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Compositional RNN Approach to Accurate Stock Price Forecasting

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Abstract

Proper stock price forecasting is crucial for making decisions during volatile and uncertain financial conditions. In this regard, the current paper provides a compositional deep learning approach for time-series multivariate forecasting by employing three types of Recurrent Neural Networks (RNNs): Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Simple Recurrent Unit (SRU). For further enhancement of the predictive ability of the models, the researchers employed the Grey Wolf Optimizer (GWO) and Random Search (RS) methods to fine-tune and optimize models' hyperparameters, leading to the evaluation of 54 model configurations. Among all considered architectures, the LSTM model optimized with GWO demonstrated the highest forecasting efficiency in terms of accuracy, minimized error rate, perfect consistency between predicted and actual stock prices, and low level of bias in stock price forecasting. Besides, the GRU-GWO model and SRU-GWO model outperformed their RS-based counterparts in terms of enhanced stability and reliability. Overall, the results proved that the use of compositional RNN architecture along with metaheuristic-based fine-tuning improved forecasting performance.

Keywords: *Compositional Deep Learning; Grey Wolf Optimizer; GRU; LSTM; Stock Price Forecasting; Recurrent Neural Networks*

1. Introduction

1.1.Background of Stock Market Forecasting

The stock market is a highly dynamical and volatile financial ecosystem whose prices fluctuate constantly due to economic state, geopolitical factors, market behavior, and investor sentiment. The changes that occur in the stock market present investment opportunities, but at the same time, they present financial risks. This makes stock market forecasting crucial in financial decision-making processes. It helps in managing portfolios and risks, and developing financial strategies. The use of accurate predictive models facilitates decision-making, allowing for efficient investment planning and portfolio management. As a result, the topic of stock price forecasting is one of the most important areas of research in computational intelligence and financial analysis.

1.2.Challenges in Financial Time-Series Prediction

As mentioned previously, the problem of financial time-series forecasting is challenging since the analyzed data has complex characteristics. Time-series data is highly nonlinear, stochastic, time-dependent, and noisy. Financial data is generated based on numerous interconnected factors such as the stock market sentiment, economic situation, political instability, investor psychology, unexpected global incidents, etc. All those factors make accurate forecasting a difficult task. The majority of predictive algorithms do not allow capturing long-range dependencies and the interconnections between different variables. Rapid price fluctuations, high noise levels, and irregular market behavior reduce the effectiveness of classical methods. Thus, there is a need for more adaptive and intelligent forecasting architectures.

1.3.Traditional Statistical and Machine Learning Approaches

For decades, classic statistical approaches such as Auto Regressive Integrated Moving Average (ARIMA) and its hybrids, namely, ARIMA-GARCH models, have been extensively used for financial predictions. The application of such statistical models was justified by their effectiveness in modeling linear and stationary relationships in the time-series data [7, 9, 10]. Additionally, sentiment-integration models, which aimed to incorporate market sentiments into statistical forecasts, were also introduced [11]. They managed to improve the effectiveness of predictive models in terms of forecasting performance. Machine learning algorithms also proved to be effective at analyzing complex and highly variable financial time-series data. Support Vector Regression (SVR), Random Forest (RF), ensemble approaches, regression trees, and other classical algorithms yielded satisfactory prediction outcomes [12–18]. Although machine learning models were better at modeling relationships between data, the limitations associated with financial time-series made it difficult to achieve high-quality predictions.

1.4.Deep Learning and RNN-Based Forecasting Models

Advancements in deep learning have changed the nature of prediction algorithms in recent years. With the help of powerful recurrent neural networks (RNN) such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), complex long-range dependencies and multivariate relations can be modeled effectively. Consequently, deep learning models have found wide application in various areas of finance including stock market prediction [19]. In recent works, new forecasting approaches combining CNN, attention mechanism, transformers, and meta-heuristic techniques were proposed to improve prediction results.

1.5.Proposed Compositional RNN Framework and Research Objectives

Even though modern deep learning models proved themselves in prediction tasks, most of them employ monolithic architectures that handle all inputs simultaneously. Such architectures do not provide sufficient opportunities for exploiting feature-specific temporal patterns. In addition, there is a requirement for more advanced architectural concepts due to high complexity of financial markets. Therefore, this work proposes a compositional RNN forecasting approach based on a combination of RNN architectures within one model. In particular, the model uses OHLCV features separately for feature-wise encoding. Structured feature fusion through concatenation and dual dropout regularization will also be applied to improve robustness of the model. Furthermore, multiple stacks of neural architectures will be optimized using Random Search (RS) and Grey Wolf Optimizer (GWO) metaheuristics.

2. Method

For methodological rigidity, scalability, and reproducibility, the current study proposes an innovative modular and systematic experiment design scheme. The workflow of the proposed methodology consists of five stages: data acquisition, preprocessing, compositional RNN architecture design, hyperparameter optimization, and performance evaluation. All stages are independently developed but consistently interconnected to ensure theoretical and experimental alignment. As main focal points, feature-wise temporal modeling, modular composition, and metaheuristic optimization are considered. Decoupling of encoding, fusion, and optimization processes allows experimenting with different variants of the RNN architecture, i.e., LSTM, GRU, and SRU, as well as different configurations[1 – 5].

2.1.Data Collection

The utilized dataset contains daily stock market history retrieved from Yahoo Finance via the YFinance library. Five core features—Open, High, Low, Close, and Volume (OHLCV)—have been selected as predictors. Such features reflect necessary information regarding the market prices and dynamics. Contrary[6 – 10] to many existing works, which rely on indicator/technical features engineering, this project uses raw data in an attempt to preserve the underlying structure of financial sequences for learning purposes. Additionally, a statistical analysis was carried out to study distributions and variances in features to ensure normalization and effective modeling.

2.2.Data Preprocessing

To ensure numerical stability and facilitate the learning process, Min-Max normalization was conducted. Input features were scaled to the range of [0, 0.95] in order to avoid dominance caused by the scale difference, especially between trading volume and prices, and to mitigate the potential issues of saturation during training[11].

Sliding windows were applied to convert the sequential data into the supervised learning format using two temporal windows, 20-day and 40-day, for learning short-term and medium-term dependencies, respectively. Generated samples consisted of three-dimensional tensors: samples x time steps x features. Sequential partitioning of the data ensured chronological integrity and avoided leaking future values into training sets; thus, training and test datasets consist of 80%/20% (4,678/1,170 samples), respectively[12 – 17].

2.3.Optimization Strategy

Effective hyperparameter tuning is one of the main approaches to improving the performance of deep learning models. As a result of experiments, two strategies of optimizing the hyperparameters were chosen: Random Search (RS) and Grey Wolf Optimizer (GWO). Several hyperparameters (e.g., recurrent units' numbers, learning rates, batch sizes, number of epochs, dropout rates) were optimized using GWO. On the contrary, RS is the stochastic search that does not take into account interdependencies between parameters; therefore, it explores the hyperparameter space randomly.

2.4.Performance Evaluation

To evaluate the forecasting power of proposed models, several statistics were used: Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Root Mean Square Percentage Error (RMSPE), Percent Bias (PBIAS), Willmott Index (WI), and Nash–Sutcliffe Efficiency (NSE). Such evaluation allows assessing predictive accuracy, errors, bias, consistency, and other important characteristics of the model[18].

2.5.Compositional RNN Architecture

Proposed forecasting model uses feature-wise compositional RNN architecture. Each of the OHLCV features is modeled separately using stacked recurrent neural networks with LSTM, GRU, or SRU cells to learn feature-specific sequences of dependencies. For regularization, dropout regularization layer is used after the recurrent cells before concatenation. Encoded features are concatenated to build a common multivariate feature vector; additional recurrent layers may be used after concatenation. To obtain the stock price prediction, dense fully connected layers are applied. To conduct a thorough investigation of compositional impact on the forecasting power of the RNN architectures, 18 structural options have been developed and explored for each model.

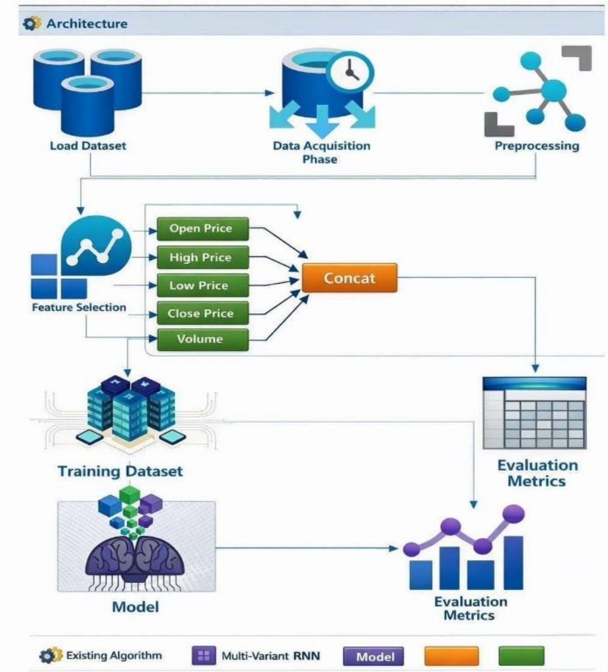

Figure 1 **Training and validation loss curves for optimized LSTM, GRU, SRU models**

3. Results And Discussion

3.1.Hyperparameter Optimization Performance

As illustrated in Table 2 and Figure 2 below, the hyperparameter optimization outcomes confirm that the Grey Wolf Optimizer (GWO) outperformed the Random Search approach in all considered RNN variants, consistently resulting in lower validation loss values. Such findings emphasize the higher efficiency and ability[19] of GWO to explore hyperparameter space and identify optimal parameter combinations. Optimized hyperparameters included: number of recurrent layers, dropouts, learning rate, batch size, and training epochs. The best-performing LSTM-GWO (1-1-0-1) configuration provided the highest forecasting quality and resulted in:

$R^2 = 99.2427\%$
RMSE = 339.3902
MAPE = 1.1721%

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RMSPE = 1.6221%
WI = 0.9981
NSE = 0.9924
PBIAS = 0.0523

The obtained results reflect exceptionally high predictive capabilities of the considered model, as evidenced by high R^2 value, very low RMSE and MAPE values, strong correlation between actual and predicted values, and absence of significant estimation bias. Figure 2 Performance of LSTM, GRU, and SRU models optimized via RS and GWO approaches[20].

3.2.Comparison of RNN Variants' Performance

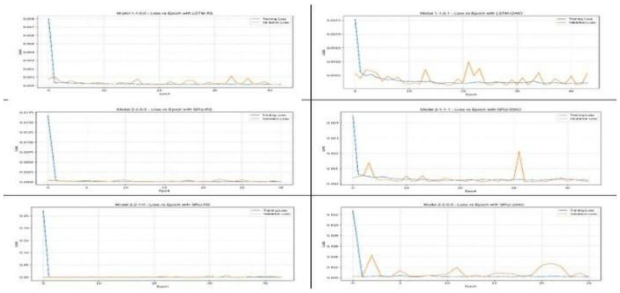


Figure 2 Proposed multi-variant compositional RNN architecture for stock price forecasting

3.3.LSTM Models

LSTM models proved the highest stability and forecasting accuracy among all the considered RNN types. Although the Random Search approach led to successful results as well, GWO further improved R^2 values and decreased RMSE and MAPE measures. Narrowly-distributed errors and extremely low bias value indicate that LSTM architectures are capable of capturing long-term dependencies existing in stock time series. In addition, the LSTM models revealed smooth convergence of training and validation losses without noticeable signs of overfitting due to generalization capability and stability of the training process.

3.4.GRU Models

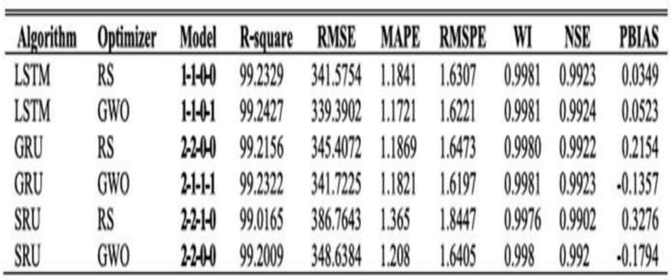
GRU models produced highly efficient forecasting results as well. The best-performing GRU-GWO (2-1-1-1) configuration generated the following forecasting metrics:
R^2 = 99.2322%
RMSE = 341.7225
MAPE = 1.1821%

Despite somewhat lower forecast accuracy in comparison with the LSTM version, GRUs exhibited very high forecasting accuracy with slight underestimation bias (PBIAS = −0.1357). As was already mentioned above, GWO optimization increased stability of the forecasting performance in comparison with RS. Finally, GRUs provided a simpler gating scheme and, therefore, higher efficiency while maintaining good predictive abilities.

3.5.SRU Models

SRU models provided sufficient performance in the context of stock price prediction but were somewhat inferior to LSTM and GRU architectures.The best-performing configuration – SRU-GWO (2-2-0-0) model – resulted in the following performance metrics:
R^2 = 99.2009%
RMSE = 348.6384
MAPE = 1.2080%

Although demonstrating high predictive accuracy, SRU models demonstrated greater dependence on market changes and higher variability. Thus, SRU models had wider error distribution with significantly higher standard deviation and, therefore, proved somewhat more unstable in terms of forecasting performance. Figure 3 Loss functions of the optimized LSTM, GRU, and SRU models.



Algorithm	Optimizer	Model	R-square	RMSE	MAPE	RMSPE	WI	NSE	PBIAS
LSTM	RS	**1-1-0-0**	99.2329	341.5754	1.1841	1.6307	0.9981	0.9923	0.0349
LSTM	GWO	**1-1-0-1**	99.2427	339.3902	1.1721	1.6221	0.9981	0.9924	0.0523
GRU	RS	**2-2-0-0**	99.2156	345.4072	1.1869	1.6473	0.9980	0.9922	0.2154
GRU	GWO	**2-1-1-1**	99.2322	341.7225	1.1821	1.6197	0.9981	0.9923	-0.1357
SRU	RS	**2-2-1-0**	99.0165	386.7643	1.365	1.8447	0.9976	0.9902	0.3276
SRU	GWO	**2-2-0-0**	99.2009	348.6384	1.208	1.6405	0.998	0.992	-0.1794

Figure 3 Comparative performance metrics of LSTM, GRU, and SRU models under RS and GWO optimization strategies

3.6.Statistical and Visual Analysis

Analysis of statistical metrics such as mean, standard deviation, skewness, and kurtosis confirm comparative performance features of the considered models. The m006Fst stable performance was exhibited by LSTM-GWO architecture. GRU-GWO models showed relatively good performance with moderate variance. The widest distribution and possible extreme deviations characterize SRU models. The use of several visualization techniques, namely box plot, violin plot, PBIAS radar plot, Taylor diagram, and training/validation loss functions, has confirmed the enhanced forecasting accuracy, decreased estimation bias, and improved stability provided by GWO optimization algorithm.

Conclusion

The suggested research presented a compositional deep learning methodology designed to enhance the accuracy of stock price predictions by combining different types of Recurrent Neural Networks (RNNs). Through the analysis of stacked LSTM, GRU, and SRU models, the research showed how the combination of structured architectural design and meta-heuristic optimization leads to superior results when forecasting multivariate financial time-series. In particular, the methodology employed a univariate encoding approach based on separate modeling of individual OHLCV attributes before feature-wise concatenation. Such an encoding technique preserves the unique temporal behavior pattern of each market attribute while ensuring the efficient integration of multivariate financial information. Additionally, dual drop-out regularization before and after the process of feature fusion enhanced the generalization capability of RNN models while reducing overfitting risk. At the same time, the systematic evaluation of multiple configurations allowed identifying the optimal layer compositions for each RNN variant. Experimental evaluation conducted on Hang Seng Index (HSI) data revealed high forecasting accuracy provided by the proposed approach. In particular, the best results were shown by the LSTM-GWO (1-1-0-1) model. The highest R^2 score recorded amounted to 99.2427%. Other indices used in the experiment showed that the model achieved extremely high prediction quality since its RMSE equaled 339.3902, MAPE – 1.1721%, RMSPE – 1.6221%, WI – 0.9981, and NSE – 0.9924. Additionally, it is worth noting that PBIAS was equal to 0.0523, which indicates that the model had negligible systematic prediction bias. The second in terms of accuracy was the GRU GWO architecture, which offered slight deterioration in the quality of forecasts but allowed significantly increasing the computational efficiency of the model. In turn, while all SRU-based models provided sufficient prediction accuracy, their stability and robustness were noticeably inferior compared to those of the proposed LSTM and GRU models. In addition, the comparative analysis of hyperparameter tuning processes showed that the Grey Wolf Optimizer was superior to the Random Search procedure in all evaluated RNN types. Specifically, it led to the decrease of validation loss, prediction error distribution range, and forecasting instability. Thus, the findings suggest that a structured compositional RNN architecture combined with meta-heuristic optimization can be considered a scalable and precise approach to stock price prediction within complicated and nonlinear financial time-series. The results of the research can become the basis for creating financial decision support tools that could help investors, analysts, and researchers make better decisions in practice. As for future directions, the methodology described in this paper can be further improved by adding attention mechanisms, hybrid architectures, additional technical indicators, and other techniques to increase adaptability and robustness.

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References

[1]. Bodie, A. Kane, and A. J. Marcus,

Investments, 11th ed., New York, NY, USA: McGraw-Hill, 2018.

[2]. F. K. Reilly, K. C. Brown, and S. J. Leeds, Invest- ment Analysis & Portfolio Management, 11th ed., Sin- gapore: Cengage Learning Asia PTE Limited, 2019.

[3]. P. Lin, S. Ma, and R. Fildes, "The extra value of on- line investor sentiment measures on forecasting stock return volatility: A large-scale longitudinal evaluation based on Chinese stock market," Expert Systems with Applications, vol. 238, 121927, 2024.

[4]. B. M. Henrique, V. A. Sobreiro, and H. Kimura, "Lit- erature review: Machine learning techniques applied to financial market prediction," Expert Syst. Appl., vol. 124, pp. 226–251, Jun. 2019.

[5]. D. Shah, H. Isah, and F. Zulkernine, "Stock market analysis: A review and taxonomy of prediction tech- niques," Int. J. Financial Stud., vol. 7, no. 2, p. 26, May 2019

[6]. Y. Zhou, H. Ren, Z. Li, and W. Pedrycz, "An anomaly detection framework for time series data: An interval- based approach," Knowledge-Based Systems, vol. 228, 107153, 2021.

[7]. J. Peng, C. Deng, and Y.-C. Chen, "Application of ARIMA time series model in stock data prediction," in Proc. Int. Conf. Intell. Inf. Hiding Multimedia Signal Process., 2023, pp. 223–232.

[8]. K. Prakhar, S. Sountharrajan, E. Suganya, M. Karthiga, and S. Kumar, "Effective stock price prediction using time series forecasting," in Proc. 6th Int. Conf. Trends Electron. Informat. (ICOEI), Apr. 2022, pp. 1636– 1640.

[9]. B. Xiao, "Prediction of U.S. stocks based on ARIMA model," in Proc. 8th Int. Conf. Financial Innov. Econ. Develop. (ICFIED), 2023, pp. 312–322.

[10]. A. Zíková and J. Veselá, "Forecasting analysis of stock prices on European markets using the ARIMA GARCH model," Statistika: Statist. Economy J., vol. 103, no. 3, pp. 342–354, Sep. 2023.

[11]. S. V. Kedar, "Stock market increase and decrease using Twitter sentiment analysis and ARIMA model," Turk- ish J. Comput. Math. Educ. (TURCOMAT), vol. 12, no. 1S, pp. 146–161, Apr. 2021.

[12]. S. Singh, K. S. Parmar, and J. Kumar, "Soft computing model coupled with statistical models to estimate fu- ture of stock market," Neural Comput. Appl., vol. 33, no. 13, pp. 7629–7647, Jul. 2021.

[13]. M. M. Kumbure, C. Lohrmann, P. Luukka, and J. Por- ras, "Machine learning techniques and data for stock market forecasting: A literature review," Expert Syst. Appl., vol. 197, Art. no. 116659, Jul. 2022.

[14]. Y. Liu, A. Ayitelieke, and J. Yu, "Short-term stock price prediction algorithm construction based on inte- grated learning of SVR and RF with bagging," High- lights Sci., Eng. Technol., vol. 22, pp. 8–15, Dec. 2022.

[15]. M. Bansal, A. Goyal, and A. Choudhary, "Stock mar- ket prediction with high accuracy using machine learn- ing techniques," Proc. Comput. Sci., vol. 215, pp. 247–265, Jan. 2022.

[16]. A. L. Gavin, P. K. Prasanna, C. V. Vedha, and A. Sinduja, "Data analysis and price prediction of stock market using machine learning regression algorithms," Adv. Sci. Technol., vol. 124, pp. 409–417, Mar. 2023.

[17]. B. T. Khoa and T. T. Huynh, "Forecasting stock price movement direction by machine learning algorithm," Int. J. Electr. Comput. Eng. (IJECE), vol. 12, no. 6,pp. 6625–6634, Dec. 2022.

[18]. Y. Huang, L. F. Capretz, and D. Ho, "Machine learning for stock prediction based on fundamental analysis," in Proc. IEEE Symp. Ser. Comput. Intell. (SSCI), Dec. 2021, pp. 1–10.

[19]. A. Quadir, S. Kapoor, A. V. C. Junni, A. K. Sivaraman,

[20]. K. F. Tee, H. Sabireen, and N. Janakiraman, "Novel optimization approach for stock price forecasting using multi-layered sequential LSTM," Appl. Soft Comput., vol. 134, Art. no. 109830, Feb. 2022