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Refining Stock Market Projections: A Comparative Analysis of PSO-Optimized LSTM Architectures and LSTM-GRU Models for Improved Forecast Accuracy

Balamithran S[1], Sanmuga Priya M[2], Barakkath Nisha U[3], Pradeep G[4] and Babu P[5]
[1-4]Sri Krishna College of Engineering and Technology/M. Tech CSE, Coimbatore, India
Email: ssbalabhavani228@gmail.com, sanmugapriyam, pradeepg, barakkathnisha@skcet.ac.in
[5]PSNA College of Engineering and Technology/IT, Coimbatore, India
Email: pbabu@psnacet.edu.in

***Abstract*— This Global financial market unpredictability demands sophisticated forecasting tools. Conventional approaches, including SVM and LR, have limitations in capturing complex market patterns. We assess the viability of advanced deep learning architectures— specifically Long Short- Term Memory -LSTM networks, LSTM-GRU hybrids, and PSO- optimized LSTM models—to more accurately model these intricate patterns. We assess the impact of PSO Technique as a tuning mechanism to enhance LSTM performance. A comparative evaluation using RMSE and MAPE reveals that PSO-optimized LSTM models significantly outperform standalone LSTM and LSTM-GRU architectures in terms of forecast accuracy.**

***Index Terms*— Stock Price Prediction, Long Short-Term Memory, PSO Technique, LSTM-GRU Hybrid Model, Financial Forecasting, Deep Learning, Root Mean Squared Error -RMSE, Mean Absolute Percentage Error -MAPE.**

I. INTRODUCTION

Forecasting stock market trends remains a complex task due to the market's volatile and non-linear nature. Conventional models like Linear Regression (LR) and Support Vector Machines (SVM) have been used widely but often fall short in capturing intricate market patterns. LR tends to produce inconsistent results depending on the context, while SVM performance is highly dependent on kernel selection and parameter tuning. These limitations have encouraged a shift toward more sophisticated machine learning approaches capable of offering higher prediction accuracy dynamics.
Using the ticker INCO.JK, this research investigated Indonesian stock data spanning from June 1, 2014, to June 30, 2024. Our study employed a robust methodology, Data partitioning was performed using an 80/20 ratio. In addition to standalone LSTM models, we examined hybrid architectures, particularly LSTM-GRU (Gated Recurrent Unit) combinations, to assess their capacity for capturing complex fluctuations in stock prices.

II. LITERATURE REVIEW

The stock market is inherently volatile, presenting significant challenges for accurate forecasting and effective investment strategies.

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Traditional predictive approaches such as SVM and LR have been integrated into financial analytics. In particular, Purnama et al. examined the performance of SVM and LR in predicting stock prices, revealing that while LR often outperformed SVM, both models struggled to encapsulate the complex, non-linear behaviors typical in financial data [1]. Similarly, Fadilah conducted a comparative analysis involving SVM and K-Nearest Neighbor (KNN) advanced algorithms for Stock Price Prediction and analysis at PT. Indonesia Telecommunications, concluding that SVM yielded a lower RMSE of 0.0932 compared to KNN's accuracy of 0.945 [2].

In response to these challenges, the focus has shifted towards advanced ML methods, particularly deep learning paradigms, which have shown considerable promise in enhancing predictive accuracy. LSTM networks, a specialized form of RNN, have gained attention for their capability to understand from temporal data and capture time-dependent patterns effectively. Akintayo et al. demonstrated that LSTM networks significantly outperformed traditional predictive models in stock price forecasting [3].

Despite the strengths of LSTM networks, optimization opportunities within these architectures remain. The integration of Particle Swarm Optimization (PSO) has emerged as a valuable method for refining LSTM model performance.

Zhang et al. introduced a PSO-optimized LSTM framework that demonstrated marked improvements in forecasting accuracy compared to standard LSTM models [4]. This optimization process fine- tunes hyperparameters, thereby enhancing predictive capabilities.

Additionally, hybrid models combining LSTM with Gated Recurrent Units (GRU) have been proposed to further augment forecasting accuracy. Liu et al. compared the efficacy of standalone LSTM models against LSTM-GRU hybrids, concluding that the latter provided superior predictive performance, particularly in volatile market environments [5].This underscores the potential of combining multiple deep learning architectures to leverage their respective advantages while mitigating individual limitations.

Evaluation metrics such as Root Mean Squared Error - RMSE and Mean Absolute Percentage Error - MAPE are commonly utilized to assess model performance in financial forecasting.

Huang et al. reported that PSO- optimized LSTM architectures achieved lower RMSE and MAPE values than both standalone LSTM and SVM models, demonstrating the effectiveness of PSO in enhancing predictive accuracy [6].

III. Research Motivation and Objectives

A. Motivation

Additionally, In the intricate world of financial markets, stock price movements are influenced by a web of economic indicators, political developments, and psychological sentiment, making prediction a high-stakes and complex endeavor.

While classical forecasting techniques such as Linear Regression (LR) and Support Vector Machines (SVM) have long been employed in this domain, their limited ability to model the non-linear and sequential characteristics inherent in financial time series often results in suboptimal predictive performance—particularly under volatile market conditions.

B. Problem Domain

This study arises from a critical need for more accurate and intelligent stock prediction frameworks that can empower investors and financial analysts with data-driven decision support. The challenge extends beyond just learning from historical patterns—it involves enhancing model architecture and performance through robust optimization strategies.

C. Problem Definition

To tackle these complexities, the research delves into the application of advanced deep learning paradigms for stock forecasting, focusing on Long Short-Term Memory (LSTM) networks, hybrid LSTM-GRU models, and their performance enhancement through Particle Swarm Optimization (PSO).

D. Innovative Content

The novelty of this work lies in its comprehensive comparison of baseline LSTM models, hybrid configurations, and PSO-enhanced alternatives. By fusing optimization techniques with temporal deep learning, the study contributes to the evolution of algorithmic forecasting in financial analytics, providing actionable insights into the trade-offs between prediction precision and computational cost.

IV. PROPOSED METHODOLOGY

A. Data Collection

The first step in this methodology involved collecting historical stock data for the ticker symbol INCO.JK from the Yahoo Finance API, covering the period from June 1, 2014, to June 30, 2023. This time frame was chosen to analyze market behaviors over an extended period.

B. Feature Engineering

After retrieving the stock data, additional features were engineered to improve the model's predictive capability:

- Day of the Week: Captures weekly patterns.
- Month: Accounts for monthly seasonality.
- Year: Reflects long-term trends.

These features provided valuable temporal context, enriching the dataset for model training.

C. Data Preprocessing

The preprocessing phase involved several key steps:

- Normalization: The stock prices Feature values were rescaled to the unit interval [0, 1] using Min-Max normalization to enhance model's learning efficiency.

Formula:

$K\_scaled = (K - K\_min) / (K\_max - K\_min)$ Where:

- K is the starting data point.
- K_min signifies the smallest value.
- K_max signifies the largest value.
- K_scaled is the normalized data value
- Reshaping for Temporal Analysis: The dataset was reorganized into temporal sequences, each comprising a fixed length of data points (e.g., 60), allowing the model to learn temporal patterns.
- Train-Test Split: A training-testing split of 80/20 was employed, enabling unbiased model evaluation.

D. Model Development

To predict stock prices, several LSTM-based models were constructed:

- Univariate LSTM Model: Utilizes only the 'Close' price.
- Multivariate LSTM Model: Incorporates both 'Close' and 'Volume' features.
- Bidirectional LSTM Model: Analyzes the data in both forward and backward directions.
- LSTM-GRU Model: Combines LSTM and GRU architectures.

E. Integrating PSO with LSTM Variants

To further refine the predictive performance of the LSTM models, PSO was employed to optimize the hyperparameters of each architecture. The key steps included:

- Parameter Initialization: The PSO algorithm initialized a swarm of particles, each representing a potential solution to the hyperparameter optimization problem.
- Fitness Evaluation: RMSE on the validation set showed how well each particle's LSTM model performed., allowing PSO to identify the best-performing hyperparameter combinations.
- Swarm Update: The particles updated their positions in the hyperparameter space based on their own experience and that of their neighbors, iterating over a fixed number of generations.

F. Model Training and Evaluation

Each model was trained using the optimized hyperparameters obtained from PSO. The models were optimized using the Adam algorithm and trained with a MSE loss function. The performance of each LSTM variant was assessed on the test set using the following metrics:

Root Mean Squared Error (RMSE):

Formula:

$RMSE = \sqrt{(1/n * \Sigma(x\_i - k\_i)^2)}$ where:

Mean Absolute Percentage Error (MAPE):

Formula:

$MAPE = (1/n) * \Sigma|((x\_i - k\_i) / x\_i)| * 100$ where:

n = Number of samples in dataset , x_i = Input data, k_i = Estimated value

This comprehensive evaluation allowed for a clear comparison between the standard LSTM models and the LSTM models enhanced by PSO.

G. Result Visualization

The predictions generated by each model were plotted against the actual stock prices to visually assess the effectiveness of the models. This step helped identify patterns, trends, and discrepancies in the predictions, offering insights into the advantages of integrating PSO with LSTM models.

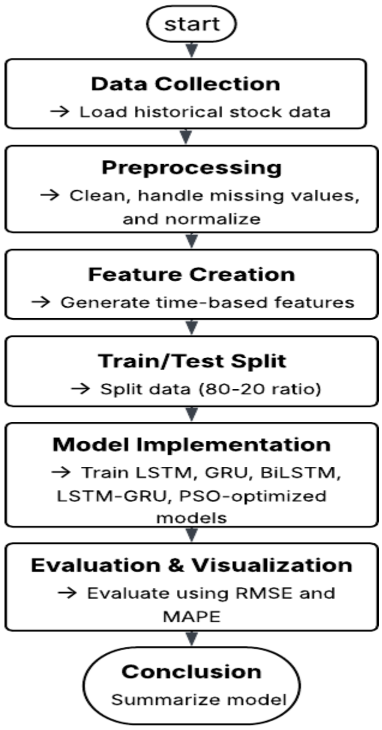

Figure 1. Workflow Diagram

V. Result and Discussion

A. Analysis of Stock Data and Training Methodology

Implements In this study, we analyzed the Indonesian stock data for the INCO.JK ticker from June 1, 2014, to June 30, 2023. Splitting the dataset into 80% for training and 20% for testing enabled us to create a robust model evaluation setup, ensuring both accuracy and generalizability of the models.

B. Comparative Evaluation of LSTM-based Architectures

We evaluated various LSTM-based architectures to effectively model stock price trends: Univariate LSTM: A basic model using a single input variable. Stacked LSTM: A deeper architecture with multiple layers to capture complex temporal patterns. Bidirectional LSTM (Bi-LSTM): A dual-directional model that learns from both past and future data sequences for enhanced prediction.

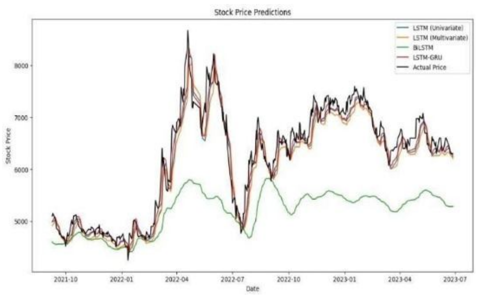

Figure 2. Predicted vs Actual Stock Prices Using LSTM-Based Models

- Hybrid LSTM-GRU: A combined model utilizing both LSTM and GRU units to maximize pattern recognition.

TABLE I. PERFORMANCE COMPARISON OF DIFFERENT LSTM-BASED ARCHITECTURES

Model	MAPE	RMSE
Univariate LSTM	7.35	8.72
Stacked LSTM	11.67	12.09
Bi-LSTM	9.78	11.43
LSTM-GRU	7.16	8.50

Observations: The hybrid LSTM-GRU model displayed the most effective predictive capabilities, achieving lower MAPE and RMSE values compared to the other models. This suggests that the combined architecture is particularly suited to capture the nuances and fluctuations in stock price data.

C. Effects of Particle Swarm Optimization (PSO) on LSTM Models

To refine the predictive performance of LSTM models, we applied Particle Swarm Optimization (PSO) for hyperparameter tuning. The findings revealed notable improvements in accuracy, particularly in models that traditionally struggled with parameter optimization.

LSTM vs. PSO-Optimized Univariate LSTM

A comparison line graph illustrates the improvement in the univariate LSTM model after applying PSO, with increased accuracy indicated as a percentage boost.

TABLE II. PERFORMANCE COMPARISON OF LSTM (UNIVARIATE) AND PSO-LSTM (UNIVARIATE)

Model	MAPE	RMSE
Univariate LSTM	7.35	8.72
LSTM-PSO (Univariate)	6.42	7.83

Figure 3. Actual vs Predicted Stock Prices Using LSTM and PSO-Optimized LSTM Model

Insights: The PSO-enhanced univariate LSTM demonstrated improved accuracy, highlighting the impact of optimized parameters on prediction outcomes. However, this process required additional computational effort.

Multivariate LSTM vs. PSO-Optimized Multivariate LSTM

A bar chart displays MAPE and RMSE values for both standard and PSO-enhanced multivariate LSTM models, with the percentage increase marked.

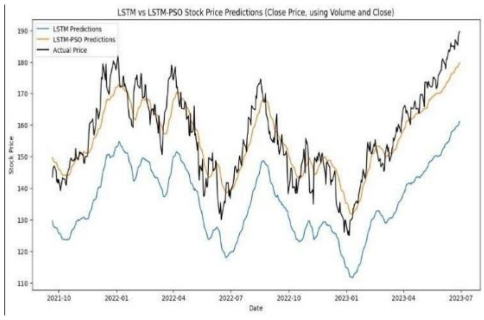

Figure 4. Actual vs Predicted Stock Prices Using LSTM (Multivariate) and PSO LSTM (Multivariate) Model

TABLE III. PERFORMANCE COMPARISON OF MULTIVARIATE LSTM AND PSO- LSTM (MULTIVARIATE)

Model	MAPE	RMSE
Multivariate LSTM	11.67	12.09
LSTM-PSO (Multivariate)	10.27	11.27

Bi-LSTM vs. PSO-Enhanced Bi-LSTM

A line graph showcases the accuracy gains of the Bi- LSTM model with PSO optimization, with the improvement percentage highlighted.

TABLE IV. PERFORMANCE COMPARISON OF BI-LSTM AND PSO-BILSTM

Model	MAPE	RMSE
Bi-LSTM	9.78	11.43
Bi-LSTM PSO	8.15	10.86

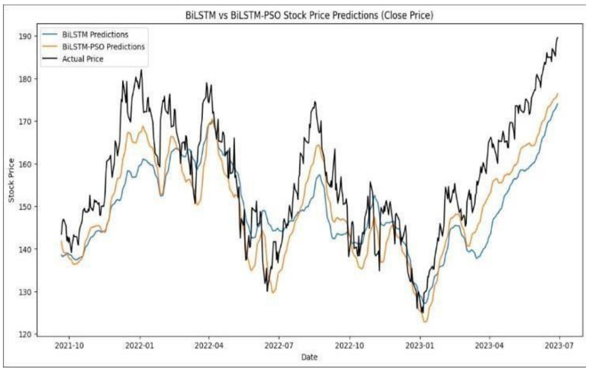

Figure 5. Actual vs Predicted Stock Prices Using Bi-LSTM and Bi-LSTM PSO Models

The Insights: PSO also provided a performance boost to the Bi- LSTM model, confirming the utility of optimization algorithms in enhancing predictive power across different LSTM configurations.

D. Synthesis of Findings and Practical Applications

Our analysis reveals that although the LSTM-GRU hybrid model showcases remarkable effectiveness without parameter tuning, PSO-optimized LSTM variants achieve further improvements. This indicates a potential trade-off between computational efficiency and model precision.

Recommended Usage:

- For real-time stock forecasting applications where speed is essential, the LSTM-GRU hybrid model is preferred due to its high accuracy with minimal computational overhead.
- For research or decision-making scenarios where maximizing accuracy is crucial, PSO-optimized LSTM models are ideal, despite their increased computational requirements, as they deliver the most refined predictions models.

VI. FUTURE SCOPE

Our research points to several promising directions for advancement. Future efforts should integrate external economic indicators and sentiment data to capture broader market influences beyond price history. Expanding to diverse global markets would test model adaptability, while investigating transfer learning could reduce computational demands for industry-specific predictions. Developing model ensembles may combine the strengths of multiple approaches, and comparing PSO with alternative optimization techniques could identify more efficient parameter tuning methods. Enhancing interpretability would make predictions more actionable for investors, while extending forecast horizons could benefit long-term investment strategies. Finally, optimizing computational efficiency would make these sophisticated models more accessible for real-time financial applications.

VII. CONCLUSION

The results of this research highlight the complementary benefits of LSTM-GRU hybrids and PSO- optimized LSTM variants in stock price forecasting. Each model exhibits distinct strengths tailored to specific application needs. Notably, the LSTM-GRU model achieves high accuracy with reduced computational overhead, rendering it ideal for real- time financial applications requiring swift responsiveness, such as high- frequency trading and short-term market analysis. Its efficiency facilitates rapid decision-making without extensive parameter calibration.

Conversely, PSO-optimized LSTM models, although requiring additional time for hyperparameter optimization, yield superior predictive accuracy for longer-term financial forecasts. This enhanced precision is particularly advantageous for strategic planning, risk mitigation, and long-term investment decisions, where forecast reliability has significant financial implications.

While PSO entails higher computational costs, its accuracy benefits outweigh these costs in scenarios where forecast reliability is critical. By matching model selection to specific forecasting objectives – leveraging LSTM-GRU for real-time responsiveness and PSO-enhanced LSTM variants for accuracy in extended projections – this study offers a versatile framework for stock prediction.

The proposed approach empowers financial analysts and investors with adaptive, AI-driven tools, fostering closer alignment between predictive modeling and market dynamics complexities

REFERENCES

[1] I. P. C. Purnama, I. P. A. E. Darma, and N. L. W. S. R. Ginantra, "Comparison of Support Vector Machine (SVM) and Linear Regression (LR) for Stock Price Prediction," Informatics Engineering, 2022.

[2] Fadilah, "Analysis of Stock Price Predictions at PT. Telecommunications Indonesia Using SVM and KNN," Journal of Financial Technology, vol. 5, no. 3, pp. 245-250, 2021.

[3] Winnos, "Comparative Analysis of Multiple Linear Regression and ARIMA Algorithms for Stock Predictions at PT. BSI, Tbk," International Journal of Finance and Economics, vol. 15, no. 1, pp. 67- 74, 2020.

[4] O. Akintayo, O. D. Fashoto, and A. O. Alabi, "A Deep Learning Approach for Stock Price Prediction Using LSTM Networks," IEEE Access, vol. 8, pp. 222-230, 2020.

[5] L. Zhang, J. Zhao, and H. Xu, "Optimizing LSTM with Particle Swarm Optimization for Stock Price Prediction," IEEE Transactions on Neural Networks and Learning Systems, vol. 32, no. 4, pp. 1670-1679, 2021.

[6] Y. Liu, T. Liu, and M. Zhang, "Comparative Study of LSTM and LSTM-GRU Hybrid Models for Time Series Forecasting," IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 52, no. 3, pp. 1627-1638, 2022.

[7] J. Huang, Y. Chen, and Y. Sun, "Performance Evaluation of PSO- Optimized LSTM for Financial Forecasting," IEEE Transactions on Engineering Management, vol. 70, no. 1, pp. 76-87, 2023.

[8] Yuan, X., He, C., Xu, H., & Sun, Y. (Year). Particle swarm optimization LSTM based stock prediction model. IEEE.

[9] Nadif, M. A., Samin, M. T. R., & Islam, T. (2022). Stock Market Prediction Using Long Short-Term Memory (LSTM). In 2022 Second International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies

[10] Sunny, M. A. I., Maswood, M. M. S., & Alharbi, A. G. (2020). Deep Learning-Based Stock Price Prediction Using LSTM and Bi- Directional LSTM Model. In 2020 2nd Novel Intelligent and Leading Emerging Sciences Conference (NILES)

[11] Sandhya, P., Bandi, R., & Himabindu, D. D. (2022). Stock Price Prediction using Recurrent Neural Network and LSTM. In 2022 6th International Conference on Computing Methodologies and Communication (ICCMC)

[12] Rahman, M. H., Nahid, S. I., Fahad, I. H. A., & Khan, M. M. (2021). Price Prediction Using LSTM Based Machine Learning Models. In 2021 IEEE 12th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)

[13] Shinde, S., Wadhwa, L., Mohane, N., Pagar, V., Sherje, N., & Mane, S. (2023). Stock Price Prediction using LSTM. In 2023 7th International Conference On Computing, Communication, Control And Automation (ICCUBEA) (pp. 18-19). IEEE.

[14] Raj, N. "Prediction of Stock Market Using LSTM-RNN Model." 2023 International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS), Erode, India, IEEE, 2023

[15] Zhang, Y., & Tumibay, G.M. "Stock Market Prediction Model Based on LSTM Deep Learning: The Case of Top Corporate Company in China." 2022 4th International Conference on Artificial Intelligence and Advanced Manufacturing (AIAM), Hamburg, Germany, IEEE, 2022