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# A Study on Financial Market Trend Prediction Based on Machine Learning Algorithms

**Omair Shafiq[1], Malti Bansal[2], Ziyang Li[3]**
[1]University of Texas at San Antonio, Texas, USA
[2]University of Texas at San Antonio, Texas, USA
[3]University of Texas at San Antonio, Texas, USA
*Corresponding author: Ziyang Li; ziyuan199234@gmail.com

**Abstract:** Accurate prediction of short-term and long-term trends in financial markets remains a challenging task due to the complexity and noise characteristics of financial time series. To address the limitations of existing methods that often produce biased prediction results, this paper proposes a financial market trend prediction approach based on machine learning techniques. Financial data are collected at fixed time intervals to construct time series sequences. Wavelet analysis is employed to preprocess the financial time series, effectively removing noise while preserving the essential characteristics of the original data. Subsequently, a long short-term memory (LSTM) neural network is utilized to learn temporal dependencies within the processed data and establish a financial market prediction model. Experimental results demonstrate that the proposed method can effectively suppress noise, smooth the original data, and achieve high prediction accuracy in both short-term and long-term trend forecasting.

**Keywords:** Machine learning, financial market, trend prediction, time series, wavelet analysis

## 1. Introduction

With the rapid development of the financial industry, increasing integration with the international financial system has been achieved. Financial market trends exhibit frequent fluctuations and high complexity, which can lead to significant economic volatility and directly affect investors, national economies, and even the global economic system. Therefore, it is of great importance to conduct in-depth analysis of financial market trends and to investigate effective methods for financial market trend prediction.

Currently, widely adopted trend prediction approaches include methods based on multi-dimensional interactive verification [1] and methods based on multi-category feature systems [2]. The former analyzes market trends from multiple dimensions such as investor psychology and behavioral characteristics, and constructs multi-dimensional decision tree models to achieve trend prediction. However, this type of method is mainly suitable for short-term trend forecasting, and its prediction accuracy decreases significantly when applied to long-term trend prediction. The latter approach inputs multiple categories of financial market features into neural networks for training, thereby realizing trend prediction. Nevertheless, this method often neglects the noise inherent in financial data, which leads to excessive fitting of noisy data during neural network training. As a result, the generalization capability of the prediction model is degraded, and large deviations may occur in prediction results.

To address the above issues, this paper proposes a financial market trend prediction method based on machine learning algorithms. For financial time series data, wavelet analysis is first employed to perform noise reduction, effectively suppressing noise components while preserving essential information. On this basis, a long short-term memory neural network is adopted to accurately predict financial market trends.

## 2. Related Work

Recent advances in machine learning have significantly improved the modeling of financial time series, particularly in addressing the challenges posed by nonlinearity, noise, and temporal dependencies. Among the preprocessing techniques, wavelet analysis has proven effective in denoising financial data while retaining essential features, thereby enhancing model robustness and reducing overfitting [3]. Convolutional and recurrent neural networks have been widely used to extract both spatial and temporal characteristics from financial sequences [4], and the integration of such architectures with wavelet-preprocessed data further improves predictive performance [5].

Attention mechanisms have become an integral part of deep learning in financial prediction tasks. Attention-based models can dynamically allocate focus across time steps in time series data, which is particularly useful in capturing key indicators for systemic risk forecasting and anomaly detection [6][7]. Additionally, causal graph modeling has been employed to enhance the interpretability and trustworthiness of predictive systems in finance [8], especially when aligned with regulatory or audit requirements. The emergence of large language models (LLMs) has further expanded the methodological toolkit for financial applications.

Knowledge-augmented LLMs have been explored for explainable financial decision-making, enabling models to reason based on structured and unstructured financial data [9]. Explainable representation learning within LLMs also supports finer sentiment and opinion classification, which is crucial for capturing market sentiment from textual sources [10]. Moreover, self-supervised learning approaches have shown promise in fraud detection scenarios where labeled data are scarce and imbalanced [11].

Uncertainty quantification and risk awareness in deep models contribute to more robust summarization and reasoning in financial tasks, especially when models must operate under ambiguity or incomplete information [12]. Reinforcement learning has also been adopted to optimize portfolio strategies and resource allocations in dynamic financial environments. Multi-agent frameworks and adaptive risk control mechanisms enable intelligent and responsive decision-making under evolving market conditions [13][14].

Even outside traditional financial applications, intelligent agent collaboration and scheduling mechanisms, such as those used in cloud-native or microservice environments, offer transferable insights for modeling complex, interdependent systems like financial markets [15][16]. Transformer-based deep learning frameworks originally developed for clinical or user modeling tasks demonstrate strong generalization and can be effectively adapted for financial risk modeling [17].

Further, Q-learning and neural scheduling methods have proven effective in optimizing workflow pipelines and can be repurposed to enhance trading strategies and financial process automation [18]. Graph neural networks, although applied in diverse domains such as human-computer interaction or natural language classification, contribute valuable architectural strategies for structured financial data representation [19][20]. Advances in modular fine-tuning and parameter-efficient adaptation strategies also offer practical benefits for scaling predictive models across various financial tasks [21].

Finally, sparse retrieval techniques combined with deep language modeling enhance fact verification capabilities in financial textual analysis, ensuring the accuracy and reliability of automated systems interpreting complex financial documents [22].

## 3. Financial Market Trend Prediction Method Based on Machine Learning Algorithms

### 3.1 Construction of Financial Data Time Series

Financial data constitute a type of time series characterized by nonlinearity, nonstationarity, and high noise. The construction of a financial data time series is performed by sampling financial data at fixed time intervals and arranging the observed samples sequentially according to temporal order [23]. By treating financial observations collected at different time instants as a continuous sequence, a time-ordered dataset can be formed for subsequent modeling and analysis. Based on this time series representation, a convolutional long short-term memory neural network is employed to construct the prediction model within a machine learning framework, where the financial data sequence is used as the model input to accomplish financial market trend prediction [24].

### 3.2 Wavelet Analysis

Financial time series are highly susceptible to external factors and therefore inevitably contain noise, which leads to pronounced nonlinear characteristics. Although long short-term memory neural networks are capable of handling nonlinear data, directly inputting noisy financial data may cause excessive fitting to noise during training, thereby degrading the generalization capability of the prediction model and reducing prediction accuracy [25]. Wavelet analysis enables multiscale signal decomposition through operations such as scaling and translation, allowing data characteristics to be analyzed at different resolutions. This approach can effectively suppress noise while preserving essential features of the original financial data, thus reducing computational complexity and prediction time [26].

To alleviate the impact of noise interference on the prediction model and improve final prediction accuracy, wavelet decomposition and reconstruction are applied as a preprocessing step before financial market trend prediction. Through wavelet-based denoising, high-frequency noise components embedded in financial time series can be removed, while the main trend information is retained. To further reduce prediction time, the wavelet decomposition process separates the data into low-frequency components that describe the overall trend and high-frequency components that reflect short-term random fluctuations. The low-frequency components can be further decomposed iteratively, as illustrated in Figure 1 [27]. By reconstructing the signal after suppressing high-frequency coefficients, noise can be efficiently eliminated and a smoothed approximation of the original data can be obtained. This process helps prevent overlearning caused by external disturbances and enhances the extrapolation capability of the prediction model.

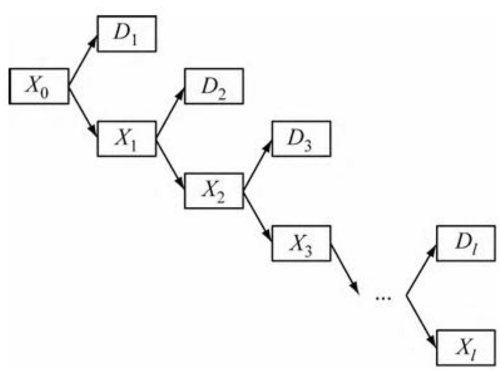


**Figure 1.** Illustration of the wavelet decomposition process

### 3.3 Construction of a Prediction Model Based on Convolutional Long Short-Term Memory Neural Networks

In conventional long short-term memory neural networks, the hidden layers are fully connected, which is effective for mapping language and textual data into trainable vector spaces but does not provide optimal representations for numerical data. Convolutional long short-term memory neural networks address this limitation by replacing fully connected operations with convolutional operations, enabling more effective representation and learning of numerical data. Therefore, a convolutional long short-term memory neural network is adopted in this study to construct the financial market trend prediction model. Within the proposed model, the wavelet-denoised financial time series, together with historical statistical features such as moving averages over different time horizons, are jointly used as input. This design enables the model to capture both temporal dependencies and spatial correlations in financial data.

The unit state update process of the convolutional long short-term memory neural network is defined as follows:

$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + W_{ci} * C_{t-1} + b_i),$$

$$C_t = f_t * C_{t-1} + i_t * \tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c),$$

$$o_t = \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} * C_t + b_o),$$

$$f_t = \sigma(W_{xf} * X_t + W_{hf} * H_{t-1} + W_{cf} * C_{t-1} + b_f),$$

$$H_t = o_t * \tanh(C_t),$$

where $i_t$, $f_t$, and $o_t$ denote the input gate, forget gate, and output gate at time step $t$, respectively, $C_t$ represents the cell state, and $H_t$ denotes the hidden state. The functions $\sigma$ and $\tanh$ are the sigmoid and hyperbolic tangent activation functions, respectively. The operator $*$ denotes convolution, and $W$ and $b$ represent convolution kernels and bias terms.

Based on the extracted temporal and spatial features, the convolutional long short-term memory neural network completes financial market trend prediction. Parameter sharing achieved through convolution operations is a key factor contributing to model generalization. However, due to the heterogeneous nature of financial trading data, which include multiple feature types such as opening price, closing price, upper limit, lower limit, and trading volume, conventional two-dimensional convolution cannot be directly applied. To address this issue, a one-dimensional convolution optimization strategy is adopted. In this approach, convolutional operations are performed along the temporal dimension while maintaining consistent channel alignment across different feature types, thereby ensuring effective parameter sharing. During model construction, the data frame size remains unchanged throughout convolution. The resulting hidden state is subsequently flattened into a vector and fed into subsequent classification layers to produce the final prediction results.

## 4. Application Case Study and Experimental Evaluation

The purpose of the application experiments is to evaluate the practical effectiveness of the proposed machine learning–based financial market trend prediction method in real-world financial market forecasting tasks. A representative financial market index is selected as the research object. The initial data required for the application experiments are obtained from a publicly available financial information platform. The collected historical data are divided into two parts: one part is used as the training set to determine the parameters of the prediction model, while the other part is used as the test set to evaluate the predictive capability of the model. Based on the collected data, the proposed method is applied to predict the financial market trends of the research object, and the corresponding experimental results are presented below.

## 4.1 Indicator Selection and Parameter Determination

Based on relevant literature and the collected initial financial data, the closing price, opening price, highest price, lowest price, 5-day average trading volume, 10-day average trading volume, 30-day average trading volume, exponential moving average, stochastic indicator, and relative strength index are selected as feature input vectors. These ten indicators are used to extract deep feature representations that influence financial market trend variations, thereby enabling financial market trend prediction for the research object.

In the prediction model, the selection of the activation function plays an important role in enabling the model to learn nonlinear characteristics inherent in financial data and significantly affects the training process. Therefore, the LeakyReLU function is adopted as the activation function in this study. The main advantage of this function lies in its relatively fast convergence speed, which can improve prediction efficiency. During the model training process, the RMSprop algorithm is selected as the optimization algorithm. In addition, based on the setting of penalty terms, the dropout strategy is employed to randomly remove a portion of hidden units, thereby preventing the prediction model from suffering from overfitting.

## 4.2 Application Test of Wavelet Analysis

Based on the collected initial financial data of the research object, an initial closing price time series is constructed. The wavelet analysis method proposed in this study is applied to decompose the initial closing price time series into four levels, and the reconstructed closing price time series is obtained accordingly, which improves the generalization ability of the subsequent prediction model. Figure 2 illustrates the comparison between the trend of the initial closing price and the trend of the reconstructed closing price after wavelet processing.

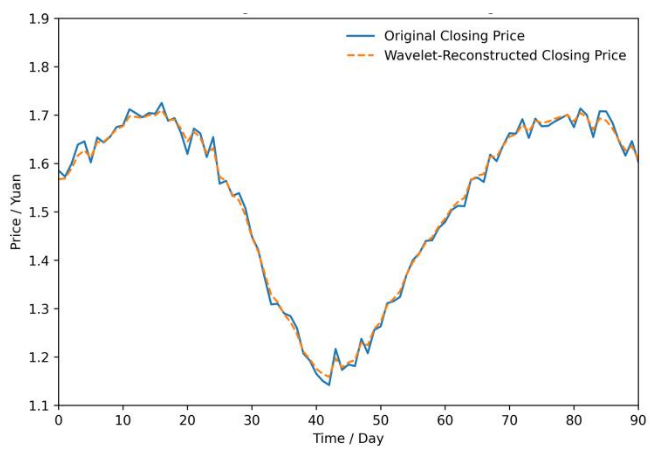


**Figure 2.** Trends of the original closing price and the reconstructed closing price

From the analysis of Figure 2, it can be observed that the wavelet analysis method effectively reconstructs the initial closing price time series, expands the data storage space, and reduces the time required to smooth the original data, thereby achieving effective noise suppression. At the same time, the reconstructed time series preserves the approximate characteristics of the original data to the greatest extent. These results demonstrate that performing trend prediction based on the reconstructed closing price time series is effective.

## 4.4 Prediction Performance Evaluation

Using the proposed prediction model, closing price trend prediction is conducted based on both the original closing price time series and the reconstructed closing price time series obtained through wavelet analysis. The predicted results are compared with the actual trend variations, and the corresponding results are illustrated in Figure 3.

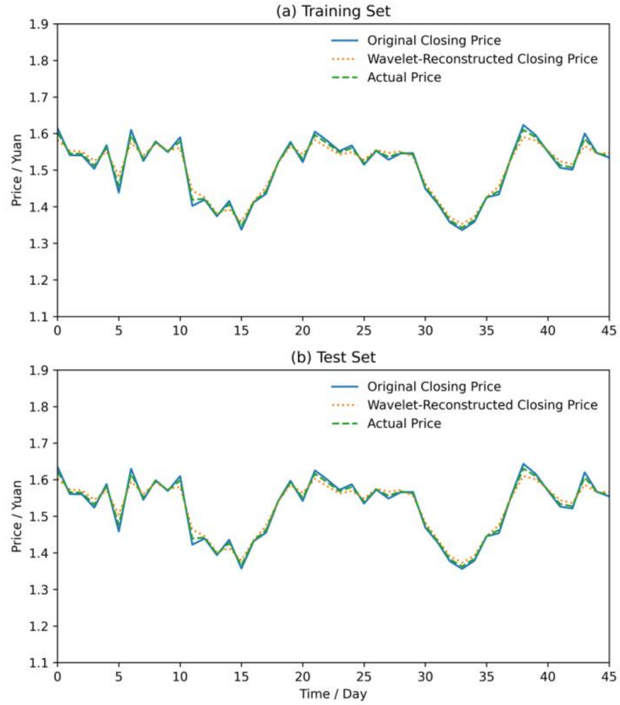


**Figure 3.** Prediction results of the proposed method

From the analysis of Figure 3, it can be observed that, within the training set, the proposed model achieves relatively accurate prediction results when trained on both the original closing price time series and the reconstructed closing price time series. The experimental results indicate that the proposed method can effectively perform trend prediction. Moreover, reconstructing the financial time series using wavelet analysis enhances the generalization capability of the prediction model, leading to improved prediction accuracy.

### 4.5 Comparison of Prediction Performance

To further evaluate the prediction performance of the proposed method, the trend prediction method based on multi-dimensional interactive verification described in [1] and the trend prediction method based on multi-category feature systems presented in [2] are selected as comparison methods. The mean absolute error $M$ and the Theil inequality coefficient $T$ are adopted as evaluation metrics to compare the prediction performance of the proposed method and the comparison methods, thereby further validating the predictive capability of the proposed approach. The calculation formulas of the two metrics are given as follows:

$$M = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{Y_t^p - Y_t^r}{Y_t^r}\right|,$$

$$T = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t^p - Y_t^r)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t^p)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t^r)^2}},$$

where $Y_t^p$ and $Y_t^r$ denote the predicted value and the actual value, respectively. The value range of $T$ is $[0, 1]$, and a smaller value indicates a higher degree of agreement between the predicted value and the actual value, corresponding to higher prediction accuracy. The value range of $M$ is also $[0, 1]$, and a smaller value indicates higher prediction accuracy.

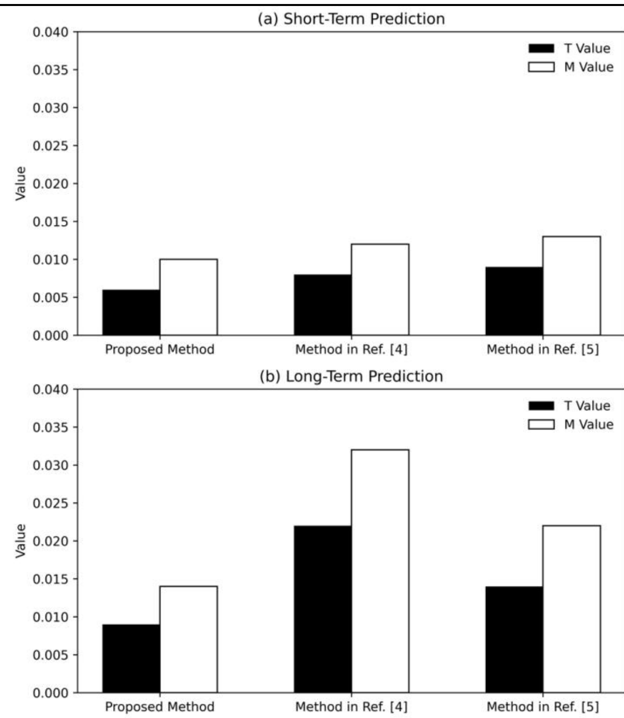


**Figure 4.** Comparison results of prediction performance

From the analysis of Figure 4(a), it can be observed that in short-term trend prediction, the differences among the evaluation metrics of the three methods are not significant. The proposed method exhibits slightly better prediction performance than the two comparison methods, while the method described in [2] yields the highest evaluation metric values, indicating the lowest prediction accuracy in short-term trend prediction.

From the analysis of Figure 4(b), it can be observed that in long-term trend prediction, the evaluation metric values of all three methods exhibit varying degrees of increase. Among them, the proposed method shows the smallest increase in evaluation metric values, whereas the method described in [1] exhibits the largest increase, which is significantly higher than that of the method described in [2]. This indicates that the method in [1] achieves the lowest overall prediction accuracy in long-term trend prediction.

Comprehensive analysis demonstrates that the proposed method achieves relatively high prediction accuracy and is applicable to trend prediction tasks across different time horizons.

## 5. Conclusion

Accurate prediction of financial market trends can assist investors in making appropriate decisions and contribute to the stability of financial markets. In this paper, a financial market trend prediction method based on machine learning algorithms is proposed. Through application experiments, the practical effectiveness of the proposed method is verified. The experimental results demonstrate that introducing machine learning algorithms into financial market trend prediction research is both feasible and effective. The findings of this study provide meaningful reference value for further research in the field of financial market trend prediction.

## References

[1] M. Atsalakis and K. Valavanis, "Surveying stock market forecasting techniques – Part II: Soft computing methods," Expert Systems with Applications, vol. 36, no. 3, pp. 5932 – 5941, 2009.

[2] J. Wang, T. Sun, B. Liu, Y. Cao, and H. Zhu, "CLVSA: A convolutional LSTM based variational sequence-to-sequence model with attention for predicting trends of financial markets," arXiv preprint arXiv:2104.04041, 2021.

[3] Q. Xu, W. Xu, X. Su, K. Ma, W. Sun, and Y. Qin, "Enhancing Systemic Risk Forecasting with Deep Attention Models in Financial Time Series," Proceedings of the 2025 2nd International Conference on Digital Economy, Blockchain and Artificial Intelligence, pp. 340 – 344, 2025.

[4] H. Wang, C. Nie, and C. Chiang, "Attention-Driven Deep Learning Framework for Intelligent Anomaly Detection in ETL Processes," arXiv preprint, 2025.

[5] Q. Gan, R. Ying, D. Li, Y. Wang, Q. Liu, and J. Li, "Dynamic Spatiotemporal Causal Graph Neural Networks for Corporate Revenue Forecasting," arXiv preprint, 2025.

[6] J. Lai, C. Chen, J. Li, and Q. Gan, "Explainable Intelligent Audit Risk Assessment with Causal Graph Modeling and Causally Constrained Representation Learning," arXiv preprint, 2025.

[7] Q. Zhang, Y. Wang, C. Hua, Y. Huang, and N. Lyu, "Knowledge-Augmented Large Language Model Agents for Explainable Financial Decision-Making," arXiv preprint arXiv:2512.09440, 2025.

[8] Y. Xing, M. Wang, Y. Deng, H. Liu, and Y. Zi, "Explainable Representation Learning in Large Language Models for Fine-Grained Sentiment and Opinion Classification," arXiv preprint, 2025.

[9] J. Lai, A. Xie, H. Feng, Y. Wang, and R. Fang, "Self-Supervised Learning for Financial Statement Fraud Detection with Limited and Imbalanced Data," arXiv preprint, 2025.

[10] S. Pan and D. Wu, "Trustworthy summarization via uncertainty quantification and risk awareness in large language models," arXiv preprint arXiv:2510.01231, 2025.

[11] R. Ying, J. Lyu, J. Li, C. Nie, and C. Chiang, "Dynamic Portfolio Optimization with Data-Aware Multi-Agent Reinforcement Learning and Adaptive Risk Control," arXiv preprint, 2025.

[12] G. Yao, H. Liu, and L. Dai, "Multi-agent reinforcement learning for adaptive resource orchestration in cloud-native clusters," Proceedings of the 2nd International Conference on Intelligent Computing and Data Analysis, pp. 680 – 687, 2025.

[13] Y. Li, S. Han, S. Wang, M. Wang, and R. Meng, "Collaborative evolution of intelligent agents in large-scale microservice systems," arXiv preprint arXiv:2508.20508, 2025.

[14] K. Gao, Y. Hu, C. Nie, and W. Li, "Deep Q-Learning-Based Intelligent Scheduling for ETL Optimization in Heterogeneous Data Environments," arXiv preprint arXiv:2512.13060, 2025.

[15] A. Xie and W. C. Chang, "Deep Learning Approach for Clinical Risk Identification Using Transformer Modeling of Heterogeneous EHR Data," arXiv preprint arXiv:2511.04158, 2025.

[16] R. Liu, R. Zhang, and S. Wang, "Graph Neural Networks for User Satisfaction Classification in Human-Computer Interaction," arXiv preprint arXiv:2511.04166, 2025.

[17] X. Song, Y. Huang, J. Guo, Y. Liu, and Y. Luan, "Multi-Scale Feature Fusion and Graph Neural Network Integration for Text Classification with Large Language Models," arXiv preprint arXiv:2511.05752, 2025.

[18] Y. Wang, D. Wu, F. Liu, Z. Qiu, and C. Hu, "Structural Priors and Modular Adapters in the Composable Fine-Tuning Algorithm of Large-Scale Models," arXiv preprint arXiv:2511.03981, 2025.

[19] P. Xue and Y. Yi, "Sparse Retrieval and Deep Language Modeling for Robust Fact Verification in Financial Texts," Transactions on Computational and Scientific Methods, vol. 5, no. 10, 2025.

[20] S. Borovykh, D. Bohte, and C. W. Oosterlee, "Conditional time series forecasting with convolutional neural networks," Expert Systems with Applications, vol. 90, pp. 1 – 11, 2017.

[21] R. F. Engle, "Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation," Econometrica, vol. 50, no. 4, pp. 987 – 1007, 1982.

[22] T. Fischer and C. Krauss, "Deep learning with long short-term memory networks for financial market predictions," European Journal of Operational Research, vol. 270, no. 2, pp. 654 – 669, 2018.

[23] X. Li, Y. Li, H. Yang, L. Yang, and X. Y. Liu, "DP-LSTM: Differential privacy-inspired LSTM for stock prediction using financial news," arXiv preprint arXiv:1912.10806, 2019.

[24] J. Patel, S. Shah, P. Thakkar, and K. Kotecha, "Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques," Expert Systems with Applications, vol. 42, no. 1, pp. 259 – 268, 2015.

[25] A. Krauss, X. Do, and N. Huck, "Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500," European Journal of Operational Research, vol. 259, no. 2, pp. 689 – 702, 2017.

[26] J. Bollen, H. Mao, and X. Zeng, "Twitter mood predicts the stock market," Journal of Computational Science, vol. 2, no. 1, pp. 1 – 8, 2011.

[27] Z. Zhang, S. Zohren, and S. Roberts, "Deep learning for day-ahead electricity price forecasting," IEEE Transactions on Power Systems, vol. 33, no. 6, pp. 6398 – 6407, 2018.