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A Review of the Application of LSTM Model in Stock Price Prediction

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ABSTRACT

Financial time series forecasting is a core issue in econometrics and statistics, and its nonlinearity, non-stationarity, and high noise characteristics pose a serious challenge to traditional statistical models such as ARIMA and GARCH. In recent years, long short-term memory networks (LSTMs) have become the mainstream model in the field of stock price prediction due to their excellent ability to capture long-term dependencies. This paper aims to systematically review and evaluate the research progress of LSTM-based stock price prediction models at home and abroad from a statistical perspective. We use the literature review method and comparative analysis method to first explain the theoretical advantages of LSTMs in dealing with the statistical characteristics of financial sequences; then we will categorize and review the existing research from three dimensions: basic application, feature enhancement, and structure optimization; finally, we analyze the relative effectiveness and applicable boundaries of LSTMs compared to traditional statistical and machine learning models. The study found that although LSTM models generally showed higher prediction accuracy, there were significant deficiencies in current research in terms of hyperparameter tuning fairness, the application of statistical significance tests (such as DM tests), and quantification of prediction uncertainty. This paper not only constructs a knowledge graph of research in this field but also provides a theoretical framework and methodological reference for subsequent researchers that takes into account both predictive performance and statistical rigor.

KEYWORDS

Long Short-Term Memory Network (LSTM); Stock price forecasting; Literature review; Deep learning

1 Introduction

1.1 Research background

Financial time series forecasting has long been a core concern in financial econometrics and statistics, and accurate forecasting is crucial for risk management, asset pricing, and the development of quantitative investment strategies. However, financial time series, such as stock prices, present distinct statistical characteristics that make their prediction highly challenging: (1) nonlinearity—stock price fluctuations are driven by the heterogeneous decisions of numerous investors and complex market sentiment, and their intrinsic dynamic mechanisms are difficult to characterize with linear models; (2) non-stationarity—statistical characteristics such as the mean and variance of the sequence evolve over time, often violating the fundamental assumption of stationarity in traditional time series analysis; (3) high noise—the market is disturbed by random events and noisy trading, resulting in an extremely low signal-to-noise ratio, with effective signals often drowned out.

In the face of these challenges, traditional statistical forecasting models reveal their limitations. Autoregressive Integrated Moving Average (ARIMA) models perform well with linearly stationary sequences but are contingent on strict linear assumptions and the premise of stationarity, proving ineffective against nonlinear models. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models and their variants can effectively capture the typical statistical phenomenon of volatility clustering, yet they remain fundamentally linear frameworks, limiting their capacity to capture complex nonlinear patterns, such as extreme volatility.

The advent of deep learning techniques, notably recurrent neural networks (RNNs), has opened new avenues for capturing complex dependencies in time series data. RNNs propagate historical information through their internal states, and their parameter sharing feature enables models to handle variable-length sequences with flexibility. However, Bengio et al. have pointed out that standard RNNs suffer from inherent issues of vanishing and exploding gradients during training, which complicates their ability to effectively learn long-term dependencies.

To address this fundamental challenge, Hochreiter and Schmidhuber (1997) introduced the Long Short-Term Memory Network (LSTM). By incorporating gating mechanisms, such as the input gate, forget gate, and output gate, along with cell states, LSTM refines the control of information flow. This significantly mitigates the gradient problem and establishes LSTM as a potent instrument for managing long sequence dependencies. In the realm of financial time series prediction, these LSTM attributes facilitate adaptive learning of nonlinear dynamic patterns, enable handling of non-stationarity, and allow for noise filtering to a certain degree. Consequently, LSTM serves as a robust complement to traditional statistical models.

1.2 Current status of research at home and abroad

In recent years, research on the application of LSTM in financial time series prediction has shown a flourishing trend, but there are different focuses at home and abroad. International research tends to concentrate on the exploration of theoretical frontiers and methodological rigor. Earlier work (by Nelson (2017) systematically validated the superiority of LSTM; more recent research has focused on architectural innovation. Fischer combines the Transformer with LSTM and actively incorporates alternative data, such as social media text and satellite images, while emphasizing statistical significance tests and quantification of predictive uncertainty in model evaluation.

In contrast, domestic research exhibits a distinct application-oriented and localized character, with a particular focus on model optimization and practical performance improvement for the A-share market. Domestic scholars have widely adopted hybrid modeling strategies, either combining LSTM with signal processing techniques (such as VMD, EEMD decomposition methods) to handle non-stationary sequences, or constructing hybrid models like CNN-LSTM to capture spatio-temporal features simultaneously. At the level of feature engineering, research actively introduces factors that fit the domestic market, such as investor sentiment indicators based on online public opinion, volume-weighted average price (VWAP), etc., and uses random forest (RF) for feature screening. Additionally, structural optimization techniques such as the attention mechanism have been widely adopted to enhance model performance.

At present, there is a convergence trend in research at home and abroad: domestic scholars are increasingly focusing on model robustness and interpretability, while international research is paying more attention to applications in emerging markets, including China. This trend is driving LSTM towards greater efficiency, robustness, and interpretability in the field of financial time series forecasting.

1.3 Research content and significance

Research Content: This paper aims to systematically review and evaluate the research progress of stock price prediction models based on LSTM both domestically and internationally. Initially, it explains the theoretical advantages of LSTM in handling financial time series. Subsequently, it classifies and critically reviews existing literature across three dimensions: basic application, feature enhancement (such as sentiment data fusion), and structure optimization (including hybrid models). Then, it comprehensively analyzes the predictive effectiveness and applicable scope of LSTM in comparison to traditional models, highlighting the shortcomings of existing studies in terms of statistical test rigor and comparative fairness. Finally, based on common issues, it looks forward to future directions such as the application of new architectures, explainability, and probability prediction.

Research Significance: This study holds significant theoretical and practical value. Theoretically, it constructs a systematic knowledge framework that integrates the statistical perspective with the application of deep learning, emphasizing the core position of methodological rigor in model evaluation. It provides a clear theoretical map and methodological guide for further research in this field. Practically, it offers financial institutions and investors a comprehensive basis for model selection and evaluation. By clarifying the applicable boundaries and potential risks of the model, it provides decision support for its rational application and transformation in quantitative investment and risk management.

2 A literature review of LSTM-based stock price prediction research

2.1 Introduction

To systematically present the research context, this chapter will review the existing literature in three major categories based on the technological evolution route: basic LSTM predictive models (verifying their basic validity), feature-enhanced LSTM models (improving performance by optimizing inputs), and structure-optimized LSTM models (improving performance by optimizing architecture). Finally, this chapter will comprehensively analyze the comparative studies of LSTM and traditional predictive models, and critically explore the methodological issues existing in the current comparative studies.

2.2 Research on basic LSTM predictive models

Early research primarily focused on verifying the fundamental effectiveness of basic LSTM structures in financial time series forecasting. These studies typically followed a uniform paradigm: preprocessing and normalizing raw stock price data, constructing samples using the sliding window method, dividing datasets chronologically, and ultimately evaluating performance using metrics such as mean square error (MSE).

After the LSTM theory matured, researchers quickly introduced it into the financial field. Nelson's pioneering work in 2017 systematically confirmed that LSTM outperforms traditional time series models in the U. S. stock market. This conclusion was quickly replicated in multiple markets around the world, with Wang demonstrating its effectiveness for Hong Kong stocks in 2019 and Zhang Jie for A-shares in 2020, initially showcasing LSTM's capabilities.In China, research by Cui Quan (2022), Wang Yuqian (2021), and Fan Junming et al. (2021) further demonstrated that the base LSTM significantly outperformed benchmark models such as ARIMA, MLP, and SVR in terms of futures market prediction accuracy. However, these studies also revealed the inherent limitations of the base model: firstly, its performance is highly sensitive to the setting of hyperparameters (such as time windows, number of hidden units), requiring extensive trial and error (Siami-Namini, 2018); secondly, the input features are singular (mainly dependent on historical price-volume data), and overfitting is prone when the model capacity does not match the data volume (Bao, 2017), resulting in a performance ceiling. These limitations indicate that further research should shift towards feature enhancement and structural optimization.

2.3 Research on feature-enhanced LSTM prediction models

In the study of feature-enhanced LSTM prediction models, fusing multi-source features to enhance the quality of input information has become a key path to significantly improve the accuracy of stock price predictions. Existing studies have achieved feature enhancement in the following dimensions: First, by introducing construction factors, Geng Jingjing et al. (2021) used the volume-weighted average price (VWAP) to construct a multi-factor input of price and volume; Second, feature screening and noise reduction. Li Hui et al. (2022) used the random forest (RF) algorithm to select highly representative features, while Peng Yan et al. (2019) used wavelet transform to decompose and filter out noise from the original price sequence. Third, fusing alternative data. Yuan Jing et al. (2024) constructed an S-AM-BiLSTM hybrid model, extracting sentiment features from investor forum texts through the TextCNN sentiment analysis module, generating sentiment indices, and fusing them as new features with multidimensional data such as historical prices and technical indicators. These features are then input into the bidirectional LSTM with attention mechanism for prediction, significantly improving prediction accuracy and highlighting the potential of multi-source heterogeneous data fusion in enhancing LSTM model performance.

These feature enhancement methods have generally been proven to effectively improve the prediction performance and robustness of LSTM models by providing richer, purer, and higher-dimensional inputs. However, multi-feature fusion also presents new challenges: the increase in feature dimensions intensifies the complexity of feature selection and engineering design; the variations in frequency and scale between multi-source data (such as low-frequency macro metrics and high-frequency trading data, text, and numerical data) require fine data alignment and normalization processing; the introduction of alternative data, such as text, significantly increases the risk of noise interference and places higher demands on data cleaning and feature representation. Therefore, how to enhance features while ensuring the quality, consistency, and efficient fusion of data has become a core issue that must be faced for further development in this field.

2.4 Research on structure-optimized LSTM prediction models

In the study of structure-optimized LSTM prediction models, scholars have developed several distinctive technical paths by improving the internal architecture of the network and introducing new computational mechanisms to enhance its ability to characterize financial time series. First, deep structural optimization, (uch as stacked LSTM, involves adding layers to the network to extract complex features at multiple time scales, significantly improving the model's expressive power. However, this approach needs to guard against the risk of overfitting caused by the increase in parameters (Fan et al., 2021) [8]. Gated simplification strategies, represented by GRU, combine input and forget gates into update gates, significantly reducing the number of parameters and improving training efficiency. Empirical studies have shown that they can achieve comparable or even better performance than LSTM in multiple tasks (Chung et al., 2014). Bidirectional structure extensions, (uch as BiLSTM, utilize future context information to enhance current state understanding and are applicable to tasks where complete sequence information can be obtained (such as Yuan Jing et al., 2023) [14]. Furthermore, the fusion of attention mechanisms enables the model to dynamically focus on key historical time steps, effectively suppressing noise and enhancing interpretability (Zhao Hongrui and Xue Lei, 2021). Finally, deep blending of heterogeneous models, (uch as CNN-LSTM, which combines the spatial feature extraction of CNN with the temporal modeling ability of LSTM, has been proven to effectively capture local patterns and dynamic evolution (Niu Xiaojian and Hou Qiming, 2025).

Overall, the structural optimization of LSTM shows a clear development trajectory from "deep extension" to "gated reduction", from "one-way recursion" to "context awareness", and with a focus on key points in "uniform processing". Different strategies have their own advantages: stacked and hybrid structures enhance representativeness but need to alleviate overfitting, GRUs balance performance and efficiency, and attention mechanisms balance performance and interpretability. Future research could focus on neural architecture search (NAS) for automated structural design and hyperparameter optimization, driving models towards greater efficiency and adaptability.

2.5 Comparative studies of LSTM with traditional predictive models

In comparative studies with traditional time series models, it has been shown that LSTM (Long Short-Term Memory networks) demonstrates significant advantages in handling nonlinear features and long-term dependencies. Compared with ARIMA models, LSTM does not require complex differential preprocessing or linear assumptions and can automatically capture complex patterns in sequences (Hyndman and Athanasopoulos, 2018; Hewamalage, 2021). Compared with the GARCH model, LSTM can not only effectively model volatility but also has the ability to integrate multi-source information and handle multiple factors such as price sequences, volatility, and market sentiment simultaneously, providing a more comprehensive predictive analysis (Kearney & Yang, 2019). These studies indicate that LSTM has a clear advantage in dealing with the nonlinearity, non-stationarity, and variable volatility of financial time series. In terms of comparison with classic machine learning models, research indicates that LSTM stands out in time series prediction tasks due to its inherent sequence modeling ability. Compared with support vector machines (SVM), LSTM can better capture the dynamic changes and time dependencies in time series and avoid the lag in prediction results caused by ignoring the time factor (Cao & Tay, 2003). Compared with random forests, LSTM can perform end-to-end learning on time series data, automatically extract and utilize time features in the data, and perform better in terms of prediction timeliness and accuracy (Taieb & Atiya, 2015). These comparative studies confirm the superiority of LSTM in handling financial sequence prediction tasks with obvious time dependence. Although the aforementioned studies generally confirm the superiority of LSTM, there are several methodological flaws in current comparative studies that need to be addressed urgently:

(1) Inconsistent hyperparameter tuning: Most studies fine-tune LSTMs, while traditional models often use default configurations. This asymmetric optimization may lead to performance bias.

(2) Insufficient application of statistical significance tests: Most studies draw conclusions merely by comparing the values of error metrics, lacking rigorous validation by statistical methods such as the Diebold-Mariano test.

(3) Inadequate robustness assessment: Insufficient testing under different market conditions (especially extreme conditions) and data frequencies affects the universality of the conclusions.

Future studies need to establish a fairer comparison framework and strengthen statistical significance tests to more accurately assess the relative performance and real-world application value of LSTM models.

3 Comprehensive discussion and research outlook

3.1 A comprehensive discussion of the current research status

After conducting a systematic review of the existing literature and cross-chapter analysis, this study identified several consensuses in stock price prediction research based on LSTM, as well as common challenges that require urgent attention. The main consensus reached in the current study is reflected in the following three aspects: First, LSTM models inherently possess advantages in capturing the long-term dependence and nonlinear characteristics of stock price time series. Their prediction accuracy and stability are generally superior to traditional time series models such as ARIMA and GARCH, as well as shallow machine learning models such as SVR and BP neural networks. This conclusion has been repeatedly verified in numerous empirical studies. Secondly, the optimization of feature engineering is a key factor in improving model performance. Research indicates that incorporating multi-source, high-dimensional features, such as volume-weighted average price (VWAP), complex network features, technical metric principal components, and alternative data, can significantly enhance the model's representation and generalization capabilities. Finally, hybrid model architectures have become the mainstream direction of evolution. By combining LSTM with CNN, RF, DMD, or other signal processing techniques (such as CNN-LSTM, RF-LSTM, DMD-LSTM), the strengths of different models can be effectively integrated to achieve a synergistic effect in predictive performance and robustness.

However, this review also reveals four prominent common problems in the field: First, models generally lack sufficient generalization ability. While they perform well in specific markets (such as A-shares) or under specific market conditions (such as one-sided markets), they exhibit instability during cross-market and cross-cycle validation, particularly when dealing with extreme market conditions (such as crashes, surges, or high-frequency oscillations). This reveals their weak adaptability to changes in market structure. Secondly, models lack interpretability. LSTM and its complex variants are essentially "black boxes," and their decision-making processes are opaque, making it difficult to provide convincing predictive evidence. This greatly limits their application in actual financial risk control and decision-making that requires clear attribution. Thirdly, the construction of the feature system is not yet complete. Existing research overly relies on traditional price-volume indicators, and the integration of multi-dimensional factors such as macroeconomics, policy events, and market sentiment is still in its infancy. There is a lack of systematic tests of the effectiveness and stability of these factors. Fourth, there are significant flaws in methodological rigor. Some studies lack fair comparisons with a sufficient number of baseline models, the degree of hyperparameter tuning is inconsistent, and statistical significance tests (such as Diebold-Mariano tests) are generally ignored, raising doubts about the reliability of the research conclusions.

3.2 Prospects for future studies

Based on the shortcomings of current research, further exploration could be conducted in the following directions in the future:

3.2.1 Model innovation

Exploring new architectures and automated design. The application potential of new architectures such as the Transformer, (hich excels at capturing long sequence dependencies, and graph neural networks (GNNs), (hich excel at modeling complex correlations between stocks, should be actively explored. Simultaneously, neural architecture search (NAS) technology can be introduced to automate and optimize the design of network structures and hyperparameters, reducing the bias and inefficiency of manual parameter tuning.

3.2.2 Data fusion

Deepening multimodal and alternative data integration. Future research will need to systematically introduce multimodal and alternative data such as macroeconomic indicators, real-time news texts, social media sentiment, and public opinion audio to build a more comprehensive and dynamic feature system. The focus should be on aligning multi-source data in terms of frequency and scale, and developing more advanced noise filtering and feature representation methods to fully unlock the predictive potential of alternative data.

3.2.3 Theoretical deepening

Focusing on explainability and uncertainty quantification. Strengthen the application of explainable artificial intelligence (XAI) tools such as SHAP and LIME in LSTM stock price prediction, breaking the "black box", and enhancing model transparency and decision-making credibility. Additionally, shift from the "point prediction" paradigm to uncertainty quantification (UQ), providing confidence intervals for prediction results to offer core support for risk management and enhance the robustness of model applications.

3.2.4 Application expansion

Promoting paradigm shifts and real-time application. Encourage research to shift from a single "point prediction" paradigm to a "range prediction" or "trend prediction" paradigm to better integrate with quantitative investment strategies such as portfolio management and risk hedging. Moreover, online learning and adaptive mechanisms should be vigorously developed to enable models to respond in real-time to changes in market structure, ultimately serving applications with extremely high real-time requirements such as high-frequency trading.

4 Conclusion

This paper systematically reviews the research progress of LSTM-based stock price prediction models both domestically and internationally. By classifying and synthesizing literature across three dimensions—basic application, feature enhancement, and structure optimization—the study confirms that the LSTM model, with its unique gating mechanism and sequence modeling capability, has a significant advantage in capturing the nonlinearity, non-stationarity, and long-range dependence of financial time series. Consequently, it has become an important research tool in this field.

The core value of this study lies not only in constructing a systematic review framework that integrates statistical perspectives with deep learning applications but also in critically pointing out the common flaws of existing studies in terms of model generalization ability, interpretability, and methodological rigor. These common problems highlight the gap that still needs to be bridged for LSTM models to transition from "laboratory precision" to "battlefield reliability."

For the academic community, this paper underscores the extreme importance of statistical tests and model evaluation fairness in future research and clearly points out promising research directions, such as fusing multimodal data, developing interpretable tools, quantifying predictive uncertainty, and exploring new architectures. For the industry, the paper provides theoretical guidance and practical inspiration for model selection, optimization, and practical application. It cautions investors against blindly pursuing prediction accuracy and encourages a full understanding of the applicable boundaries and potential risks of different models, to make more rational decisions and promote the scientific application and effective implementation of deep learning models in financial forecasting.

In summary, LSTM and related models have shown great potential in stock price prediction, but there is still a long way to go for their mature application. Future research should, on the basis of enhancing model transparency and robustness, actively explore new architectures, new data, and new paradigms to jointly drive research in this field towards a more reliable, practical, and insightful direction.

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