Principal Component Analysis

Component	Eigenvalue	Percentage of Variance	Cumulative Percentage	Eigenvalue	Percentage of Variance	Cumulative Percentage
First Component	4.17	69.44%	69.44%	4.17	69.44%	69.44%
Second Component	1.75	29.23%	98.67%	1.75	29.23%	98.67%
Third Component				0.08	1.32%	99.99%
Fourth Component				0.00	0.01%	100.00%
Fifth Component				0.00	0.00%	100.00%
Sixth Component				0.00	0.00%	100.00%

This section clearly articulates the methodological approach and the analytical outcomes derived from the application of dimensionality reduction techniques and deep learning models in forecasting stock prices.

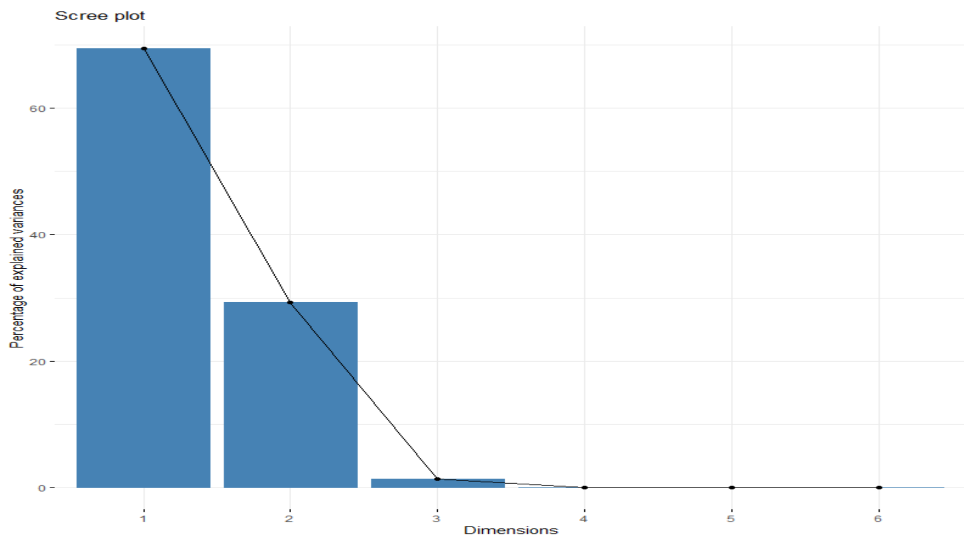


Figure 3: Principal component analysis results

Singular Value Decomposition (SVD)

Table 4: Results of analysis of individual values

Component	Singular Values	Scatter Percentage	Cumulative Percentage of Dispersion
First Component	99.99405	99.99405%	99.99405%
Second Component		0.00307%	99.99712%
Third Component		0.00192%	99.99904%
Fourth Component		0.00091%	99.99995%
Fifth Component		0.00%	100.00%

Sixth Component		0.00%	100.00%

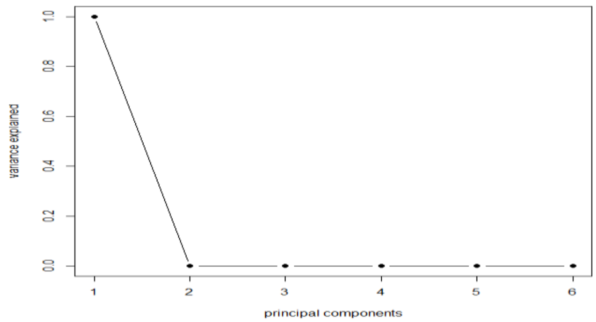
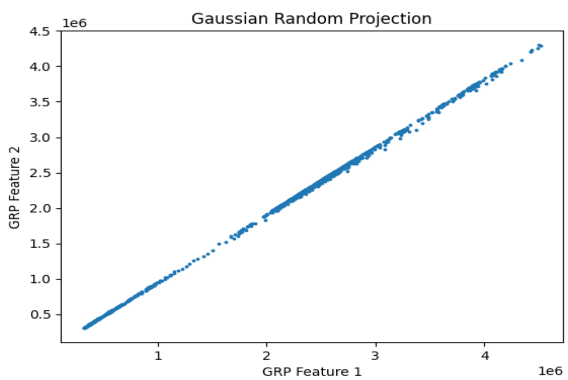


Figure 4: Single value analysis results

Gaussian Random Projection (GRP)

Gaussian Random Projection (GRP) is a dimensionality reduction technique that projects high-dimensional data onto a lower-dimensional space by multiplying the original data matrix by SS, the Gaussian randomness matrix. This process helps to maintain even relationships between data points while reducing the number of dimensions. The choice of the number of dimensions (KK), like other dimensionality reduction techniques, depends on the trade-off between preserving pairwise relations and the computational cost. A random Gaussian matrix of size $M \times K$M×K (where MM is the original number of dimensions and KK is the reduced number of dimensions) is generated, with each entry drawn from a standard normal distribution. Then, multiplying the original data matrix XX by GG yields a matrix of reduced dimensions.

Figure 5: Distribution of two features against monotony



Analysis Results from Forecast Models

LSTM Model Results

As depicted in Figure 3, the algorithms—PCA/LSTM (a hybrid model of Principal Component Analysis (PCA) and Long Short-Term Memory (LSTM) networks), SVD/LSTM (a hybrid model of Singular Value Decomposition (SVD) and LSTM networks), and GRP/LSTM (a hybrid model of Gaussian Random Projection (GRP) and LSTM networks)—employ PCA, SVD, and GRP methods to reduce dimensions while LSTM is used for time-series forecasting.

In the second step, PCA, SVD, and GRP were utilized to reduce data dimensions, preserving crucial information while removing less important features. The optimal number of features and explanatory variables for each dimensionality reduction method was determined using results from Tables 3 and 4, as well as Scree diagrams from Figures 3, 4, and 5.

Data Segmentation: In the third step, the data were divided into training (80%) and testing (20%) datasets. This allocation allows for effective network training and subsequent validation.

LSTM Network Design: This stage involved configuring a 6-layer LSTM network with 50 units per layer. Dropout layers (0.2) were positioned between the first two layers to prevent overfitting. The fifth layer also utilized 50 units, and the final layer used one unit to finalize the LSTM model architecture. This network configuration accepts components derived from dimensionality reduction methods as input. The LSTM model was trained using the Adam optimizer and Mean Squared Error (MSE) loss function, with 50 epochs and a batch size of 32 to maintain computational efficiency.

Model Evaluation: To evaluate the model, metrics such as Mean Square Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) were used, as reported in Table 5 below.

Performance Insights: After parameter adjustments, the PCA/LSTM and GRP/LSTM methods achieved the desired results on the 13th iteration, while the SVD/LSTM method reached it on the 12th iteration. According to the results presented in Table 5 and based on all three error evaluation criteria (RMSE, MAE, MSE), the PCA/LSTM method exhibited lower errors compared to the SVD/LSTM and GRP/LSTM methods.

This structured analysis highlights the effectiveness of integrating dimensionality reduction techniques with LSTM networks to enhance forecasting accuracy in time-series data.

Table 5: Errors and Precision of Forecast Models (Combination of Dimensionality Reduction and LSTM)

Algorithm	MSE	MAE	RMSE
LSTM_PCA	0.013536	0.094399	0.116344
LSTM_SVD	0.022777	0.120106	0.150920

LSTM_GRP	0.058442	0.222947	0.241749

Analysis of Graphical Results

- Figures 6 to 14 relate to the prediction results through hybrid models of dimensionality reduction combined with LSTM. Specifically:
- Figures 6, 9, and 12 display the graphs of the prediction process based on the loss function MSE for PCA/LSTM, SVD/LSTM, and GRP/LSTM algorithms, respectively.
- Figures 7, 10, and 3-13 present charts of the pre-price distribution forecasts compared with the actual prices for the PCA/LSTM, SVD/LSTM, and GRP/LSTM models.
- Figures 8, 11, and 3-14 show the curves of actual prices related to experimental data and values predicted by the LSTM network.

Reviewing these graphs, it is evident that the curve resulting from the PCA/LSTM model closely aligns with the actual price curve, indicating a higher accuracy in predictions when compared to the SVD/LSTM and GRP/LSTM models. These visual representations provide a clear comparison of how each model performs in terms of accuracy and fidelity to real-world data.

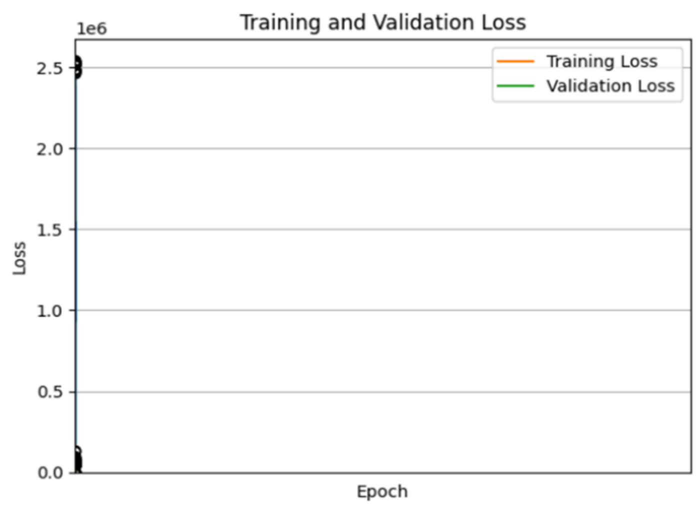


Figure 6: function chart for PCA/LSTM algorithm

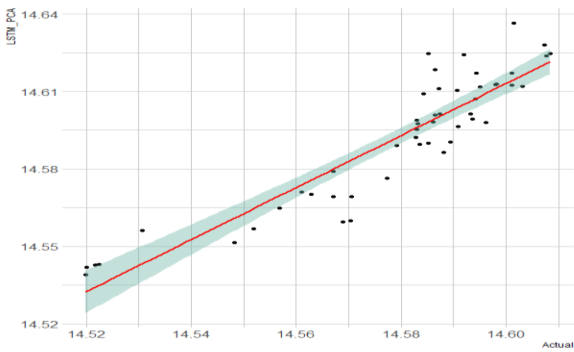


Figure 7: Forward price distribution chart Estimated based on the actual price of the model PCA/LSTM

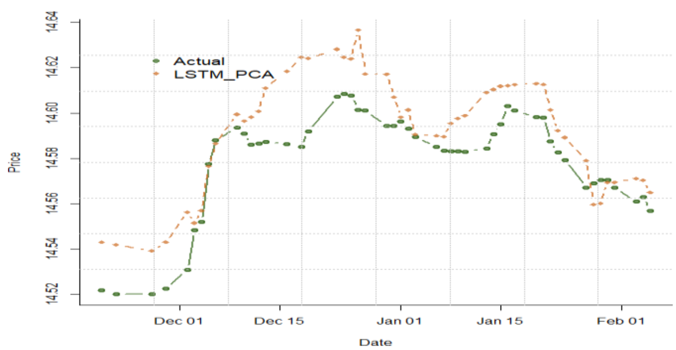


Figure 8 (Chart of the price ¬predicted by the model   PCA/LSTM) and the actual price

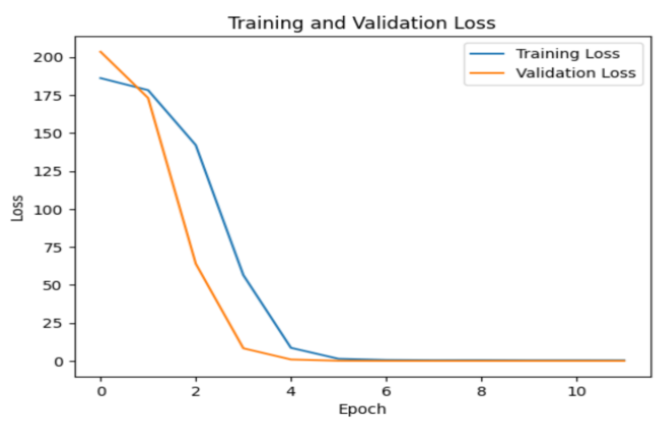


Figure 9 function diagram for SVD/LSTM algorithm

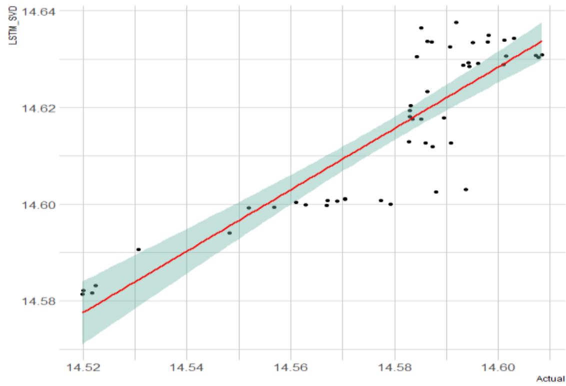


Figure 10: The distribution chart of the forward price Estimated based on the actual price of the model SVD/LSTM

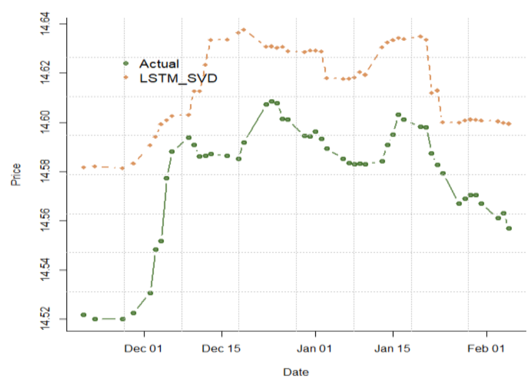


Figure 11: Chart of the price ¬predicted by the model (SVD/LSTM) and the actual price

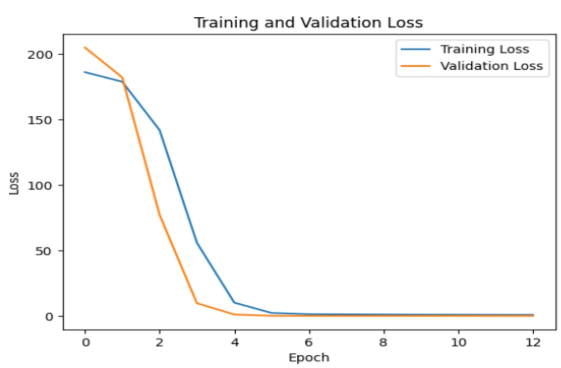


Figure 12: Loss function diagram for GRP/LSTM algorithm

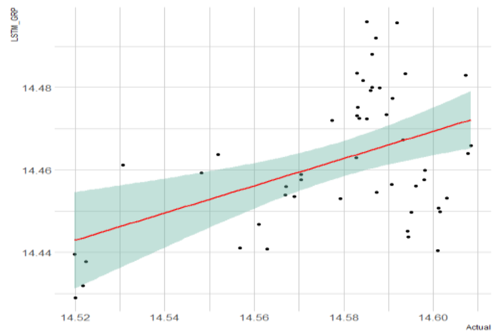


Figure 13: Price distribution chart Estimated based on the actual price of the model GRP/LSTM

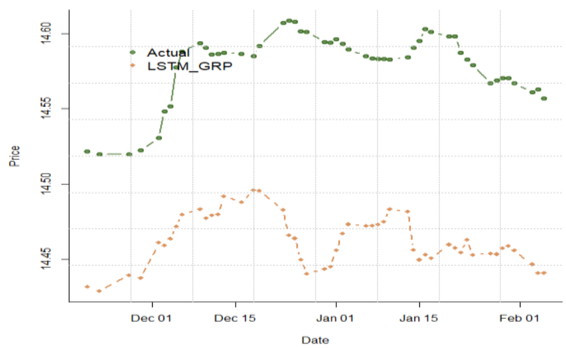


Figure 14: Chart of the price ¬predicted by the model (GRP/LSTM) and the actual price

Overall Analysis of Charts

In this section, we analyze the charts resulting from the forecast models. This analysis is critical as it demonstrates that certain analyses and simplifications cannot be achieved solely based on error metrics. The predicted price and actual price comparison charts from various research models (Figures 8, 11, 14) indicate that the PCA/LSTM model provides more accurate predictions due to the closeness of the predicted data to the original data. Particularly, the values in Figures 14, 11, and 8 exhibit a higher correspondence to the actual prices compared to other models, highlighting the effectiveness of the LSTM method combined with dimension reduction techniques for stock market data in Iran.

The distribution charts of original values versus predicted values are displayed in Figures 7 and 10. Furthermore, the distribution charts derived from the GRP dimension reduction method show this method's lower accuracy compared to other methods discussed in this research.

Responses to the Research Questions

Considering the obtained results, we can now answer the research questions Table 6 illustrates the prediction performance results of deep learning algorithms without using dimensionality reduction techniques. Comparing the results from Table 6 with those in Tables 3, 4, and 5 provides valuable insights for answering the questions of this research.

Table 6: Errors and Precision of Forecast Models Using Deep Learning Algorithms

Algorithm	MSE	MAE	RMSE
LSTM	0.029196	0.152368	0.170869
RNN	0.089117	0.244707	0.298524
CNN	0.209143	0.391634	0.457322

Discussion of Results

Comparison with Dimensionality Reduction Techniques: When comparing the results from Table 6 with those from Tables 3, 4, and 5, it is evident that dimensionality reduction techniques do not consistently enhance the accuracy of deep learning algorithms for stock price prediction in Tehran Stock Exchange market. However, the PCA dimension reduction method specifically improves LSTM's performance, as evidenced by the results in Table 3 compared to those in Table 6.

Effectiveness of PCA: Based on the MSE, MAE, and RMSE criteria evaluated in Tables 4 and 5, all deep learning algorithms—LSTM, RNN, and CNN—perform better when combined with the PCA dimensionality reduction method compared to other methods like SVD and GRP. SVD outperforms GRP in effectiveness.

PCA's Impact on LSTM: Comparing the results of Table 6 with Table 3 based on model performance evaluation criteria shows that PCA dimensionality reduction leads to better LSTM network performance.

Limitations of GRP: Comparing the results of Table 6 with those of Table 5 reveals that GRP dimensionality reduction does not positively affect LSTM network performance.

Overall Performance: Among the algorithms discussed in this study, the PCA/LSTM algorithm outperforms the other models.

PCA/LSTM Model Performance: According to the evaluation criteria presented in this research, the PCA/LSTM model exhibits the lowest error rates compared to other models. This supports the hypothesis that dimensionality reduction methods can positively affect deep learning algorithm performance, although not all dimensionality reduction methods tested showed positive results. This finding aligns with those of Sharif Far et al. (1401) and Song et al. (2023), indicating that hybrid models of dimensionality reduction coupled with precision artificial intelligence outperform other models.

Table 7: Errors and Precision of Forecast Models Using Deep Learning Algorithms

Algorithm	MSE	MAE	RMSE
LSTM	0.029196	0.152367	0.170869
LSTM_PCA	0.013536	0.094399	0.116344
LSTM_SVD	0.022777	0.120106	0.15092
LSTM_GRP	0.058442	0.222947	0.241749

Comparative Analysis of Dimension Reduction Techniques: Comparing dimensionality reduction methods with artificial intelligence techniques shows that PCA can enhance deep learning performance more effectively than other methods, consistent with findings by Zheng and He (2021). GRP Model Evaluation: Based on all three evaluation criteria (MSE, MAE, RMSE), GRP models perform less effectively than other dimensionality reduction methods, indicating poorer performance.

6.Conclusion

This research validates the effectiveness of dimensionality reduction and deep learning methods for forecasting future stock prices in Tehran stock market. The PCA method is identified as the most effective dimension reduction technique when combined with deep learning algorithms, particularly LSTM, due to its superior performance in prediction accuracy. Conversely, the GRP method shows weaker performance due to its less effective dimensionality reduction capabilities.

Practically, this research aims to assist individuals active in trading and stock transactions by providing a model that increases the accuracy and profitability of their trades. This research underscores the importance of combining advanced financial knowledge and artificial intelligence to design models that can accurately predict stock market prices.

Given the limitations of the current and past research in this area, future researchers might consider: A) Exploring other artificial intelligence-based forecasting algorithms, such as Bayesian networks or hybrid networks, B) Enhancing model accuracy through optimization algorithms to fine-tune hyperparameters, C) Applying forecasting algorithms to other stock price indices like

OTC or the top 50 market index, D) Integrating dimensionality reduction methods with other deep learning algorithms like PCA/LSTM_RNN, E) Developing models based on natural language processing and analyzing the impact of social network information on stock market prices. These directions could further the development of sophisticated models that harness the power of AI and deep learning in financial markets.

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