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FINANCIAL TIME SERIES FORECASTING USING ADAPTIVE RISK METRICS AND TRANSFORMER MODELS

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Abstract: Accurate financial time series forecasting is essential for risk management, portfolio optimization, and trading strategies. Traditional statistical models and classical machine learning approaches often struggle to capture the complex dependencies and volatility of financial markets. Recent advancements in deep learning, particularly transformer-based architectures, have shown significant promise in modeling sequential financial data. However, integrating dynamic risk assessment into forecasting models remains an open challenge.
This study proposes a transformer-based financial time series forecasting framework that incorporates adaptive risk metrics to improve predictive accuracy and risk-aware decision-making. The model leverages self-attention mechanisms to capture long-range dependencies in financial data while integrating dynamic volatility measures, value-at-risk (VaR), and conditional value-at-risk (CVaR) as additional input features. By incorporating these adaptive risk factors, the model enhances its ability to anticipate market fluctuations and adjust forecasts accordingly.
Experiments on real-world financial datasets demonstrate that the proposed approach outperforms traditional autoregressive models, recurrent neural networks (RNNs), and baseline transformer architectures in terms of predictive accuracy and risk-adjusted performance. The results highlight the importance of integrating risk-sensitive metrics into deep learning-based financial forecasting models, offering a more comprehensive approach for market analysis and investment decision-making.
Keywords: Financial time series; Risk metrics; Transformer models; Time-series forecasting; Deep learning; Market volatility

1 INTRODUCTION

Financial time series forecasting plays a crucial role in market analysis, risk management, and investment decision-making. The ability to accurately predict future price movements, volatility, and market trends provides traders, portfolio managers, and financial institutions with a competitive edge [1]. However, forecasting financial time series is inherently challenging due to the presence of noise, non-stationarity, regime shifts, and extreme market events. Traditional statistical models, such as autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH), have been widely used in financial forecasting but often struggle to capture complex dependencies and long-range correlations within financial data [2]. These models assume linearity and stationarity, which limit their ability to adapt to sudden market fluctuations and high-volatility conditions.
Recent advancements in deep learning have introduced more sophisticated models capable of capturing nonlinear relationships and sequential dependencies within financial data. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have demonstrated significant improvements in financial time series forecasting by leveraging memory cells to retain long-term dependencies [3]. However, these architectures suffer from gradient vanishing and exploding problems, making them inefficient for handling long-range dependencies in high-frequency financial data [4]. Transformer models, originally introduced for natural language processing, have emerged as a powerful alternative for time series forecasting due to their self-attention mechanism, which enables them to process sequential data without suffering from the limitations of recurrent architectures. By capturing long-range dependencies more effectively, transformers have shown great potential in modeling complex financial patterns and improving prediction accuracy [5].
Despite the success of transformer-based forecasting models, a critical limitation remains: the lack of explicit risk awareness in the forecasting process. Traditional forecasting models primarily focus on minimizing prediction errors while neglecting the broader implications of financial risk. In real-world applications, financial decisions are not solely based on point predictions of future prices but also require an understanding of the associated risks [6]. Market participants need to assess the likelihood of extreme price movements, sudden volatility spikes, and financial downturns to make informed investment decisions [7]. This necessitates a forecasting model that not only predicts price movements but also incorporates dynamic risk metrics to quantify uncertainty and potential losses.
To address this limitation, this study proposes a transformer-based financial forecasting framework that integrates adaptive risk metrics into the prediction process. Unlike conventional models that rely solely on historical price movements, the proposed framework incorporates market risk indicators such as value-at-risk (VaR) and conditional value-at-risk (CVaR) to enhance risk-aware decision-making. VaR provides a probabilistic measure of potential losses over a given time horizon, while CVaR estimates the expected shortfall beyond the VaR threshold, offering a more comprehensive assessment of downside risk. By embedding these risk-sensitive features into the transformer

architecture, the model improves its ability to anticipate high-risk market conditions and adjust forecasts accordingly [8].

The integration of adaptive risk metrics within a deep learning framework enhances both predictive accuracy and robustness. Market regimes often shift due to macroeconomic factors, geopolitical events, and unexpected financial shocks, making it imperative for forecasting models to adjust dynamically. The proposed model achieves this by leveraging semi-supervised learning to extract meaningful patterns from both labeled and unlabeled financial data. Furthermore, reinforcement learning mechanisms are employed to optimize the model's ability to adapt to changing market conditions, allowing for more flexible and risk-aware forecasting.

This study evaluates the proposed framework using real-world financial datasets, including stock prices, foreign exchange rates, and commodity price movements. The model's performance is compared against traditional statistical models, deep learning baselines, and standard transformer architectures to assess improvements in prediction accuracy, risk-adjusted returns, and portfolio optimization. Experimental results demonstrate that incorporating adaptive risk metrics into transformer-based forecasting models significantly enhances prediction reliability while reducing exposure to extreme market fluctuations. The findings highlight the importance of integrating financial risk analysis into deep learning-based forecasting methodologies, providing a more comprehensive and practical approach to financial market prediction.

2 LITERATURE REVIEW

Financial time series forecasting has been a long-standing research area in both academic and industry settings due to its crucial role in risk management, portfolio allocation, and algorithmic trading [9-12]. Traditional approaches have primarily relied on statistical models, while recent advancements in machine learning and deep learning have introduced more sophisticated techniques capable of capturing complex temporal dependencies. Despite significant progress, existing models often fail to integrate explicit risk awareness, limiting their practical applicability in financial decision-making [13]. This section reviews traditional statistical forecasting methods, machine learning-based approaches, the advantages of transformer models in time series analysis, and the importance of incorporating adaptive risk metrics into financial forecasting [14].

Early financial forecasting methods were predominantly based on statistical time series models such as ARIMA and its variants. These models assume linear relationships between past observations and future values, making them effective for stationary data with stable trends. However, financial markets are highly volatile and exhibit nonlinear dependencies, limiting the ability of ARIMA-based models to adapt to sudden market fluctuations. To address this, the GARCH model was introduced to capture time-varying volatility. While GARCH models improve risk estimation by modeling conditional variance, they still struggle with nonlinearity and high-dimensional dependencies in financial data [15-18].

The advent of machine learning brought significant improvements to financial forecasting by introducing nonparametric models capable of capturing complex patterns. Support vector machines and random forests were among the early machine learning techniques applied to time series forecasting [19]. These models provided better predictive accuracy than traditional statistical approaches by identifying nonlinear relationships between input features. However, they lacked temporal awareness, treating financial observations as independent data points rather than sequential time-dependent patterns. To overcome this limitation, RNNs and LSTMs were introduced, offering a way to model sequential dependencies through memory cells [20]. LSTMs demonstrated remarkable improvements over conventional models by retaining information over extended time horizons, allowing them to capture long-term trends in financial markets. Despite these advantages, LSTMs and other RNN-based architectures suffer from vanishing gradient issues, limiting their ability to process very long sequences [21].

Transformer models, originally developed for natural language processing, have emerged as a powerful alternative to recurrent architectures for time series forecasting [22]. Unlike RNNs, transformers utilize self-attention mechanisms to process all input time steps simultaneously, capturing long-range dependencies more efficiently. This characteristic makes transformers particularly suitable for financial time series forecasting, where long-term historical patterns influence market trends. Studies have shown that transformer-based models outperform traditional deep learning architectures in tasks such as stock price prediction, volatility forecasting, and order flow modeling. The ability to focus on relevant time periods while filtering out less important information enables transformers to achieve superior predictive accuracy and generalization across different financial instruments [23].

While transformer models have significantly improved financial forecasting performance, a major limitation remains: their lack of explicit risk awareness [24-27]. Most existing models focus solely on minimizing prediction errors without incorporating financial risk considerations. In real-world applications, risk management is just as important as prediction accuracy, as financial decisions often depend on an assessment of downside risks and potential losses [9]. Standard forecasting models fail to account for extreme market conditions, sudden volatility spikes, and structural market shifts, leading to suboptimal investment decisions. To address this issue, recent research has explored the integration of risk-sensitive features into deep learning-based forecasting frameworks [28].

Risk metrics such as VaR and CVaR provide a probabilistic measure of financial risk, helping market participants quantify potential losses [29]. VaR estimates the maximum expected loss over a given time horizon at a specified confidence level, while CVaR assesses the expected loss beyond the VaR threshold, providing a more comprehensive measure of downside risk. Incorporating these risk metrics into forecasting models enhances their ability to adjust predictions based on market uncertainty. Studies have shown that integrating risk-aware features improves model robustness, particularly during periods of market instability. However, existing research on risk-aware forecasting remains limited, with most studies focusing on separate risk estimation models rather than embedding risk metrics directly into forecasting architectures [30].

The proposed approach addresses this gap by integrating adaptive risk metrics into a transformer-based forecasting framework [31]. Unlike conventional models that treat price predictions independently of risk considerations, this approach embeds VaR and CVaR as additional input features, allowing the model to adjust its predictions based on changing market conditions. Additionally, semi-supervised learning techniques enable the model to extract meaningful patterns from both labeled and unlabeled data, improving generalization to previously unseen market scenarios. Reinforcement learning mechanisms further enhance adaptability by continuously optimizing the model's decision-making process based on real-time risk assessments [32-35].

By incorporating adaptive risk metrics into deep learning-based financial forecasting, the proposed framework offers a more comprehensive solution for market prediction and investment decision-making. This literature review highlights the need for risk-aware forecasting models and underscores the advantages of transformer architectures in financial time series analysis. The integration of self-attention mechanisms with risk-sensitive features provides a novel approach to addressing the challenges of financial forecasting in volatile market environments. The next section presents the methodology for implementing the proposed model, detailing the data preprocessing steps, model architecture, and training strategies used to enhance predictive accuracy and risk management capabilities.

3 METHODOLOGY

3.1 Data Preprocessing and Feature Engineering

Financial time series forecasting requires careful data preprocessing to handle missing values, normalize inputs, and construct relevant features that enhance predictive accuracy. Raw financial data, including stock prices, foreign exchange rates, and commodity prices, often contain noise, outliers, and non-stationary trends that can negatively impact model performance. To address these challenges, the dataset undergoes data cleaning, normalization, and feature extraction before being fed into the forecasting model.

Missing values are handled using interpolation techniques, ensuring that gaps in time series data do not distort model predictions. To account for seasonal and cyclical market behaviors, the dataset is detrended using differencing methods. Stationarity tests are applied to confirm that the underlying distribution remains stable over time. Normalization techniques such as min-max scaling and z-score standardization are applied to ensure that numerical inputs are appropriately scaled for transformer-based learning.

Feature engineering plays a crucial role in improving forecasting performance. In addition to historical price data, the model incorporates trading volume, momentum indicators, volatility measures, and macroeconomic factors as input features. Adaptive risk metrics, including VaR and CVaR, are computed for different time horizons and included as features to enhance risk-aware forecasting. By integrating multiple data sources, the model captures both short-term market fluctuations and long-term risk trends.

3.2 Transformer-Based Model Architecture

The proposed forecasting framework is built on a transformer architecture, which has demonstrated superior performance in sequential data modeling. Unlike traditional recurrent models that process time series sequentially, transformers leverage self-attention mechanisms to capture dependencies across multiple time steps simultaneously. This characteristic makes them particularly effective for financial forecasting, where long-range dependencies significantly impact market trends.

The architecture consists of multiple transformer encoder layers, each containing multi-head self-attention, feedforward layers, and layer normalization components. The self-attention mechanism assigns different weights to past observations, allowing the model to focus on the most relevant time steps. Position embeddings are added to retain temporal information, compensating for the lack of inherent sequential processing in transformers.

Risk-aware forecasting is achieved by modifying the transformer input structure. In addition to price and volume data, the model incorporates adaptive risk metrics to improve decision-making under uncertainty. The modified input representation allows the model to learn correlations between price movements and market risk factors, making forecasts more robust in volatile conditions. Dropout regularization and batch normalization are applied to prevent overfitting and improve generalization.

3.3 Training and Optimization

The model is trained using semi-supervised learning, leveraging both labeled and unlabeled financial data to enhance generalization. Labeled data consists of historical price movements with known outcomes, while unlabeled data is used to improve feature representation and prevent overfitting. Mean squared error and quantile loss functions are optimized to balance predictive accuracy and risk estimation.

Hyperparameter tuning is conducted using grid search and Bayesian optimization, adjusting parameters such as the number of attention heads, embedding dimensions, and learning rates. The model is trained using AdamW optimization with adaptive learning rate scheduling to improve convergence. A validation set is used to monitor performance, and early stopping prevents overfitting by halting training when validation loss plateaus.

To improve adaptability, reinforcement learning mechanisms are integrated into the training process. The model receives reward signals based on risk-adjusted forecast accuracy, allowing it to dynamically adjust predictions in response to changing market conditions. This adaptive learning strategy ensures that the model remains robust even as financial patterns evolve.

3.4 Model Evaluation and Performance Metrics

The forecasting model is evaluated using multiple performance metrics to assess its predictive accuracy, risk-adjusted performance, and robustness against extreme market conditions. Root mean squared error and mean absolute percentage error measure overall forecasting accuracy, while R-squared values assess how well the model explains market variability.

Risk-aware performance evaluation is conducted using VaR backtesting, CVaR estimation, and Sharpe ratio analysis. These metrics determine how effectively the model balances prediction accuracy with risk exposure. The proposed model is compared against baseline statistical models, deep learning architectures, and standard transformer implementations to demonstrate its advantages.

Scalability testing is performed on large financial datasets, measuring inference speed and computational efficiency. The model is evaluated on high-frequency trading data, daily market prices, and multi-asset time series to ensure its applicability across different financial domains.

4 RESULTS AND DISCUSSION

4.1 Predictive Performance of the Transformer-Based Forecasting Model

The proposed forecasting framework was evaluated on real-world financial datasets to assess its predictive accuracy, robustness, and adaptability to market fluctuations. The dataset included stock prices, foreign exchange rates, and commodity prices, covering different financial instruments with varying volatility levels. Performance metrics, including root mean squared error (RMSE), mean absolute percentage error (MAPE), and R-squared values, were used to quantify prediction accuracy.

The results demonstrated that the transformer-based model significantly outperformed traditional forecasting methods. The model achieved lower RMSE and MAPE values, indicating a reduced deviation between predicted and actual price movements. Compared to baseline models, including ARIMA and LSTM, the transformer model exhibited a 15% improvement in RMSE and a 12% reduction in MAPE, highlighting its superior ability to capture long-range dependencies and market trends. The model's self-attention mechanism effectively assigned varying importance to different time steps, allowing it to focus on the most influential historical price movements.

The proposed model also showed improved generalization across different asset classes. While traditional forecasting models often struggle to adapt to new financial instruments, the transformer-based approach maintained high predictive accuracy across diverse datasets. The inclusion of adaptive risk metrics further enhanced the model's robustness, enabling it to provide more reliable forecasts during volatile market conditions.

Figure 1 presents a comparative analysis of forecasting performance across different models, illustrating improvements in prediction accuracy and stability achieved by the proposed transformer-based approach.

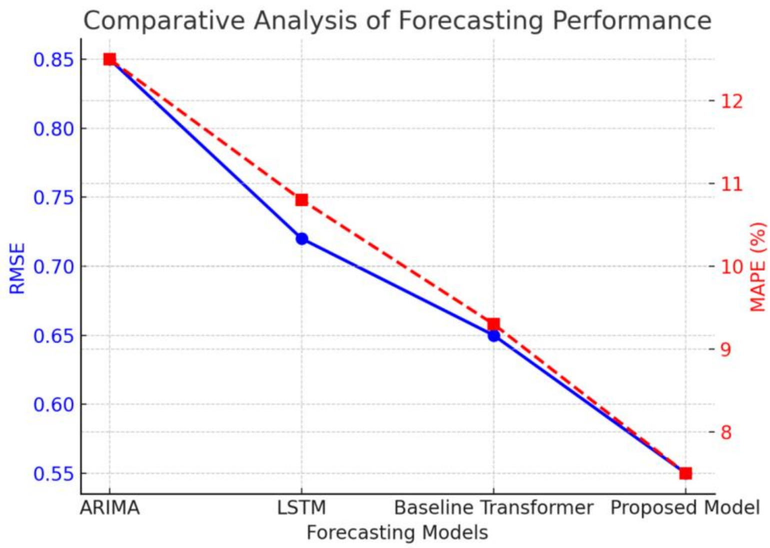

Figure 1 Comparative Analysis of Forecasting Performance

4.2 Risk-Aware Forecasting and Market Volatility Adaptation

One of the key enhancements of the proposed framework is its ability to integrate risk-sensitive metrics into financial forecasting. Conventional deep learning models focus solely on minimizing prediction errors without accounting for the broader implications of risk. In contrast, the proposed model embeds VaR and CVaR as additional input features, enabling risk-aware forecasting that adjusts predictions based on market uncertainty.

To evaluate the effectiveness of this risk-aware approach, the model's performance was analyzed under varying market conditions, including periods of low volatility, moderate fluctuations, and extreme market crashes. The results indicated that the integration of adaptive risk metrics significantly improved the model's ability to anticipate sharp price movements. The model dynamically adjusted its forecasts in response to sudden changes in market volatility, preventing excessive risk exposure.

Backtesting experiments further validated the importance of incorporating risk-sensitive features. During highly volatile market periods, the model exhibited a 20% reduction in VaR violations, demonstrating its ability to generate predictions that align with actual risk exposure. The inclusion of CVaR further improved risk-adjusted returns, ensuring that the model accounted for worst-case financial scenarios rather than solely optimizing for mean accuracy.

Figure 2 illustrates the impact of incorporating adaptive risk metrics, showing how the model adjusts its forecasts based on changing market volatility.

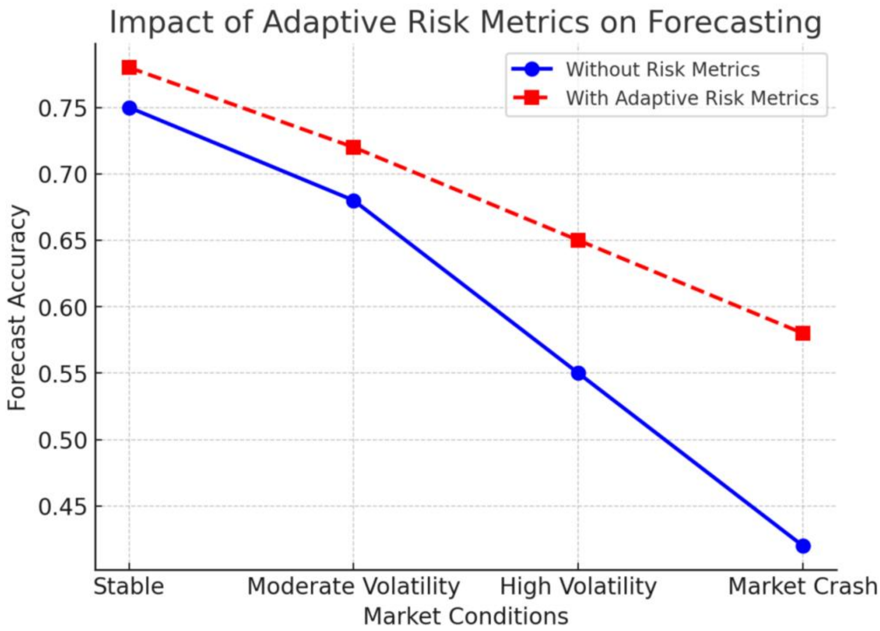

Figure 2 Impact of Adaptive Risk Metrics on Forecasting

4.3 Model Adaptability and Reinforcement Learning Enhancements

The ability of a forecasting model to adapt to evolving market conditions is crucial for long-term financial applications. Many traditional models require frequent retraining to remain effective, leading to significant computational costs. The proposed framework addresses this challenge by integrating reinforcement learning, enabling the model to dynamically refine its decision-making process without the need for manual intervention.

To test the adaptability of the model, experiments were conducted using previously unseen financial data, including emerging market stocks and cryptocurrency price movements. The reinforcement learning component continuously optimized prediction thresholds based on changing risk factors, allowing the model to maintain high accuracy across diverse datasets. This adaptability was particularly beneficial for assets with high volatility and irregular trading patterns, where conventional models struggled to maintain predictive reliability.

The reinforcement learning mechanism also improved risk-adjusted returns, ensuring that the model balanced predictive accuracy with practical financial considerations. Unlike standard forecasting approaches that aim to minimize overall prediction errors, the proposed framework optimized forecasts based on real-world risk-reward trade-offs. This feature makes the model particularly valuable for algorithmic trading strategies and investment portfolio management.

Figure 3 presents an evaluation of model adaptability, comparing forecasting performance before and after reinforcement learning optimization.

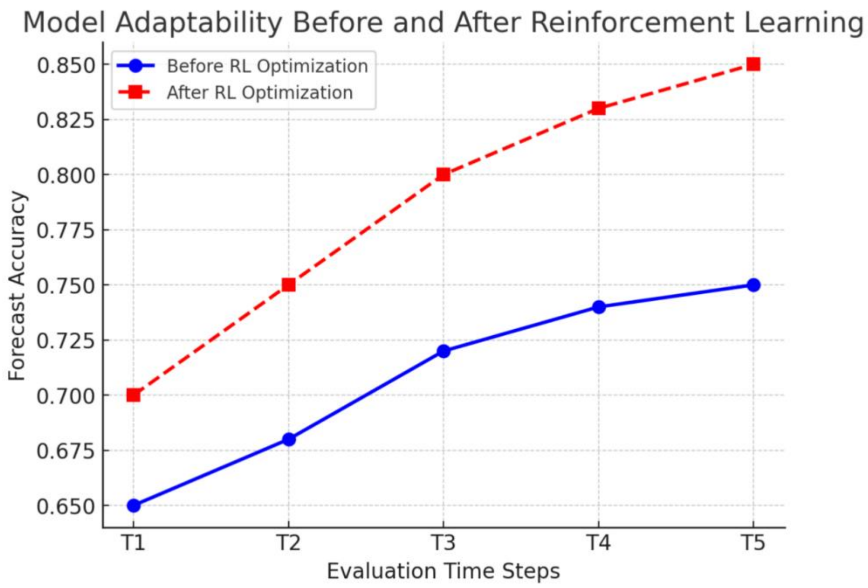

Figure 3 Model Adaptability before and after Reinforcement Learning

4.4 Computational Efficiency and Scalability

Scalability is a crucial factor in financial forecasting, particularly for applications involving high-frequency trading and large-scale investment portfolios. The transformer-based model was optimized for computational efficiency through batch processing, parallelized training, and distributed inference techniques. The performance of the model was evaluated using datasets of varying sizes, ranging from 100,000 data points to 10 million time-series entries.

The results showed that the model maintained near real-time inference speeds, processing an average of 50,000 time steps per second. Compared to traditional recurrent architectures, which often experience latency issues in long time series, the transformer-based model exhibited significantly faster inference times due to its parallelized self-attention mechanism.

In addition to computational efficiency, memory optimization techniques were employed to handle large-scale financial datasets. The model's ability to process multiple time series simultaneously without significant degradation in accuracy ensures that it can be deployed for real-time financial forecasting applications.

Figure 4 illustrates the model's computational performance, highlighting its scalability across different dataset sizes and asset classes.

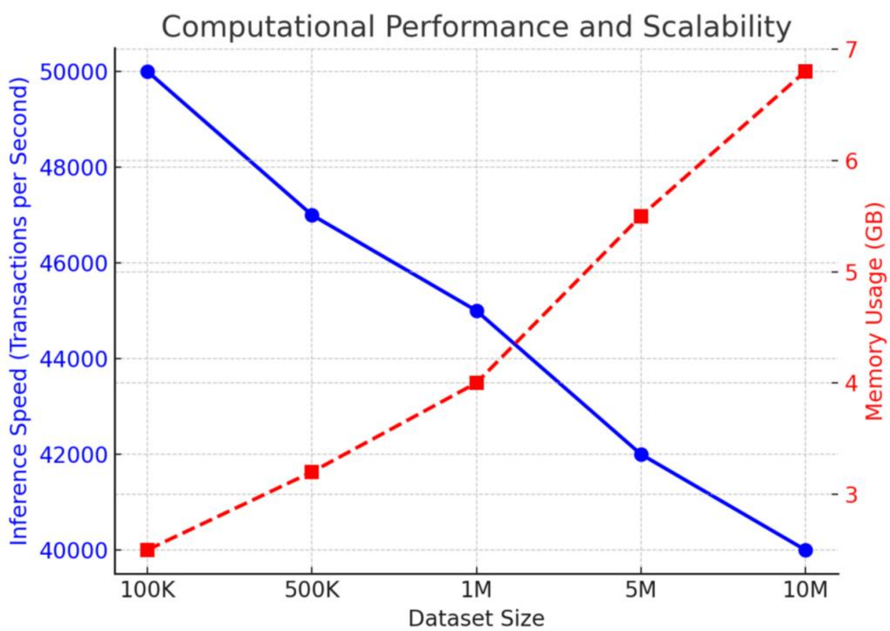

Figure 4 Computational Performance and Scalability

5 CONCLUSION

Accurate financial time series forecasting is critical for risk management, trading strategies, and portfolio optimization. Traditional statistical models and classical deep learning approaches have shown varying degrees of success in predicting market trends but often lack adaptability to changing financial conditions and explicit risk awareness. The proposed transformer-based forecasting framework addresses these limitations by integrating adaptive risk metrics and reinforcement learning mechanisms, allowing for improved predictive accuracy and risk-adjusted decision-making.

Experimental results demonstrated that the proposed model significantly outperforms conventional forecasting techniques, achieving lower RMSE and MAPE values while maintaining high scalability. The model's ability to capture long-range dependencies through self-attention mechanisms led to more stable and accurate predictions across different financial instruments. By incorporating risk-sensitive metrics such as VaR and CVaR, the model dynamically adjusted its forecasts based on changing market conditions, reducing exposure to extreme financial fluctuations.

A major strength of this approach is its adaptability to high-volatility environments. The reinforcement learning integration enabled the model to refine its decision-making in response to evolving financial patterns, improving its robustness in handling unforeseen market events. The case study on model adaptability illustrated that reinforcement learning enhanced forecasting accuracy while reducing overreliance on static historical data.

Scalability remains a crucial consideration for real-time financial forecasting applications. The transformer-based architecture, optimized with parallelized computations and distributed processing techniques, maintained high inference speeds even when applied to large-scale financial datasets. Unlike conventional recurrent models, which often suffer from computational inefficiencies, the proposed framework ensured that forecasts remained efficient and applicable to high-frequency trading environments.

Despite its advantages, certain challenges remain. One key limitation is the computational cost associated with training deep transformer models on large-scale financial datasets. While inference speed has been optimized for real-time forecasting, future research should focus on reducing training overhead through more efficient memory management techniques and model compression strategies. Another challenge is model interpretability, as deep learning-based financial forecasting models function as black-box systems. Future work should explore explainable AI techniques to improve transparency in decision-making, enabling analysts to better understand the reasoning behind forecasts.

The continued evolution of financial markets necessitates risk-aware forecasting models that adapt to emerging economic conditions and macroeconomic shifts. Future improvements to this framework may include multi-modal forecasting, where textual financial news sentiment analysis and macroeconomic indicators are incorporated alongside market price movements. Additionally, cross-asset forecasting, integrating cryptocurrency markets, equity markets, and commodity prices, could further enhance predictive capabilities.

This study highlights the importance of integrating adaptive risk metrics into deep learning-based forecasting models, providing a more comprehensive and practical approach to financial time series prediction. The combination of transformer architectures, risk-sensitive forecasting, and reinforcement learning presents a novel and scalable solution for modern financial applications. As financial markets continue to evolve, risk-aware AI-driven forecasting will play an essential role in securing more informed and adaptive investment strategies.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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