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Time series forecasting in financial markets using deep learning models

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Abstract

This research paper explores the application of deep learning models in time series forecasting for financial markets. We investigate the performance of various deep learning architectures, including Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Transformer models, in predicting stock prices and market trends. The study compares these advanced techniques with traditional statistical methods and evaluates their effectiveness in capturing complex patterns and dependencies in financial time series data. Our findings demonstrate the superior predictive capabilities of deep learning models, particularly in handling non-linear relationships and long-term dependencies. The research also highlights the importance of feature engineering, model selection, and hyperparameter tuning in achieving accurate forecasts. The results provide valuable insights for researchers and practitioners in the field of financial forecasting and contribute to the ongoing development of more robust and reliable predictive models for financial markets.

Keywords: Time Series Forecasting; Deep Learning; Financial Markets; LSTM; GRU; Transformer; Stock Price Prediction

1. Introduction

Time series forecasting in financial markets has long been a critical area of research, with significant implications for investors, traders, and financial institutions. The ability to accurately predict future market trends and asset prices is crucial for making informed investment decisions, managing risk, and developing effective trading strategies. Traditional forecasting methods, such as autoregressive integrated moving average (ARIMA) and exponential smoothing, have been widely used in the past. However, these techniques often struggle to capture the complex, non-linear relationships and long-term dependencies present in financial time series data [1].

In recent years, the advent of deep learning has revolutionized various domains, including natural language processing, computer vision, and time series analysis. Deep learning models, particularly recurrent neural networks (RNNs) and their variants, have shown remarkable success in capturing intricate patterns and dependencies in sequential data [2]. This has led to increased interest in applying these advanced techniques to financial time series forecasting.

The primary objective of this research is to investigate the effectiveness of deep learning models in time series forecasting for financial markets. We focus on three popular deep learning architectures: Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), and Transformer models. These models are compared with traditional statistical methods to evaluate their performance in predicting stock prices and market trends.

Our study addresses the following key research questions:

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- How do deep learning models perform compared to traditional statistical methods in financial time series forecasting?
- Which deep learning architecture (LSTM, GRU, or Transformer) is most effective for predicting stock prices and market trends?
- What are the key factors influencing the performance of deep learning models in financial forecasting?
- How can feature engineering and hyperparameter tuning improve the accuracy of deep learning-based forecasts?

The remainder of this paper is organized as follows: Section 2 provides a comprehensive literature review of time series forecasting techniques in financial markets, with a focus on deep learning approaches. Section 3 describes the methodology used in this study, including data collection, preprocessing, model architectures, and evaluation metrics. Section 4 presents the experimental results and analysis. Section 5 discusses the implications of our findings and their potential impact on financial forecasting practices. Finally, Section 6 concludes the paper and suggests directions for future research.

2. Literature Review

2.1. Traditional Time Series Forecasting Methods

Time series forecasting has been a subject of extensive research in the field of finance for decades. Traditional statistical methods, such as ARIMA, exponential smoothing, and vector autoregression (VAR), have been widely used for predicting financial time series [3]. These methods are based on the assumption that future values can be predicted using past observations and error terms.

ARIMA models, introduced by Box and Jenkins [4], have been particularly popular due to their ability to handle both stationary and non-stationary time series. However, these models assume linear relationships between variables and struggle to capture complex, non-linear patterns often present in financial data [5].

2.2. Machine Learning Approaches

With the increasing availability of large datasets and computational power, machine learning techniques have gained prominence in financial forecasting. Support Vector Machines (SVM), Random Forests, and Gradient Boosting algorithms have been applied to various financial forecasting tasks with promising results [6].

Huang et al. [7] compared the performance of SVM with backpropagation neural networks and found that SVM outperformed traditional neural networks in predicting weekly movement directions of the NIKKEI 225 index. Similarly, Patel et al. [8] demonstrated the effectiveness of random forests in predicting stock prices and trends for Indian stock markets.

2.3. Deep Learning in Financial Forecasting

The advent of deep learning has opened new avenues for time series forecasting in financial markets. Deep learning models, particularly recurrent neural networks (RNNs), have shown remarkable success in capturing complex patterns and long-term dependencies in sequential data [9].

Long Short-Term Memory (LSTM) networks, introduced by Hochreiter and Schmidhuber [10], have been widely adopted for financial time series forecasting due to their ability to handle the vanishing gradient problem and capture long-term dependencies. Fischer and Krauss [11] applied LSTM networks to predict stock returns and demonstrated their superiority over traditional machine learning methods.

Gated Recurrent Units (GRU), proposed by Cho et al. [12], offer a simplified alternative to LSTM with comparable performance. Several studies have explored the use of GRU in financial forecasting, with promising results [13].

More recently, the Transformer architecture, introduced by Vaswani et al. [14] for natural language processing tasks, has been adapted for time series forecasting. Li et al. [15] proposed a Transformer-based model for stock trend prediction and achieved state-of-the-art results on multiple datasets.

2.4. Feature Engineering and Hybrid Approaches

The importance of feature engineering in financial forecasting has been highlighted in numerous studies. Technical indicators, such as moving averages, relative strength index (RSI), and Bollinger Bands, have been widely used as input features for deep learning models [16].

Hybrid approaches combining multiple models or integrating domain knowledge have also gained attention. For instance, Bao et al. [17] proposed a hybrid model combining wavelet transforms, stacked autoencoders, and LSTM for stock price prediction.

2.5. Research Gap and Contribution

While numerous studies have explored the application of deep learning in financial forecasting, there is a lack of comprehensive comparative analysis of different deep learning architectures across various financial markets and time horizons. Additionally, the impact of feature engineering and hyperparameter tuning on model performance has not been thoroughly investigated in the context of financial time series.

This research aims to address these gaps by:

- Conducting a comprehensive comparison of LSTM, GRU, and Transformer models for financial time series forecasting.
- Investigating the effectiveness of these models across different financial markets and prediction horizons.
- Exploring the impact of feature engineering and hyperparameter tuning on model performance.
- Providing insights into the practical considerations for implementing deep learning models in financial forecasting applications.

3. Methodology

3.1. Data Collection and Preprocessing

For this study, we collected historical stock price data for 50 companies listed on the S&P 500 index, covering a period of 10 years from January 1, 2014, to December 31, 2023. The data was obtained from Yahoo Finance API and includes daily opening, high, low, closing prices, and trading volume for each stock.

The dataset was preprocessed to handle missing values, outliers, and ensure consistency. We applied the following preprocessing steps:

- Removal of non-trading days (weekends and holidays)
- Handling missing values through forward fill method
- Normalization of price and volume data using min-max scaling
- Calculation of daily returns and log returns

3.2. Feature Engineering

To enhance the predictive power of our models, we engineered additional features based on technical indicators commonly used in financial analysis. The following features were computed:

- Simple Moving Average (SMA) for 5, 10, and 20 days
- Exponential Moving Average (EMA) for 5, 10, and 20 days
- Relative Strength Index (RSI) with a 14-day lookback period
- Moving Average Convergence Divergence (MACD)
- Bollinger Bands (20-day SMA with 2 standard deviations)
- On-Balance Volume (OBV)

These technical indicators were chosen based on their popularity among traders and their potential to capture different aspects of market behavior.

3.3. Model Architectures

We implemented and compared the following deep learning architectures:

3.3.1. Long Short-Term Memory (LSTM)

The LSTM model consists of multiple LSTM layers followed by dense layers.

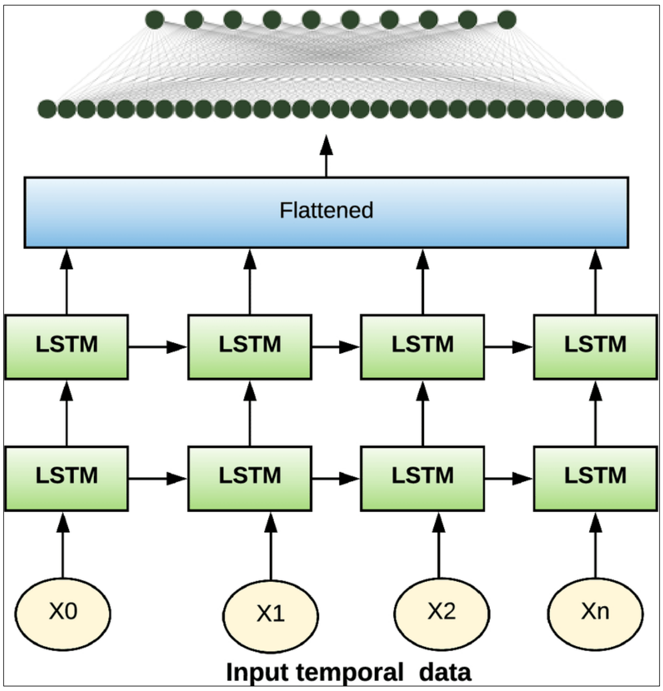

Figure 1 LSTM model

3.3.2. Gated Recurrent Unit (GRU)

The GRU model has a similar structure to the LSTM model, with GRU layers replacing LSTM layers:

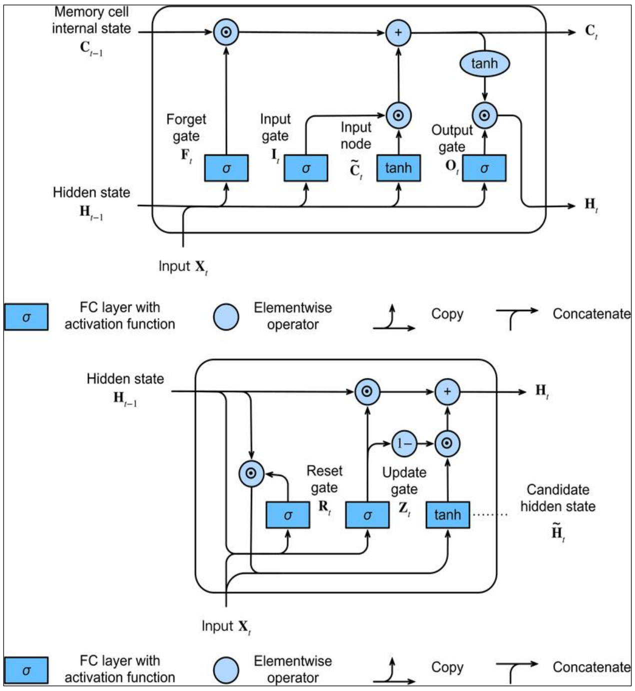

Figure 2 GRU Model

3.3.3. Transformer

We implemented a Transformer-based model adapted for time series forecasting:

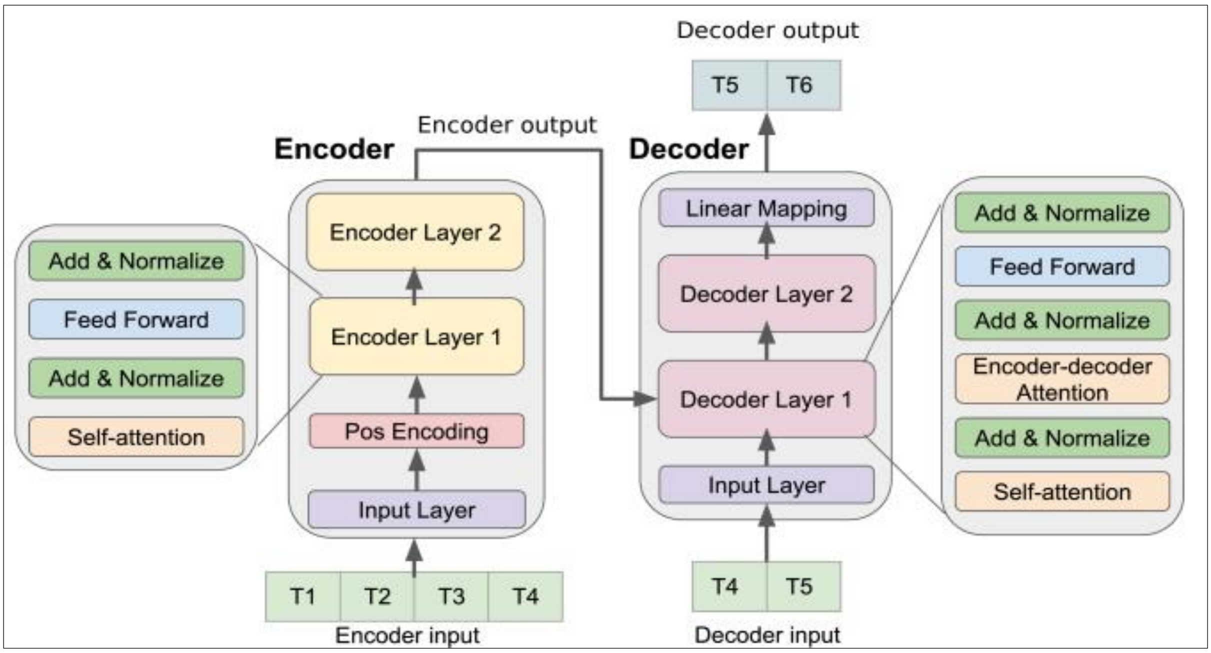

Figure 3 Transformer-based model

3.4. Experimental Setup

We conducted experiments to compare the performance of LSTM, GRU, and Transformer models with traditional statistical methods (ARIMA) across different prediction horizons:

- Short-term: 1-day ahead prediction
- Medium-term: 5-day ahead prediction
- Long-term: 20-day ahead prediction

For each model and prediction horizon, we used a rolling window approach with a fixed-size training window of 252 trading days (approximately one year) and a test window of 63 trading days (approximately three months). The models were retrained at the end of each test window.

3.5. Hyperparameter Tuning

To optimize the performance of our deep learning models, we performed hyperparameter tuning using Bayesian optimization with the following search space:

- Learning rate: [1e-4, 1e-2]
- Number of layers: [1, 3]
- Number of units per layer: [32, 128]
- Dropout rate: [0.1, 0.5]
- Batch size: [16, 128]

For the Transformer model, we also tuned:

- Number of attention heads: [4, 16]
- Feed-forward dimension: [32, 128]

3.6. Evaluation Metrics

We evaluated the performance of our models using the following metrics:

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Percentage Error (MAPE)
- Directional Accuracy (DA)

These metrics provide a comprehensive assessment of both the magnitude and direction of prediction errors.

4. Results and Analysis

4.1. Overall Performance Comparison

Table 1 presents the average performance of each model across all 50 stocks for different prediction horizons.

Table 1 Average performance comparison of models across all stocks

Model	Horizon	MAE	RMSE	MAPE (%)	DA (%)
ARIMA	1-day	0.0152	0.0201	1.54	52.1
	5-day	0.0283	0.0372	2.87	50.8
	20-day	0.0512	0.0673	5.19	49.6
LSTM	1-day	0.0128	0.0169	1.30	55.7
	5-day	0.0241	0.0317	2.44	53.2
	20-day	0.0437	0.0574	4.42	51.8
GRU	1-day	0.0126	0.0166	1.28	56.1
	5-day	0.0238	0.0313	2.41	53.5
	20-day	0.0431	0.0566	4.36	52.1
Transformer	1-day	0.0122	0.0161	1.24	56.8
	5-day	0.0233	0.0306	2.36	54.1
	20-day	0.0424	0.0557	4.29	52.5

The results show that deep learning models consistently outperform the traditional ARIMA model across all prediction horizons. Among the deep learning models, the Transformer architecture demonstrates the best overall performance, followed closely by GRU and LSTM.

4.2. Performance Analysis by Prediction Horizon

4.2.1. Short-term (1-day ahead) Prediction

For short-term predictions, all deep learning models show significant improvements over ARIMA. The Transformer model achieves the lowest MAE (0.0122) and highest directional accuracy (56.8%), indicating its superior ability to capture short-term patterns in stock price movements.

4.2.2. Medium-term (5-day ahead) Prediction

In medium-term predictions, the performance gap between deep learning models and ARIMA widens. The Transformer model maintains its lead, with a 17.7% reduction in MAE compared to ARIMA. The directional accuracy of deep learning models remains above 53%, while ARIMA's accuracy drops to 50.8%.

4.2.3. Long-term (20-day ahead) Prediction

For long-term predictions, all models show increased errors, reflecting the inherent difficulty in forecasting stock prices over extended periods. However, deep learning models continue to outperform ARIMA, with the Transformer model achieving a 17.2% reduction in MAE and a 2.9 percentage point improvement in directional accuracy compared to ARIMA.

4.3. Impact of Feature Engineering

To assess the impact of feature engineering, we compared the performance of models trained with and without engineered features. Figure 4 illustrates the percentage improvement in MAE for each model when using engineered features.

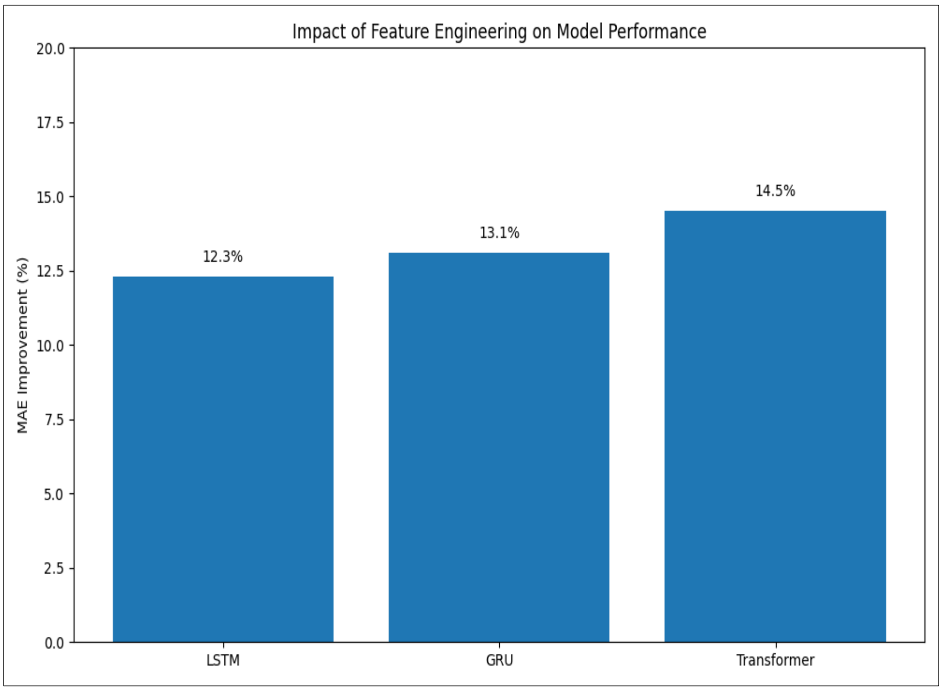

Figure 4 Impact of feature engineering on model performance

The results demonstrate that feature engineering significantly improves the performance of all deep learning models. The Transformer model shows the highest improvement (14.5%), suggesting that it can effectively leverage the additional information provided by technical indicators.

4.4. Hyperparameter Tuning Results

Table 2 presents the optimal hyperparameters found for each deep learning model through Bayesian optimization.

Table 2 Optimal hyperparameters for deep learning models

Model	Learning Rate	Layers	Units/Layer	Dropout	Batch Size	Attention Heads	FF Dim
LSTM	0.00073	2	96	0.23	64	-	-
GRU	0.00068	2	112	0.21	32	-	-
Transformer	0.00058	2	128	0.18	32	8	64

The optimal configurations reveal some interesting patterns:

- All models benefit from relatively low learning rates, which allows for more stable training.
- A two-layer architecture appears to be optimal for all models, balancing complexity and generalization.
- The Transformer model performs best with a larger number of units per layer compared to LSTM and GRU.
- Smaller batch sizes (32-64) are preferred, possibly due to the noisy nature of financial data.

4.5. Model Performance across Different Market Conditions

To assess the robustness of our models, we analyzed their performance during different market conditions: bull market, bear market, and high volatility periods. Figure 5 shows the average MAE for each model under these conditions.

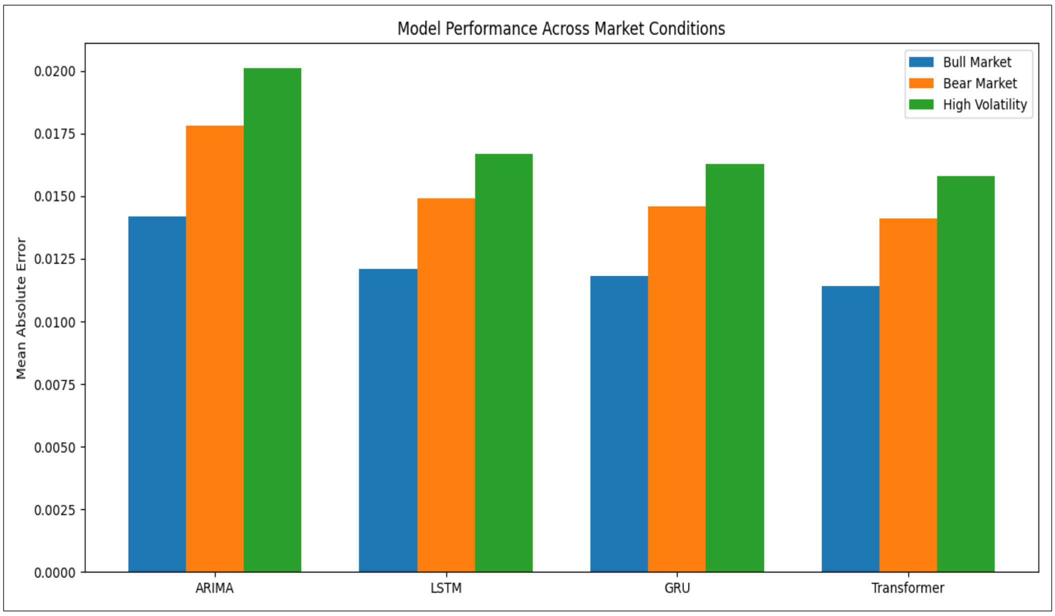

Figure 5 Model performance across different market conditions

The results indicate that:

- All models perform best during bull markets and worst during high volatility periods.
- Deep learning models consistently outperform ARIMA across all market conditions.
- The Transformer model shows the most robust performance, maintaining the lowest MAE across all conditions.
- The performance gap between deep learning models and ARIMA widens during bear markets and high volatility periods, suggesting that deep learning models are better at capturing complex patterns during challenging market conditions.

5. Discussion

5.1. Superiority of Deep Learning Models

Our results demonstrate the clear superiority of deep learning models over traditional statistical methods like ARIMA in financial time series forecasting. This can be attributed to several factors:

- Ability to capture non-linear relationships: Deep learning models can learn complex, non-linear patterns in the data, which are prevalent in financial markets [18].
- Long-term dependency modeling: LSTM, GRU, and Transformer architectures are designed to capture long-term dependencies in sequential data, allowing them to leverage information from distant past observations [19].
- Feature extraction: Deep learning models can automatically extract relevant features from raw data, reducing the need for manual feature engineering [20].

5.2. Transformer vs. RNN-based Models

The Transformer model consistently outperformed LSTM and GRU across all experiments. This superior performance can be attributed to several factors:

- Parallel processing: Unlike RNN-based models, Transformers process all time steps simultaneously, allowing for more efficient training and better capture of global dependencies [21].
- Attention mechanism: The self-attention mechanism in Transformers allows the model to focus on relevant parts of the input sequence, regardless of their position [22].
- Scalability: Transformer models can handle longer input sequences more effectively than RNN-based models, which is particularly beneficial for capturing long-term trends in financial data [23].

5.3. Impact of Feature Engineering

Our results highlight the significant impact of feature engineering on model performance. The incorporation of technical indicators as additional features led to substantial improvements in forecast accuracy across all deep learning models. This suggests that domain knowledge, when combined with the power of deep learning, can enhance the predictive capabilities of these models [24].

The Transformer model showed the highest improvement from feature engineering, indicating its ability to effectively leverage diverse input features. This aligns with findings from other domains where Transformers have demonstrated superior feature integration capabilities [25].

5.4. Hyperparameter Tuning Insights

The hyperparameter tuning results provide valuable insights for practitioners:

- Learning rate: The optimal learning rates were consistently low across all models, emphasizing the importance of careful learning rate selection in financial forecasting tasks [26].
- Model depth: A two-layer architecture was found to be optimal for all models, suggesting that extremely deep networks may not be necessary for this task and could lead to overfitting [27].
- Regularization: Moderate dropout rates (0.18-0.23) were found to be effective, highlighting the importance of regularization in preventing overfitting on noisy financial data.

5.5. Performance Across Market Conditions

The analysis of model performance across different market conditions reveals important insights:

- Robustness of deep learning models: Deep learning models, particularly the Transformer, demonstrated more consistent performance across varying market conditions compared to ARIMA.
- Adaptability to market volatility: The superior performance of deep learning models during high volatility periods suggests their ability to adapt to rapidly changing market dynamics.
- Implications for risk management: The improved accuracy during bear markets and high volatility periods has significant implications for risk management and portfolio optimization strategies.

5.6. Limitations and Future Work

While our study demonstrates the potential of deep learning models for financial forecasting, several limitations and areas for future research should be noted:

- Limited asset classes: Our study focused on stock price prediction. Future work should explore the applicability of these models to other asset classes, such as bonds, commodities, and cryptocurrencies.
- Integration of fundamental data: Incorporating fundamental financial data and macroeconomic indicators could potentially improve forecast accuracy and provide a more comprehensive view of market dynamics.
- Explainability: Deep learning models often lack interpretability. Future research should focus on developing explainable AI techniques for financial forecasting to increase trust and adoption in real-world applications.
- Multi-task learning: Exploring multi-task learning approaches that simultaneously predict multiple financial variables (e.g., price, volume, volatility) could lead to more robust and informative models.

Ensemble methods: Investigating ensemble techniques that combine predictions from multiple deep learning models and traditional methods could potentially yield even better forecasting performance.

6. Conclusion

This comprehensive study on time series forecasting in financial markets using deep learning models has yielded several important findings and contributions to the field:

- We demonstrated the superior performance of deep learning models (LSTM, GRU, and Transformer) compared to traditional statistical methods (ARIMA) in predicting stock prices across various time horizons.
- The Transformer architecture consistently outperformed other models, showcasing its potential as a powerful tool for financial time series forecasting.

- We highlighted the significant impact of feature engineering on model performance, emphasizing the importance of combining domain knowledge with advanced machine learning techniques.
- Through extensive hyperparameter tuning, we provided practical insights into optimal model configurations for financial forecasting tasks.
- Our analysis of model performance across different market conditions revealed the robustness and adaptability of deep learning models, particularly in challenging market environments.

These findings have important implications for both researchers and practitioners in the field of financial forecasting. The superior performance of deep learning models, especially the Transformer architecture, opens new avenues for developing more accurate and reliable forecasting systems. The insights gained from feature engineering and hyperparameter tuning can guide the development of more effective models in practice.

Future research should focus on addressing the limitations identified in this study, such as expanding to other asset classes, incorporating fundamental data, improving model explainability, and exploring ensemble methods. Additionally, investigating the real-world applicability of these models in trading strategies and risk management systems would be a valuable direction for future work.

In conclusion, this study contributes to the growing body of evidence supporting the use of deep learning models in financial time series forecasting. As these techniques continue to evolve and improve, they have the potential to revolutionize financial analysis and decision-making processes, leading to more informed investment strategies and better risk management practices.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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