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Machine Learning in Financial Time Series Forecasting: A Systematic Review

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Abstract

Time series analysis holds significant theoretical and practical value in the financial field. Due to the complex characteristics of financial time series, such as nonlinearity, dynamics, and chaos, constructing effective prediction models remains a key research direction in both academia and industry. In recent years, with the rapid development of machine learning technology, its application in financial time series prediction achieves remarkable progress. However, most studies remain fragmented and under-reviewed. This paper systematically reviews key research on time series prediction models based on machine learning in the financial field, focusing on analyzing the theoretical modeling and application effects of different models, as well as summarizing the data resources used. It not only compares the performance differences among various models but also discusses the limitations in current prediction modeling processes and proposes possible future improvement directions, aiming to provide references for researchers and practitioners in model selection and optimization. In addition, this paper incorporates the context of computational intelligence and big data, explores the potential value of integrated research approaches, and aims to offer new ideas for advancing the field of financial time series prediction.

Keywords: machine learning, time series forecasting, fintech

1. Introduction

The financial time series refers to consecutive data points collected over time, reflecting the historical behavior of financial assets and economic indicators, such as stock prices, exchange rates, and oil prices. These sequences are typically non-stationary, exhibiting time-varying statistical characteristics and clustering phenomena, which makes their analysis both challenging and crucial (Khan, S., 2020). The analysis of such data supports key financial tasks, including predicting future price trends, managing risks through measures such as value at risk, optimizing algorithms, and improving investment portfolios (Shahi, T. B., Shrestha, A., Neupane, A., & Guo, W., 2020). Additionally, modern methods also incorporate relevant factors such as market sentiment in news articles and social media, technical indicators, and macroeconomic indicators to enhance prediction accuracy (Ibrahim, S., Chen, W., Zhu, Y., Chen, P. Y., Zhang, Y., & Mazumder, R., 2022). However, there are still some challenges, such as the non-stationarity and structural mutations of financial data, high noise in market fluctuations, and the complexity of high-frequency data processing (Drachal, K., 2021; Abbasimehr, H., & Paki, R., 2022). Solving these challenges requires advanced methods like hybrid models, to improve the robustness and reliability of financial time series analysis in practical applications (Zhang, S., Luo, J., Wang, S., & Liu, F., 2023). The future research focus in this field lies in improving these technologies to better capture market dynamics, enhance predictive capabilities, and thereby optimize risk management.

Financial time series play a crucial role in modern finance, enabling market participants to cope with uncertainties, seize opportunities, and prevent potential risks. Accurate predictions of asset prices and market trends form the basis of investment decisions, allowing individual investors to more effectively seize market opportunities (Selvin, S., Vinayakumar, R., Gopalakrishnan, E. A., Menon, V. K., & Soman, K. P., 2017; Montenegro, C., & Molina, M., 2019). In the field of risk management, time series modeling is an important tool for estimating potential losses through indicators such as risk value and for formulating robust strategies to withstand adverse market fluctuations (Arashi, M., & Rounaghi, M. M., 2022; Amirshahi, B., & Lahmiri, S., 2023). The rise of algorithmic trading further highlights the importance of complex time series analysis, as trading system prediction models can execute complex strategies at millisecond speeds (Gao, J., 2024; Sebastião, H., & Godinho, P., 2021). These applications collectively enhance market efficiency and reduce transaction costs. Based on this crucial foundation, this paper aims to find the optimal model to increase profits or reduce investment risks, thereby addressing the actual financial problems that arise in a rapidly changing environment.

This article compiles multiple authoritative professional papers, which employ various types of methods. These methods include traditional statistical approaches (e.g., Autoregressive Integrated Moving Average Model (ARIMA) and Autoregressive Conditional Heteroskedasticity Model (GARCH)) (Khan, S., 2020; Afeef, M., Ihsan, A., & Zada, H., 2018) as well as contemporary machine learning (e.g., XGBoost and GRU) (Gao, J., 2024; Li, X., Wang, J., Tan, J., Ji, S., & Jia, H., 2022) and deep learning technologies (e.g., Transformer and RNN) (Busari, G. A., & Lim, D. H., 2021; Muhammad, T., Aftab, A. B., Ibrahim, M., Ahsan, M. M., Muhu, M. M., Khan, S. I., & Alam, M. S., 2023). Through rigorous comparative analysis, we evaluate the relative advantages and limitations of these models in different market conditions and asset categories, with particular attention to their performance in volatility prediction and trend prediction (Hamayel, M. J., & Owda, A. Y., 2021; Livieris, I. E., Kiriakidou, N., Stavroyiannis, S., & Pintelas, P., 2021). Additionally, we also focus on some innovative forecasting methods. Through the application of integration methods, we further enhance the robustness of the predictions (Kurani, A., Doshi, P., Vakharia, A., & Shah, M., 2023). These models can better meet the needs of investors, companies, and financial institutions in complex financial markets.

The following section briefly summarizes the main machine learning techniques covered in the selected articles of this study. The organizational structure of the remaining part of this article is as follows: Section 2 focuses on some basic related work. It provides an overview of the data types used in financial time series modeling from the data perspective and summarizes the modeling techniques from classical statistical models to modern machine learning and deep learning methods from the model perspective. Section 3 conducts a comparative analysis of the models selected from the relevant literature. Section 4 discusses the contributions, challenges, and research gaps of the existing methods, such as the interpretability of deep models or multimodal integration. Section 5 presents the conclusions and key issues that require further research and analyzes the future development direction of financial time series.

2. Related Work

2.1 Financial Time Series Ecosystem

The financial time series ecosystem undergoes significant changes, shifting from relying on traditional structured data to integrating multiple multimodal inputs, thereby providing richer market insights (Cheng, D., Yang, F., Xiang, S., & Liu, J., 2022). Quantitative models mainly utilize structured time series data, such as stock prices, trading volumes, and fundamental economic indicators, which form the basis of early prediction methods. However, the increasing complexity of the financial market and the demand for predictive advantages prompt the introduction of other data sources, including financial news and social media. In Paper 24, Google News is cited, and a pre-trained BERT model in the financial field is used for sentiment analysis to extract the emotional polarity from the news. Finally, emotional information is input as an external factor into the model. In Paper 29, tweet information from Twitter is cited, and the sentiment of the tweets is analyzed using natural language processing (NLP) techniques. The investor sentiments are extracted and finally input into the Transformer model. These data can capture market conditions, emerging trends, and the fluctuations of event impacts, while traditional data sets often fail to cover these aspects. This expansion reflects that combining structured numerical data with unstructured background information can improve model performance (Samee, N. A., Atteia, G., Alkanhel, R., Alhussan, A. A., & AlEisa, H. N., 2022). Although environmental, social, and governance factors can reveal long-term risks not shown in financial statements, integrating these heterogeneous data streams presents numerous challenges, including the issue of time synchronization between high-frequency trading data and the slowly changing news cycle (Abedin, M. Z., Moon, M. H., Hassan, M. K., & Hajek, P., 2025; Abbasimehr, H., & Paki, R., 2022). There are also problems, such as noise filtering in unstructured text data (Fang, Y., Wang, W., Wu, P., & Zhao, Y., 2023) and maintaining the interpretability of the model when integrating different data types (Jabeur, S. B., Mefteh-Wali, S., & Viviani, J. L., 2024). The shift towards multimodal financial analysis highlights the need for advanced preprocessing techniques (Yu, H., & Song, S., 2025) and the ability to extract meaningful hybrid modeling methods from this complex, interrelated data ecosystem (Zhang, S., Luo, J., Wang, S., & Liu, F., 2023; Shi, Y., Wang, Y., Qu, Y., & Chen, Z., 2024), while also addressing its inherent inconsistencies and uncertainty issues.

2.2 Existing Methods for Time Series Analysis

The field of financial time series analysis undergoes significant methodological changes, evolving from traditional statistical models to complex machine learning and deep learning architectures. Each method has its unique advantages but also faces specific limitations. Traditional statistical methods, such as ARIMA, GARCH, and Vector Autoregression Model (VAR), lay the foundation for model construction with their rigorous mathematical theories and interpretability. They are particularly suitable for modeling linear relationships and volatility clustering in stationary time series. However, these models often struggle to capture nonlinear patterns and are unable to adapt to sudden market regime changes (Zhang, S., Luo, J., Wang, S., & Liu, F., 2023). Machine learning techniques such as random forest (Jabeur, S. B., Mefteh-Wali, S., & Viviani, J. L., 2024), support vector regression (Kurani, A., Doshi, P., Vakharia, A., & Shah, M., 2023; Abedin, M. Z., Moon, M. H., Hassan, M. K., & Hajek, P., 2025), and XGBoost (Gao, J., 2024) address some of these limitations through effective complex feature engineering, enabling better simulation of complex nonlinear relationships (Kurani, A., Doshi, P., Vakharia, A., & Shah, M., 2023). However, their performance still highly depends on the quality and relevance of the constructed features. The emergence of deep learning has completely transformed this field, adopting architectures such as Long Short-Term Memory (LSTM), GRUs, Temporal CNNs, and the recent Transformers (Tao, Z., Wu, W., & Wang, J., 2024). These architectures can automatically learn hierarchical representations and capture long-range temporal dependencies without the need for explicit feature engineering (Cheng, D., Yang, F., Xiang, S., & Liu, J., 2022; Lu, W., Li, J., Wang, J., & Qin, L., 2021). Nevertheless, these advantages come at the cost of a large amount of data requirements, higher overfitting risks, and reduced model interpretability, all of which are crucial issues in risk-sensitive financial applications (Yu, P., & Yan, X., 2020; Montenegro, C., & Molina, M., 2019; Cheng, D., Yang, F., Xiang, S., & Liu, J., 2022; Livieris, I. E., Kiriakidou, N., Stavroyiannis, S., & Pintelas, P., 2021; Md, A. Q., Kapoor, S., AV, C. J., Sivaraman, A. K., & Tee, K. F., 2023). Current research is increasingly inclined to adopt hybrid models, which integrate the advantages of the aforementioned methods. These include the attention mechanism for more accurate pattern recognition (Lu, W., Li, J., Wang, J., & Qin, L. 2021; Abbasimehr, H., & Paki, R., 2022; Tao, Z., Wu, W., & Wang, J., 2024), knowledge transfer learning in the financial field (Fang, Y., Wang, W., Wu, P., & Zhao, Y., 2023; Ibrahim, S., Chen, W., Zhu, Y., Chen, P. Y., Zhang, Y., & Mazumder, R., 2022), and multimodal architectures that combine numerical time series with visual data from news or social media (Li, X., Wang, J., Tan, J., Ji, S., & Jia, H., 2022; Ferdus, M. Z., Anjum, N., Nguyen, T. N., Jisan, A. H., & Raju, M. A. H., 2024).

3. Comparative Analysis

In recent years, research in the field of financial time series prediction tends to adopt hybrid models. These models combine the advantages of multiple techniques and significantly enhance prediction performance and the ability to integrate multimodal data through the combination of various data sources. Such models gradually become the core trend in the field of financial prediction. However, many shortcomings still exist in the research on financial time series prediction. These aspects will be introduced in detail later.

3.1 General Comparison

Sequence	Paper	Year	Author	Publication	Citation
1	Stock Price Prediction Using RNN and LSTM	2017	J Patel, M Patel, M Darji	Journal of Emerging Technologies and Innovative Research	14
2	Forecasting Stock Prices through Univariate ARIMA Modeling	2018	M Afeef, A Ihsan, H Zada	NUML International Journal of Business & Management	36
3	A DNN Approach to Improving the Short-Term Investment Criteria for S&P500 Index Stock Market	2019	C Montenegro, M Molina	Proceedings of the 2019 3rd International Conference on E-commerce, E-Business and E-Government	6
4	Stock Price Forecasting with Deep Learning: A Comparative Study	2020	TB Shahi, A Shrestha, A Neupane, W Guo	MDPI mathematics	168
5	ARIMA Model for Accurate Time Series Stocks Forecasting	2020	S Khan	International Journal of Advanced Computer Science and Applications	174
6	Stock price prediction based on deep neural networks	2020	P Yu, X Yan	Neural computing & applications	426
7	Forecasting crude oil real prices with averaging time-varying VAR models	2021	K Drachal	Resources Policy	58
8	A Comprehensive Comparative Study of Artificial Neural Network (ANN) and Support Vector Machines (SVM) on Stock Forecasting	2021	A Kurani, P Doshi, A Vakharia, M Shah	Annals of Data Science	644
9	Deep learning-based exchange rate prediction during the COVID-19 pandemic	2021	MZ Abedin, MH Moon, MK Hassan,	Annals of Operations Research	133

			P Hajek		
10	A Novel Cryptocurrency Price Prediction Model Using GRU, LSTM and bi-LSTM Machine Learning Algorithms	2021	MJ Hamayel, AY Owda	MDPI AI	288
11	Forecasting and trading cryptocurrencies with machine learning under changing market conditions	2021	H Sebastião, P Godinho	Financial Innovation	254
12	A CNN-BiLSTM-AM method for stock price prediction	2021	W Lu, J Li, J Wang, L Qin	Neural Computing and Applications	580
13	Crude oil price prediction: A comparison between AdaBoost-LSTM and AdaBoost-GRU for improving forecasting performance	2021	GA Busari, DH Lim	Computers & Chemical Engineering	157
14	An Advanced CNN-LSTM Model for Cryptocurrency Forecasting	2021	IE Livieris, N Kiriakidou, S Stavroyiannis, P Pintelas	MDPI electronics	194
15	Financial time series forecasting with multi-modality graph neural network	2022	D Cheng, F Yang, S Xiang, J Liu	Pattern Recognition	378
16	Improving time series forecasting using LSTM and attention models	2022	H Abbasimehr, R Paki	Journal of Ambient Intelligence and Humanized Computing	281
17	A graph neural network-based stock forecasting method utilizing multi-source heterogeneous data fusion	2022	X Li, J Wang, J Tan, S Ji, H Jia	Multimedia Tools and Applications	38
18	Analysis of market efficiency and fractal feature of NASDAQ stock exchange: Time series modeling and forecasting of stock index using ARMA-GARCH model	2022	M Arashi, MM Rounaghi	Future business journal	49
19	Hybrid Feature Reduction Using PCC-Stacked Autoencoders for Gold/Oil Prices Forecasting under COVID-19 Pandemic	2022	NA Samee, G Atteia, R Alkanhel, AA Alhussan, HN AlEisa	MDPI electronics	18

20	Transformer-Based Deep Learning Model for Stock Price Prediction: A Case Study on Bangladesh Stock Market	2022	T Muhammad, AB Aftab, M Ibrahim, MM Ahsan, MM Muhu, SI Khan, MS Alam	International Journal of Computational Intelligence and Applications	83
21	Knowledge Graph Guided Simultaneous Forecasting and Network Learning for Multivariate Financial Time Series	2022	S Ibrahim, W Chen, Y Zhu, PY Chen, Y Zhang, R Mazumder	Proceedings of the Third ACM International Conference on AI in Finance	8
22	Medium- to long-term nickel price forecasting using LSTM and GRU networks	2022	AC Ozdemir, K Buluş, K Zor	Resources Policy	81
23	Oil price forecasting: A hybrid GRU neural network based on decomposition–reconstruction methods	2023	S Zhang, J Luo, S Wang, F Liu	Expert Systems with Applications	115
24	Hybrid deep learning and GARCH-family models for forecasting volatility of cryptocurrencies	2023	B Amirshahi, S Lahmiri	Machine learning with applications	67
25	A sentiment-enhanced hybrid model for crude oil price forecasting	2023	Y Fang, W Wang, P Wu, Y Zhao	Expert systems with applications	46
26	TSF-Transformer: a time series forecasting model for exhaust gas emission using Transformer	2023	Z Li, X Zhang, Z Dong	Applied Intelligence	26
27	Novel optimization approach for stock price forecasting using multi-layered sequential LSTM	2023	AQ Md, S Kapoor, CJ AV, AK Sivaraman, KF Tee	Applied Soft Computing	156
28	Forecasting gold price with the XGBoost algorithm and SHAP interaction values	2024	SB Jabeur, S Mefteh-Wali, JL Viviani	Annals of Operations Research	315
29	Integrated GCN-LSTM stock prices movement prediction based on knowledge-incorporated graphs	2024	Y Shi, Y Wang,	International Journal of Machine Learning and	34

	construction		Y Qu, Z Chen	Cybernetics	
30	Series decomposition Transformer with period-correlation for stock market index prediction	2024	Z Tao, W Wu, J Wang	Expert Systems with Applications	45
31	The Influence of Social MEDIA on Stock Market: A Transformer-Based Stock Price Forecasting with External Factors - Neliti	2024	MZ Ferdus, N Anjum, TN Nguyen, AH Jisan, MAH Raju	Journal of Computer Science and Technology Studies	12
32	Using Generative Pre-Trained Transformers (GPT) for Electricity Price Trend Forecasting in the Spanish Market	2024	A Menéndez Medina, JA Heredia Álvaro	MDPI energies	9
33	Application of XGBoost in the A-shares stock market forecasting	2025	J Gao	Proceedings of the 2024 5th International Conference on Big Data Economy and Information Management	1
34	Natural Gas Futures Price Prediction Based on Variational Mode Decomposition–Gated Recurrent Unit/Autoencoder/Multilayer Perceptron–Random Forest Hybrid Model	2025	H Yu, S Song	MDPI sustainability	1
35	A novel probabilistic carbon price prediction model: Integrating the Transformer framework with mixed-frequency modeling at different quartiles	2025	M Ji, J Du, P Du, T Niu, J Wang	Applied Energy	3

First, a basic table is used to summarize the relevant literature. This table lists 35 research articles focused on financial market prediction in chronological order. Each entry contains seven key columns: serial number (sorted by the publication time), paper title, publication year, author, journal name, and the number of citations. The number of citations serves as an indicator of academic influence.

It is worth noting that among the most cited papers, several influential models stand out: XGBoost is used in a comprehensive comparative study of artificial neural networks (ANN) and support vector machines (SVM) for stock prediction, and this study receives 644 citations; a study based on deep learning and combined with ARIMA for stock price prediction receives 426 citations; a hybrid CNN-BiLSTM-AM model receives 580 citations. These citation numbers highlight the trend of adopting more complex machine learning applications in financial time series analysis.

3.2 Data and Model Comparison

Sequence	Time Duration	Data Type	Frequency	Model
1	01/01/2016 - 01/01/2018	stock price	daily	RNN, LSTM, CNN
2	01/02/2008 - 12/29/2017	stock price	daily	DNN, LSTM, MLP
3	04/07/2015 - 04/07/2020	Stock price	daily	ARIMA
4	03/20/2011 - 11/14/2019	Stock price	daily	LSTM, GRU
5	06/07/2013 - 06/06/2018	stock price	daily	DNN
6	01/23/2004 - 11/19/2018	stock price	daily	ARIMA
7	08/01/2018 - 11/01/2018	Temperature and pressure data of the exhaust pipe of a heavy-duty truck	per second	Transformer
8	01/04/2005 - 12/28/2018	stock price	daily	XGBoost
9	06/1986 - 06/2019	oil price	Monthly	TVP-VAR
10	Shanghai Composite Index: 07/01/1991 – 06/30/2020 Shenzhen Component Index: 07/31/1991 – 05/31/2022 Hang Seng Index: 07/31/1991 – 05/31/2022 Supplementary Datasets (S&P 500, CAC 40, etc.): 01/04/2010 – 12/28/2018	Stock market data	daily	Transformer, SDTP
11	No exact time	stock price	Monthly/daily/yearly	ANN, SVM, PCA
12	07/01/1991 - 06/30/2020	stock data	Daily	CNN, BiLSTM, AM
13	01/1986 - 12/2019	stock price/ Unemployment data/ transportation data	Monthly	linear regression, neural networks, random forest, LightGBM, CatBoost, XGBoost
14	Non-COVID-19 period: 01/03/2000 - 12/31/2019 COVID-19 period: 01/31/2020 - 12/14/2020	exchange rate	Daily	LSTM, Bi-LSTM, Regression Tree, Support Vector Regression, Random Forest Regression
15	01/01/2018 - 12/31/2019	Stock price/ Stock price/ Knowledge graph data	daily	MAGNN
16	No exact time	stock data/ transportation data/ economic	No information provided regarding	LSTM, multi-head attention

		data	the data frequency	
17	02/07/2018 - 02/07/2022	Closing price of cryptocurrencies	daily	DFFNN, LSTM
18	01/22/2018 - 06/30/2021	Cryptocurrency prices	daily	RNN, MAPE, GRU
19	08/15/2015 - 03/03/2019	Cryptocurrency trading data	Daily	linear models, random forest, support vector machines
20	WTI crude oil price: 08/02/2010 - 12/31/2019 / Brent crude oil price: 08/02/2010 - 12/31/2019	oil price	Daily	VMD, SE, GRUs
21	12/2022 - 03/2023	Stock market data/ Social media data	daily	Transformer, LSTM
22	10/23/2009 - 06/23/2021	crude oil price	daily	CEEMDAN, LSTM
23	01/01/2010 - 06/30/2022	Crude oil price	daily	FinBERT-VMD-Att-BiGRU
24	04/01/2020 – 09/30/2021	crude oil price/ gold price	daily	RNN
25	01/01/2017 - 10/31/2020	Cryptocurrency price	daily	DNN
26	03/1991 - 05/2021	Metal prices	monthly	LSTM, GRU
27	01/11/2013 - 11/25/2019	Stock transaction data/News Data	daily	GRU, LSTM
28	2013 - 2016	Stock market data	daily	GregNets
29	2018 - 2023	The electricity market price in Spain	weekly/monthly	GPT
30	01/03/2017 - 09/30/2021	Stock trading data	daily	GCN-LSTM
31	Shanghai Carbon Price: 01/12/2014 - 07/07/2024 Hubei Carbon Price: 05/04/2014 - 07/07/2024	Carbon price data/ Data of influencing factors	weekly/ daily	QRTransformer-MIDAS
32	11/23/2016 - 11/23/2021	The stock price of Samsung	daily	MLS LSTM
33	04/04/1990 - 05/28/2024	Natural gas futures price	daily/ monthly	GRU, AE, MLP
34	2000 - 2016	Stock Index	yearly	ARMA-GARCH
35	10/2012 - 12/2020	Stock trading data	daily/ weekly	Transformer

The following is a summary of the model and dataset information of the articles in tabular form. Each entry contains five key columns: serial number, dataset time, dataset type, dataset frequency, and the main prediction model or technology.

Through a systematic analysis of 35 relevant papers, it is observed that research on financial time series prediction shows diverse characteristics in data type selection. Researchers mainly use three types of data: market price data, multimodal auxiliary data, and environmental energy data. Market price data serves as the basic research material, including 20 stock prices, 5 crude oil prices, and 4 cryptocurrency prices, with high-frequency daily data accounting for the highest proportion. For special fields such as carbon prices (Ji, M., Du, J., Du, P., Niu, T., & Wang, J., 2025) and electricity prices (Menéndez Medina, A., & Heredia Álvaro, J. A., 2024), weekly/monthly frequency data is used. The use of multimodal auxiliary data reflects the progress of prediction methods, including macroeconomic indicators and social media sentiment data (Ferdus, M. Z., Anjum, N., Nguyen, T. N., Jisan, A. H., & Raju, M. A. H., 2024). These data are fused with price data through attention mechanisms (Lu, W., Li, J., Wang, J., & Qin, L., 2021; Abbasimehr, H., & Paki, R., 2022; Tao, Z., Wu, W., & Wang, J., 2024) or graph neural networks (Cheng, D., Yang, F., Xiang, S., & Liu, J., 2022; Li, X., Wang, J., Tan, J., Ji, S., & Jia, H., 2022; Shi, Y., Wang, Y., Qu, Y., & Chen, Z., 2024), significantly enhancing the model's ability to depict market complexity. Environmental energy data (such as PM2.5 concentration and crude oil inventory) becomes a key variable in specific domain predictions (Fang, Y., Wang, W., Wu, P., & Zhao, Y., 2023; Yu, H., & Song, S., 2025). The main differences in data lie in the frequency dimension: traditional ARIMA models (Khan, S., 2020; Afeef, M., Ihsan, A., & Zada, H., 2018; Arashi, M., & Rounaghi, M. M., 2022) primarily handle single-frequency data, whereas hybrid models such as QRTransformer-MIDAS (Ji, M., Du, J., Du, P., Niu, T., & Wang, J., 2025) can simultaneously process exogenous variables at daily frequency and target variables at weekly or monthly frequency. In the structural dimension, simple models depend on structured numerical data, while advanced architectures like Transformer (Muhammad, T., Aftab, A. B., Ibrahim, M., Ahsan, M. M., Muhu, M. M., Khan, S. I., & Alam, M. S., 2023; Tao, Z., Wu, W., & Wang, J., 2024; Ferdus, M. Z., Anjum, N., Nguyen, T. N., Jisan, A. H., & Raju, M. A. H., 2024; Li, Z., Zhang, X., & Dong, Z., 2023) are capable of handling non-structured data, including text and graphs. This evolution trend in data usage reflects the shift in prediction research from single-time-series analysis to the integration of multiple information.

In the model analysis of these 35 papers, we find that while traditional models such as ARIMA (Khan, S., 2020; Afeef, M., Ihsan, A., & Zada, H., 2018) still dominate due to their simplicity and effectiveness in short-term stock price forecasting—especially under stationary data—recent research increasingly favors adaptive hybrid deep learning architectures. In the field of deep learning methods, especially LSTM (Selvin, S., Vinayakumar, R., Gopalakrishnan, E. A., Menon, V. K., & Soman, K. P., 2017; Yu, P., & Yan, X., 2020; Montenegro, C., & Molina, M., 2019; Abedin, M. Z., Moon, M. H., Hassan, M. K., & Hajek, P., 2025; Lu, W., Li, J., Wang, J., & Qin, L., 2021; Ozdemir, A. C., Buluş, K., & Zor, K., 2022) and Transformer-based models (Muhammad, T., Aftab, A. B., Ibrahim, M., Ahsan, M. M., Muhu, M. M., Khan, S. I., & Alam, M. S., 2023; Li, Z., Zhang, X., & Dong, Z., 2023) are widely adopted due to their outstanding accuracy in capturing complex and nonlinear patterns. Hybrid approaches that combine CNN-BiLSTM techniques (Lu, W., Li, J., Wang, J., & Qin, L., 2021) or graph neural networks (GNNs) (Cheng, D., Yang, F., Xiang, S., & Liu, J., 2022; Li, X., Wang, J., Tan, J., Ji, S., & Jia, H., 2022; Shi, Y., Wang, Y., Qu, Y., & Chen, Z., 2024) with temporal models show particularly promise in breaking through performance limitations with multi-source data. Decomposition and reconstruction frameworks such as VMD-GRU and VMD-GRUN-AE-MLP-RF models proposed in papers. Zhang, S., Luo, J., Wang, S., & Liu, F. (2023) and Yu, H., & Song, S. (2025) effectively optimize the prediction of non-stationary series through signal decomposition techniques and achieve remarkable success in crude oil and natural gas price prediction. In addition, the integration of attention mechanisms and graph neural networks becomes a major highlight. Models such as CNN-BiLSTM-AM (Lu, W., Li, J., Wang, J., & Qin, L., 2021) and GNN-based multi-source heterogeneous data fusion (Li, X., Wang, J., Tan, J., Ji, S., & Jia, H., 2022) enhance key feature extraction through attention, while architectures such as GCN-LSTM (Shi, Y., Wang, Y., Qu, Y., & Chen, Z., 2024) and knowledge graph-guided multivariate time series models

(Ibrahim, S., Chen, W., Zhu, Y., Chen, P. Y., Zhang, Y., & Mazumder, R., 2022) use graph structures to capture market correlation and achieve a forecast accuracy of over 57% in stock forecasts. The widespread adoption of Transformer architectures (Muhammad, T., Aftab, A. B., Ibrahim, M., Ahsan, M. M., Muhu, M. M., Khan, S. I., & Alam, M. S., 2023; Li, Z., Zhang, X., & Dong, Z., 2023) further advances long-term dependency modeling. For example, the SDTP model (Tao, Z., Wu, W., & Wang, J., 2024) significantly outperforms traditional methods through periodic correlation decomposition, and QRTransformer-MIDAS (Ji, M., Du, J., Du, P., Niu, T., & Wang, J., 2025) introduces a unified interval and probability forecasting framework to forecast carbon prices. It is also worth noting that ensemble methods like XGBoost (Gao, J., 2024; Jabeur, S. B., Mefteh-Wali, S., & Viviani, J. L., 2024) and others (Busari, G. A., & Lim, D. H., 2021) perform strongly in scenarios where interpretability is required, such as gold and oil price forecasting. At the same time, the shift towards multimodal frameworks (Fang, Y., Wang, W., Wu, P., & Zhao, Y., 2023; Ferdus, M. Z., Anjum, N., Nguyen, T. N., Jisan, A. H., & Raju, M. A. H., 2024) highlights the increasing importance of incorporating external factors—such as social media and news sentiment—especially during turbulent times such as the COVID-19 pandemic (Abedin, M. Z., Moon, M. H., Hassan, M. K., & Hajek, P., 2025; Fang, Y., Wang, W., Wu, P., & Zhao, Y., 2023). Overall, the field is moving toward complex, hybrid, and multimodal systems that provide broad applicability and high forecasting accuracy across different financial assets.

Although existing research makes significant progress in financial time series forecasting, several critical gaps remain unaddressed, particularly in the context of high-frequency trading, dynamic multi-source integration, and practical deplorability. Although studies such as Hamayel, M. J., & Owda, A. Y., (2021) (GRU/LSTM comparison) and Amirshahi, B., & Lahmiri, S. (2023) (GARCH-DL hybrids) explore the application of models in cryptocurrencies, most focus on daily data, while integrated research on hybrid models and economic evaluation indicators (such as the Sharpe ratio) for high-frequency data (e.g., seconds/minutes) and real-time response mechanisms to sudden market events (e.g., policy changes or black swan events) is still scarce. Secondly, the dynamic integration capability of multi-source real-time data needs to be strengthened: although Ferdus, M. Z., Anjum, N., Nguyen, T. N., Jisan, A. H., & Raju, M. A. H. (2024) (Transformer with social media) and Ibrahim, S., Chen, W., Zhu, Y., Chen, P. Y., Zhang, Y., & Mazumder, R. (2022) (knowledge graphs) attempt to integrate external data, most models (e.g., MAGNN in Cheng, D., Yang, F., Xiang, S., & Liu, J. (2022) and GCN-LSTM in Shi, Y., Wang, Y., Qu, Y., & Chen, Z. (2024)) rely on historical static data, and systematic frameworks for real-time event response remain underdeveloped (Fang, Y., Wang, W., Wu, P., & Zhao, Y. (2023)'s FinBERT-VMD-Att-BiGRU targets only specific crisis periods). Additionally, cross-market generalization research is scarce (e.g., Ji, M., Du, J., Du, P., Niu, T., & Wang, J. (2025)'s carbon price model lacks extension to commodities like oil or metals). Finally, the connection between model interpretability and practical investment decisions is weak: while Jabeur, S. B., Mefteh-Wali, S., & Viviani, J. L. (2024) (XGBoost-SHAP) and Fang, Y., Wang, W., Wu, P., & Zhao, Y. (2023) (sentiment analysis) introduce explainability tools, only a few studies (e.g., Gao, J. (2024)'s XGBoost portfolio construction) directly convert predictions into actionable strategies.

4. Discussion

The field of financial time series prediction makes significant progress through the continuous development of statistical, deep learning, and hybrid modeling methods. Traditional statistical methods, such as ARIMA, lay the foundation for time series analysis and can provide reliable short-term predictions, as demonstrated in references (Khan, S., 2020) & Afeef, M., Ihsan, A., & Zada, H., 2018), where the ARIMA model shows extremely high accuracy in stock price prediction. However, these models often struggle with long-term predictions and non-linear patterns, highlighting the necessity for more complex technologies. The emergence of deep learning completely transforms this field, with LSTM networks becoming the dominant tool due to their ability to capture long-term dependencies in sequence data. For example, Selvin, S., Vinayakumar, R., Gopalakrishnan, E. A., Menon, V. K., & Soman, K. P. (2017) and Yu, P., & Yan, X. (2020) demonstrate the superiority of LSTM and other deep neural networks in handling noisy and non-stationary financial data, achieving more accurate predictions. Further innovations, such as the integration of attention mechanisms, improve model performance by focusing on key temporal features, as shown in studies of Lu, W., Li, J., Wang, J., & Qin, L. (2021) and Abbasimehr, H., & Paki, R. (2022), where combining LSTM with multi-head attention significantly improves prediction accuracy, as the attention mechanism can dynamically weight important time steps, addressing the limitations of using LSTM models alone. Hybrid methods further expand the boundaries of research, integrating the advantages of multiple methods. For instance, Zhang, S., Luo, J., Wang, S., & Liu, F. (2023) and Fang, Y., Wang, W., Wu, P., & Zhao, Y. (2023) introduce a hybrid framework integrating signal decomposition techniques (VMD) with deep learning models (e.g., GRU, BiGRU), achieving outstanding performance in volatile markets like crude oil. Similarly, Tao, Z., Wu, W., & Wang, J. (2024) and Ferdus, M. Z., Anjum, N., Nguyen, T. N., Jisan, A. H., & Raju, M. A. H. (2024) utilize Transformer-based models combined with periodic correlations and external factors (such as social media sentiment) to enhance stock market predictions. These innovations highlight the transition from independent models to integrated systems that utilize multiple data sources and advanced architectures to enhance model accuracy. Future research should continue to explore interdisciplinary integration, such as knowledge graphs (Ibrahim, S., Chen, W., Zhu, Y., Chen, P. Y., Zhang, Y., & Mazumder, R., 2022) and generative models (Menéndez Medina, A., & Heredia Álvaro, J. A., 2024), to further enhance predictive capabilities. In summary, the development from statistical models like ARIMA to deep learning and hybrid systems reflects the maturation of this field. Although ARIMA still has value in short-term predictions, LSTM and hybrid models based on attention mechanisms set new standards for accuracy and robustness.

Although significant progress has been made in financial time series prediction, several challenges and research gaps remain unresolved, especially in the interpretability of deep learning models and the integration of multimodal data. For instance, deep learning models such as LSTM and those based on the Transformer architecture demonstrate outstanding performance in capturing complex patterns in financial data (Selvin, S., Vinayakumar, R., Gopalakrishnan, E. A., Menon, V. K., & Soman, K. P., 2017; Lu, W., Li, J., Wang, J., & Qin, L., 2021; Muhammad, T., Aftab, A. B., Ibrahim, M., Ahsan, M. M., Muhu, M. M., Khan, S. I., & Alam, M. S., 2023). However, their "black box" nature poses a key challenge, as stakeholders in financial applications often require transparent decision-making processes. Although some studies, such as Jabeur, S. B., Mefteh-Wali, S., & Viviani, J. L. (2024) and Fang, Y., Wang, W., Wu, P., & Zhao, Y. (2023), attempt to address this issue by introducing SHAP values or attention mechanisms to enhance interpretability, these methods still have limitations in providing comprehensive explanations for model predictions. Future research should focus on developing more powerful interpretability frameworks, such as hybrid models combining symbolic reasoning with deep learning, to fill this gap. Another challenge lies in how to effectively integrate multimodal data, such as combining time series data with textual information from news or social media (Cheng, D., Yang, F., Xiang, S., & Liu, J., 2022; Li, X., Wang, J., Tan, J., Ji, S., & Jia, H., 2022; Ferdus, M. Z., Anjum, N., Nguyen, T. N., Jisan, A. H., & Raju, M. A. H., 2024). The inherent differences in data structures (e.g., numerical and textual types), frequencies (e.g., high-frequency trading data and irregularly updated news), and noise features (e.g., market noise and language ambiguity) make this integration complex. While time series data is structured and continuous, text data is unstructured and sparse, which requires complex preprocessing and alignment techniques (Li, X., Wang, J., Tan, J., Ji, S., & Jia, H., 2022). Moreover, noise in financial news, such as ambiguous sentiment or irrelevant information, if not properly filtered, reduces the performance of the model (Shahi, T. B., Shrestha, A., Neupane, A., & Guo, W., 2020; Fang, Y., Wang, W., Wu, P., & Zhao, Y., 2023). Current methods, such as graph neural networks (Cheng, D., Yang, F., Xiang, S., & Liu, J., 2022) or models based on the Transformer (Ferdus, M. Z., Anjum, N., Nguyen, T. N., Jisan, A. H., & Raju, M. A. H., 2024), make progress in addressing these challenges, but often face difficulties in scalability or real-time processing. Future research should continue to explore more advanced fusion technologies, dynamically weighting multi-modal inputs based on their relevance and reliability and developing effective methods for handling asynchronous data streams. Addressing these gaps is crucial for establishing more accurate prediction systems in the constantly evolving financial environment.

5. Conclusion and Future Direction

The field of financial time series prediction witnesses essential development, transitioning from traditional statistical models to advanced deep learning architectures. LSTM completely transforms this field by capturing the long-term temporal dependencies in noisy and non-stationary data, while Transformer further expands the boundaries with its self-attention mechanism, excelling in simulating complex market dynamics and integrating multimodal data. The decomposition-reconstruction framework and attention-enhanced models in hybrid methods further narrow the gap by combining the advantages of these methods. However, several challenges remain, including the "black box" limitation of deep learning models, which hinders their interpretability, and the difficulty in effectively integrating heterogeneous data sources with time series due to differences in structure, frequency, and noise.

Looking to the future, large language models and multimodal Transformer architectures represent promising frontiers in the field of financial prediction. Future research focuses on leveraging their ability to integrate text, numerical, and graphical data into a unified framework, enabling real-time analysis of market sentiment, news events, and high-frequency trading data. Additionally, solutions address interpretability issues through hybrid artificial intelligence systems and dynamic adaptation to market environments. Moreover, combining cross-market generalization, high-frequency modeling with domain-specific knowledge graphs further enhances prediction accuracy and operability, providing investors with more effective investment advice. By advancing in these directions, the field moves toward more transparent and accurate prediction systems.

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