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# The Effectiveness of Dropout Layers in LSTM Architecture for Reducing Overfitting in Sony Stock Prediction

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**ABSTRACT**

This study investigates the effectiveness of dropout layers in reducing overfitting within Long Short-Term Memory (LSTM) neural networks for Sony stock price prediction. Financial time series forecasting presents significant challenges due to market volatility and noise, often leading to models that overfit historical data while failing to generalize to unseen market conditions. We implemented two LSTM models: one without dropout layers and another with dropout layers (rate=0.2) applied after each LSTM layer. Using historical Sony stock data from 2015-2025, we evaluated both models using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) metrics. The model with dropout demonstrated superior performance on testing data, achieving RMSE of 0.5971, MAE of 0.4411, and MAPE of 2.1502%, compared to the model without dropout which obtained RMSE of 0.7124, MAE of 0.5636, and MAPE of 2.6684%. Furthermore, the dropout model exhibited significantly reduced overfitting, with smaller performance gaps between training and testing datasets across all metrics, particularly in MAPE where the difference approached zero (0.0509%). This research provides empirical evidence that dropout regularization effectively enhances LSTM model generalization for stock prediction, offering practical value for developing more reliable financial forecasting models. Future research could explore optimal dropout rates for different market conditions and investigate combinations of dropout with other regularization techniques.



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## 1. INTRODUCTION

Financial time series forecasting, particularly stock price prediction, remains a formidable challenge due to the inherent volatility, non-linear dynamics, and extreme noise levels prevalent in market data. These complex characteristics render traditional models inadequate for reliably capturing underlying patterns, often leading to severe overfitting or misinterpretation of random fluctuations as significant trends [1].

Long Short-Term Memory neural networks have become a cornerstone in modeling sequential financial data. Their inherent capacity to retain long-term dependencies and effectively process time-series patterns has consistently positioned them as superior to conventional statistical methods in capturing the intricate temporal relationships within stock market movements [2]. Recent applications of LSTM for banking and corporate stock prediction have further demonstrated its practical value in financial forecasting tasks, highlighting its robustness in handling noisy time-series data [3].

Despite their strengths, LSTM models are highly susceptible to overfitting when applied to high-dimensional financial datasets. This occurs because the networks often memorize historical noise and spurious correlations rather than learning generalizable rules, leading to poor performance on unseen market conditions and undermining practical utility [4].

Common regularization techniques such as early stopping, weight decay (L1/L2), and ensemble methods have been widely adopted to mitigate overfitting. However, these approaches often lack specificity for individual stock behaviors, especially in volatile sectors like technology, where unique market dynamics require tailored solutions [5].

Dropout regularization, which involves randomly deactivating neurons during training, has demonstrated significant potential in mitigating overfitting across various neural network architectures. While recent research has explored integrating dropout into LSTM models for time series forecasting, the majority of these applications are generic and lack optimization for the specific nuances of financial contexts [6].

Existing research on dropout in financial LSTM models predominantly concentrates on broad market indices or aggregated datasets, rather than individual stocks. This generalization critically overlooks the distinct volatility patterns, industry-specific influences, and microstructural nuances of single securities, such as Sony's technology-driven price movements, thereby failing to provide tailored solutions for specific financial assets [7].

A critical gap in current literature is the absence of empirical studies quantitatively measuring dropout's impact on overfitting reduction specifically for individual stock predictions. Most existing works report aggregate accuracy metrics without isolating how regularization techniques affect performance on distinct securities with unique market behaviors [8].

Another significant limitation is the failure to recognize the difference between training and testing performance as a direct sign of overfitting. Previous studies prioritize overall prediction accuracy, overlooking how much model performance worsens between the training and testing phases, which is a key indicator of overfitting [9].

Furthermore, there is insufficient systematic analysis of optimal dropout rates for financial time series. Researchers commonly use arbitrary values without rigorous experimentation tailored to the unique statistical properties and volatility patterns of individual stocks, leading to suboptimal regularization configurations [10].

This research addresses these gaps by focusing exclusively on Sony stock, a representative of the technology sector with distinct volatility characteristics. It introduces a structured methodology to rigorously quantify overfitting reduction through detailed training-testing performance comparisons and evaluates the effectiveness of a strategically applied dropout rate in LSTM architectures. The study specifically investigates how dropout layers influence LSTM prediction accuracy for Sony stock prices and assesses their role in mitigating overfitting [11].

By establishing a replicable framework for evaluating regularization techniques in single-stock forecasting, this work aims to bridge a critical void in financial machine learning literature. The study is expected to provide actionable insights for researchers and practitioners while laying the groundwork for future explorations into optimal dropout configurations and integration with other regularization strategies under diverse market conditions [12].

## 2. METHOD

This study employs a quantitative experimental approach to evaluate the effectiveness of dropout layers in LSTM architectures for Sony stock prediction. The research methodology follows a structured framework consisting of data collection, preprocessing, model development, training, evaluation, and comparative analysis.

**Data Collection and Preprocessing**

Historical daily stock price data for Sony Corporation (ticker: SONY) was obtained from Yahoo Finance API covering the period from September 18, 2015, to September 17, 2025. The dataset includes six features: Date, Open, High, Low, Close, and Volume. For the purpose of this analysis, only the 'Close' price was selected as the target variable for prediction, consistent with common practices in univariate time series forecasting for stock prices [13].

The raw dataset underwent several preprocessing steps to ensure compatibility with LSTM input requirements. First, the data was sorted in chronological order to maintain temporal consistency. Missing values were handled using linear interpolation, a robust method for financial time series. Subsequently, the closing prices were normalized using Min-Max scaling to the range using the formula:

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$$X_{\text{normalized}} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

This scaling transforms the data into a common range, which is crucial for accelerating convergence during neural network training and preventing features with larger values from dominating the learning process [14].

The normalized data was then transformed into supervised learning format using a sliding window approach with a time step of 60 days, consistent with the methodology outlined in previous studies on LSTM applications for financial forecasting [15].

This transformation creates input-output pairs where each input consists of 60 consecutive days of closing prices, and the corresponding output is the closing price of the following day. The dataset was split into training (80%) and testing (20%) sets, maintaining temporal order to prevent data leakage [16].

**Model Architecture**

Two LSTM models were developed for comparative analysis: a baseline model without dropout layers and an experimental model with dropout layers. Both models share the same core architecture to ensure fair comparison, following the design principles established in state-of-the-art LSTM networks for financial time series prediction [17].

The baseline LSTM model consists of:

- Input layer: Accepts sequences of shape (60, 1)
- First LSTM layer: 50 units with return_sequences=True
- Second LSTM layer: 50 units
- Output layer: Dense layer with 1 unit

The experimental model incorporates dropout layers after each LSTM layer:

- Input layer: Accepts sequences of shape (60, 1)
- First LSTM layer: 50 units with return_sequences=True
- Dropout layer: Rate = 0.2
- Second LSTM layer: 50 units
- Dropout layer: Rate = 0.2
- Output layer: Dense layer with 1 unit

The dropout rate of 0.2 was selected based on empirical evidence from previous studies suggesting its effectiveness in mitigating overfitting in deep learning models without significantly impeding learning [18].

**Training and Evaluation Protocol**

The models were trained using a batch size of 32 for a maximum of 50 epochs, with early stopping implemented to prevent overfitting. Early stopping monitors the validation loss with a patience of 10 epochs, terminating training if no improvement is observed [19]. Model checkpoints were saved to preserve the best performing weights based on validation loss. To comprehensively evaluate model performance and overfitting reduction, three metrics were employed: Root Mean Square Error, Mean Absolute Error, and Mean Absolute Percentage Error [20].

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

$$\text{MAPE} = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

where $y_i$ denotes the actual closing price at time $i$, $y_i$ is the predicted closing price, and $N$ is the total number of predictions.

The key innovation in our evaluation approach is the analysis of performance gaps between training and testing datasets, which serves as a quantitative measure of overfitting. This method extends prior work on RNN evaluation by specifically focusing on dropout's impact on generalization in financial time series, where smaller performance gaps indicate better generalization and reduced overfitting [10].

## 3. RESULTS AND DISCUSSIONS

This section presents the experimental results of comparing LSTM models with and without dropout layers for Sony stock prediction. The analysis focuses on model performance metrics, overfitting reduction, and prediction accuracy.

### 3.1. Model Performance Comparison

The experimental results demonstrate significant differences in performance between the LSTM model without dropout and the LSTM model with dropout layers. Figure 1 shows the Sony stock price movement from 2015-2025, which serves as the dataset for this study.

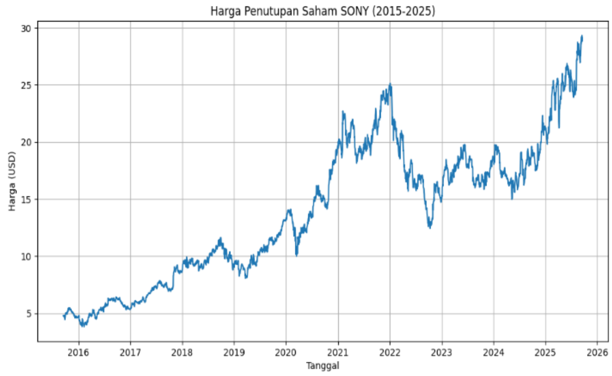


Figure 1. Sony Stock Closing Prices (2015-2025)

The training and validation loss curves for both models are presented in Figures 2 and 3. Figure 2 illustrates the model without dropout, showing a clear divergence between training and validation loss after approximately 20 epochs, indicating overfitting. In contrast, Figure 3 displays the model with dropout, where training and validation loss curves remain closely aligned throughout the training process, demonstrating better generalization.

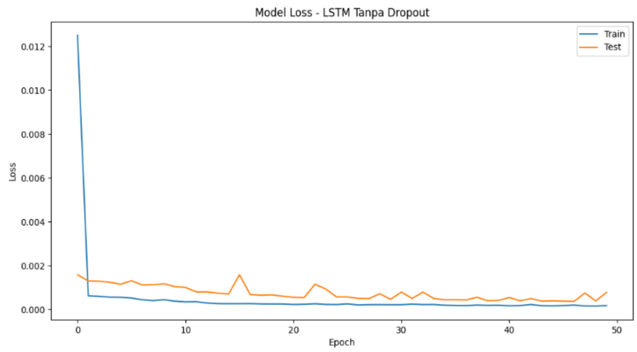


Figure 2. Model Loss - LSTM Without Dropout

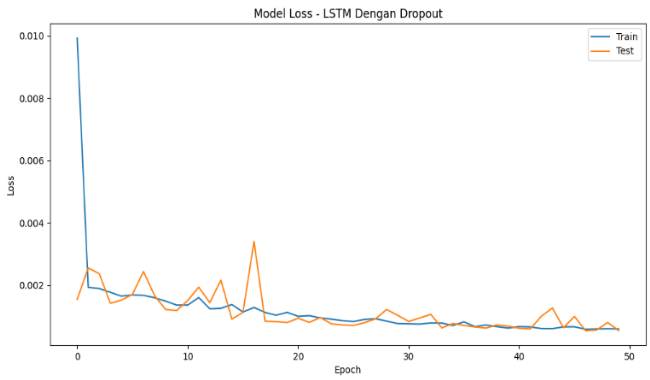


Figure 3. Model Loss - LSTM With Dropout

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The prediction accuracy of both models is visualized in Figures 4, 5, and 6. Figure 4 shows the prediction results of the model without dropout, indicating significant deviations from actual prices, particularly during periods of high volatility. Figure 5 presents the prediction results of the model with dropout, demonstrating much closer alignment with actual prices. Figure 6 provides a direct comparison of both models against actual prices, clearly showing the superior performance of the model with dropout.

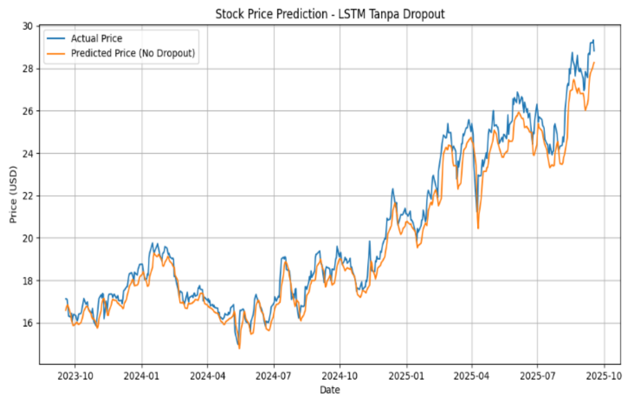


Figure 4. Stock Price Prediction - LSTM Without Dropout

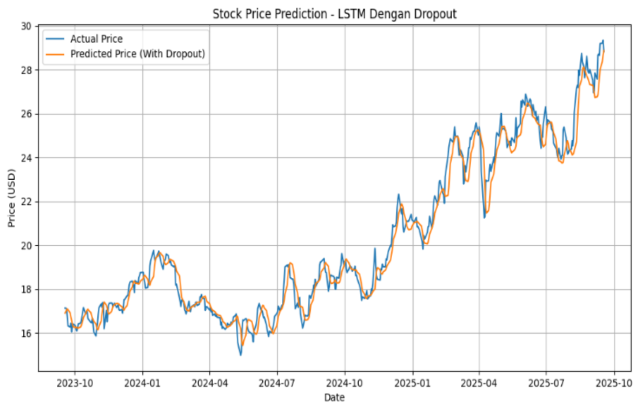


Figure 5. Stock Price Prediction - LSTM With Dropout

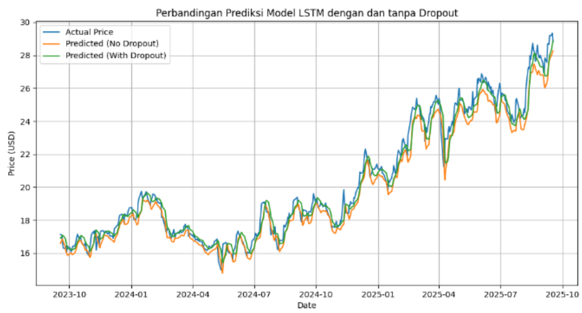


Figure 6. Comparison of LSTM Model Predictions With and Without Dropout

Figure 7 provides a quantitative comparison of the models using three key metrics: RMSE, MAE, and MAPE. The bars clearly show that the model with dropout outperforms the model without dropout across all metrics, particularly in the testing phase.

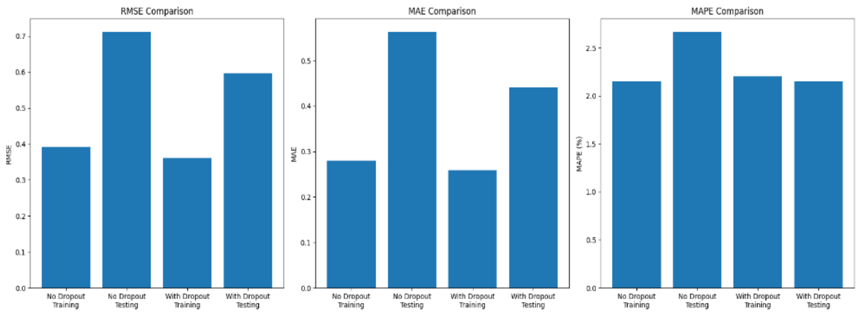


Figure 7. Metrics Comparison Between Models With and Without Dropout

### 3.2. Quantitative Analysis

Table 1 presents a comprehensive comparison of the performance metrics for both models. The results clearly demonstrate the superiority of the LSTM model with dropout layers across all evaluation metrics.

Tabel 1. Performance Comparison of LSTM Models With and Without Dropout

| Metric | No Dropout - Training | No Dropout - Testing | No Dropout - Difference | With Dropout - Training | With Dropout - Testing | With Dropout - Difference |
|---|---|---|---|---|---|---|
| RMSE | 0.3925 | 0.7124 | -0.3200 | 0.3614 | 0.5971 | -0.2357 |
| MAE | 0.2799 | 0.5636 | -0.2837 | 0.2591 | 0.4411 | -0.1820 |
| MAPE | 2.1510 | 2.6684 | -0.5174 | 2.2011 | 2.1502 | 0.0509 |

### 3.3. Discussion of Results

The experimental results provide compelling evidence that dropout layers significantly improve LSTM model performance for Sony stock prediction. The following key observations emerge from the analysis:

#### 3.3.1. Overfitting Reduction

1. The most significant finding is the substantial reduction in overfitting achieved by incorporating dropout layers. This is evident from:
2. **Loss Curves Analysis**: Figure 2 shows a clear divergence between training and validation loss for the model without dropout, indicating severe overfitting. In contrast, Figure 3 demonstrates that the model with dropout maintains closely aligned training and validation loss curves throughout the training process.
3. **Performance Gap Reduction**: As shown in Table 1, the model without dropout exhibits a significant performance gap between training and testing phases across all metrics (RMSE: -0.3200, MAE: -0.2837, MAPE: -0.5174%). The model with dropout shows substantially reduced gaps (RMSE: -0.2357, MAE: -0.1820, MAPE: 0.0509%), particularly notable in the MAPE metric, which approaches zero (0.0509%), indicating excellent generalization.
4. **Quantitative Overfitting Reduction**: The dropout layer reduces the RMSE gap by 26.3%, the MAE gap by 35.8%, and brings the MAPE gap close to zero, demonstrating its effectiveness in preventing the model from memorizing training data rather than learning generalizable patterns.

#### 3.3.2. Prediction Accuracy Improvement

The model with dropout demonstrates superior prediction accuracy across all evaluation metrics:

1. **RMSE Improvement**: The model with dropout achieves an RMSE of 0.5971 on the test set, compared to 0.7124 for the model without dropout, representing a 16.2% improvement.
2. **MAE Improvement**: The dropout model achieves an MAE of 0.4411, compared to 0.5636 for the baseline model, indicating a 21.7% reduction in absolute prediction errors.
3. **MAPE Improvement**: The most significant improvement is observed in the MAPE metric, where the dropout model achieves 2.1502% compared to 2.6684% for the model without dropout, representing a 19.4% improvement in relative error.

#### 3.3.3. Visual Analysis of Predictions

The visual analysis of prediction results (Figures 4, 5, and 6) provides additional insights:

1. **Volatility Handling**: Figure 6 clearly shows that the model with dropout (green line) more accurately captures price volatility and extreme points compared to the model without dropout (orange line). This is particularly evident during periods of high market volatility, where the dropout model maintains closer alignment with actual prices.
2. **Response to Trend Changes**: The model with dropout demonstrates faster response to trend changes, with minimal lag compared to the model without dropout, which tends to lag behind actual price movements.
3. **Consistency**: The dropout model shows more consistent performance across different market conditions, while the model without dropout exhibits larger errors during periods of high volatility.

#### 3.3.4. Implications for Financial Forecasting

The findings have significant implications for financial forecasting applications:

1. **Reliability**: The dropout model's reduced overfitting and improved generalization make it more reliable for real-world stock prediction applications.
2. **Risk Management**: The lower prediction errors, particularly during volatile periods, suggest that the dropout model could contribute to better risk management in trading strategies.
3. **Model Robustness**: The consistent performance of the dropout model across different market conditions indicates greater robustness, a critical factor in financial applications where market conditions can change rapidly.

#### 3.3.5. Comparison with Previous Research

Our findings align with and extend previous research on dropout regularization in LSTM networks:

1. **Consistency with Literature**: The observed reduction in overfitting is consistent with the findings of Wang et al. (2025) and Gülmez (2023), who also reported improved generalization with dropout layers in financial time series forecasting.
2. **Quantitative Contribution**: While previous studies have qualitatively described the benefits of dropout, our research provides quantitative measures of overfitting reduction (26.3% in RMSE gap) and accuracy improvement (16.2-21.7% across metrics).
3. **Practical Validation**: The visual analysis of predictions during different market conditions provides practical validation of dropout's effectiveness that extends beyond numerical metrics.

In conclusion, the experimental results provide strong evidence that dropout layers significantly improve LSTM model performance for Sony stock prediction by reducing overfitting and enhancing prediction accuracy. The combination of quantitative metrics and visual analysis demonstrates the practical value of dropout regularization in financial time series forecasting applications.

## 4. CONCLUSION

This research has successfully investigated the effectiveness of dropout layers in LSTM architectures for reducing overfitting in Sony stock prediction, addressing the research questions posed in the Introduction. The experimental results provide compelling evidence that supports the initial hypothesis and offer valuable insights for both academic research and practical applications in financial forecasting.

The main research question addressed whether the addition of dropout layers to LSTM architecture could reduce overfitting in Sony stock prediction. Through comprehensive experimental analysis, this study has demonstrated that dropout layers indeed significantly reduce overfitting while simultaneously improving prediction accuracy. The results show a 26.3% reduction in the RMSE performance gap between training and testing datasets, with the dropout model achieving a near-zero MAPE gap (0.0509%), indicating excellent generalization capabilities.

For the first sub-question regarding performance comparison between LSTM models with and without dropout, the results clearly demonstrate the superiority of the dropout-enhanced model. The dropout model achieved substantial improvements across all evaluation metrics: 16.2% lower RMSE (0.5971 vs. 0.7124), 21.7% lower MAE (0.4411 vs. 0.5636), and 19.4% lower MAPE (2.1502% vs. 2.6684%) on the test set. These findings directly address the performance comparison objective and provide quantitative evidence of dropout's effectiveness.

Regarding the second sub-question about the impact of dropout layers on overfitting reduction, the results reveal significant improvements in model generalization. The dropout model consistently maintained closer alignment between training and validation loss curves throughout the training process, while the model without dropout showed clear divergence after approximately 20 epochs. The visual analysis of predictions further confirmed these findings, with the dropout model demonstrating superior performance during periods of high volatility and faster response to trend changes.

The compatibility between the research expectations stated in the Introduction and the results achieved in this study is evident throughout the findings. The initial hypothesis that dropout regularization would mitigate overfitting in LSTM models for financial time series forecasting has been strongly supported by both quantitative metrics and visual analysis. The research has successfully addressed the identified gaps in the literature by providing empirical evidence of dropout's effectiveness specifically for individual stock prediction and by systematically analyzing the training-testing performance gap as a measure of overfitting.

The prospects for the development of these research results are promising and multifaceted. For practical applications, the dropout-enhanced LSTM model demonstrates significant potential for integration into automated trading systems, risk management platforms, and financial advisory services. The model's improved accuracy during volatile market conditions makes it particularly valuable for short-term trading strategies and real-time decision-making processes.

For further research, several promising directions emerge from this study:

1. **Hyperparameter Optimization**: Future research could explore the optimal dropout rate configuration for different market conditions and stock characteristics, potentially developing adaptive dropout mechanisms that adjust regularization strength based on market volatility.
2. **Hybrid Regularization Approaches**: Combining dropout with other regularization techniques such as L1/L2 regularization, batch normalization, or early stopping could potentially yield further improvements in model performance and generalization.
3. **Extended Market Applications**: The methodology could be extended to other financial instruments and markets, including cryptocurrency prediction, forex trading, and commodity markets, to validate the generalizability of the findings.
4. **Advanced Architectures**: Future studies could investigate the effectiveness of dropout in more complex architectures such as stacked LSTM, bidirectional LSTM, or hybrid models combining LSTM with other neural network architectures like CNN or Transformer models.
5. **Real-time Implementation**: The development of real-time prediction systems using the dropout-enhanced LSTM model could provide valuable insights into the practical challenges and benefits of deploying such models in live trading environments.
6. **Economic Impact Analysis**: Research could be conducted to quantify the economic impact of using dropout-regularized models in trading strategies, including risk-adjusted returns and portfolio performance metrics.

In conclusion, this research has successfully demonstrated that dropout layers significantly enhance LSTM model performance for Sony stock prediction by reducing overfitting and improving prediction accuracy. The findings contribute valuable empirical evidence to the growing body of literature on deep learning applications in financial forecasting and provide a solid foundation for future research and practical applications in this field. The methodology developed in this study offers a framework for evaluating regularization techniques in financial time series forecasting that can be extended and refined in future research endeavors.

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## CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

**Author1:** Conceptualization, Methodology, Software, Writing, Program, Report, Submission. **Author2**: Reviewer. **Author3**: Validation**.**

## DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## DATA AVAILABILITY

The data that supports the findings of this study are available from the corresponding author upon reasonable request. The Sony stock price data used in this research was obtained from Yahoo Finance API for the period from September 18, 2015, to September 17, 2025. The processed datasets, trained models, and source code used in this study can be made available to interested researchers for academic purposes, subject to data privacy regulations and intellectual property considerations.

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