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Advanced Stock Market Forecasting: A Comparative Analysis of ARIMA-GARCH, LSTM, and Integrated Wavelet-LSTM Models

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Abstract: In the era of big data, accurate forecasting of corporate data is crucial for formulating effective strategies and decisions. This paper focuses on the prediction of key corporate indicators, taking TSLA, JD, MSFT, and TCEHY as case studies. It explores the application of three forecasting models: ARIMA-GARCH, LSTM, and Wavelet-LSTM. By comparing the predictive accuracy of these models, we find that each model has its strengths and weaknesses under different data characteristics. The study not only emphasizes the importance of accurate forecasting for corporate management and market prediction but also summarizes the adaptability and limitations of different models in dealing with complex time series data, providing valuable reference and insights for similar forecasting tasks.

1. Introduction

In the midst of the intricate and ever-changing global financial markets, the stock market, serving as a barometer of economic activities, has had its volatility and trend forecasting at the forefront of academic and industrial attention. Accurate forecasting of the stock market poses a highly challenging yet critical issue for investors, garnering widespread interest among financial time series analysts, researchers, and experts who strive to unravel the intricate underlying mechanisms that govern stock price movements [1,2]. However, crafting a function or system capable of precisely predicting stock price movements is a daunting task due to the stock prices' volatile, complex, nonlinear, and often unstable nature, coupled with significant noise, rendering them difficult to predict precisely [1,2]. Nowadays, with the rapid advancements in big data and artificial intelligence technologies, various techniques, fundamentals, and statistical measures have been proposed and employed for stock market prediction, leading to an increasingly diversified and sophisticated landscape of financial time series prediction and analysis methodologies [2]. Among the myriad of forecasting models, ARIMA-GARCH, LSTM (Long Short-Term Memory networks), and Wavelet-LSTM demonstrate robust adaptability and flexibility in the face of the stock market's complexity and uncertainty. These models can automatically adjust their parameters and structures in response to changing market phases and conditions, addressing the market's dynamic evolution and gaining widespread application and recognition in stock market analysis. This paper aims to compare the accuracy of these three models in analyzing the US stock market and draw corresponding conclusions.

The Autoregressive Integrated Moving Average (ARIMA) model, a classic in time series analysis, excels at capturing linear trends and seasonal features in data. Meanwhile, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model effectively models the volatility in time series, addressing the heteroskedasticity and volatility clustering phenomena in financial data. The use of either ARIMA or GARCH model is prevalent in time series modeling and prediction research, particularly in analyzing financial time series data [3]. Combining ARIMA with GARCH not only captures the long-term trends of the stock market but also more accurately depicts its short-term volatility characteristics, providing investors with a more comprehensive view of market information.

In recent years, Artificial Neural Networks (ANNs) have seen extensive utilization for forecasting financial data [4]. The Long Short-Term Memory (LSTM) network, a variant of Recurrent Neural Networks (RNNs) in deep learning, specializes in handling long-term dependencies in sequential data. Sepp Hochreiter and Jurgen Schmidhuber first introduced this algorithm in Neural Computing [5]. In financial time series forecasting, LSTM can automatically learn the historical patterns of stock price movements, accounting for nonlinear factors in the market, thereby enhancing prediction accuracy and robustness. Additionally, LSTM adapts to dynamic changes in the market environment, offering investors more flexible decision support.

Wavelet Transform is a multi-scale analysis method that extracts crucial hidden information and salient temporal features from raw time series data [2]. In stock market analysis, Wavelet Transform uncovers short-term fluctuations, medium-term trends, and long-term cycles in stock prices, helping investors comprehend market dynamics more comprehensively. Moreover, its robust

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noise reduction capability mitigates the impact of market noise on prediction results, enhancing analysis accuracy. A compelling strategy involves merging a deep learning model with wavelet transform, offering a hybrid approach that is both intriguing and potentially powerful [6]. The Wavelet-LSTM model integrates the strengths of wavelet transform and LSTM models. By decomposing financial time series data through wavelet transform, it reduces the instability of the data. Then, it leverages the LSTM model to deeply mine the long-term dependencies within the wavelet coefficients. This combined model is capable of more effectively handling complex and non-stationary stock data, thereby enhancing prediction accuracy.

The US, as one of the world's largest economies, boasts a stock market with a long history, robust institutional framework, diverse investment instruments, and extensive international influence. Choosing the US stock market as the research subject not only provides abundant data samples and practical experiences but also offers valuable references for global investors. Furthermore, the volatility and complexity of the US stock market serve as an excellent validation platform for the model systems discussed in this paper, facilitating further verification and optimization of their application effects in financial time series prediction.

This paper utilizes three models, namely ARIMA-GARCH, LSTM (Long Short-Term Memory networks), and Wavelet-LSTM, to forecast and analyze the data of four companies in the US stock market over five years. By comparing the relevant data, it concludes which model provides the most accurate analysis of the operational rules of the stock market.

The rest of this paper is organized as follows. Section 2 describes recent related works. Section 3 explains the proposed prediction system. Section 4 provides experimental results and discussion, and Section 5 concludes this study.

2. Literature Review

Predicting and modeling the returns of various financial assets is a profoundly researched area within economic and financial studies [5]. Among the various methodologies employed, the ARIMA-GARCH model, LSTM (Long Short-Term Memory Network), and Wavelet-LSTM each exhibit distinct advantages and application scenarios.

The ARIMA-GARCH hybrid model, a relatively recent development, has garnered considerable interest and attention [3]. The inherent volatility of financial time series data poses a significant challenge in accurately forecasting future trends [7]. Traditional models, such as ARIMA and GARCH, often struggle to concurrently meet the demands of preserving data trends while maintaining high prediction accuracy. Conversely, the hybrid ARIMA-GARCH model offers a potential solution by balancing these two objectives, ensuring that both the trend of the data and the precision of predictions are preserved over the forecast horizon [8]. By combining the strengths of the ARIMA (Autoregressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models, the ARIMA-GARCH model provides a more comprehensive analysis of financial time series data, enhancing prediction accuracy and risk management capabilities. This model finds widespread applications in financial market forecasting, investment strategy formulation, and risk management.

The LSTM neural network represents a specialized form of recurrent neural network (RNN) [9]. It is a widely recognized and established RNN architecture [10], particularly adept at handling sequential data, such as financial time series. Regarded as an advanced iteration of RNN, LSTM excels in leveraging historical data to demonstrate a high level of adaptability in analyzing time series data [5]. This type of recurrent network has achieved remarkable success in addressing diverse problems due to its ability to differentiate between recent and earlier examples by assigning varying weights, while simultaneously discarding irrelevant memories to accurately predict the next output [11]. Through its unique gating mechanisms (forget gate, input gate, and output gate), LSTM effectively captures long-term dependencies in time series, a task that traditional RNNs struggle with. In financial markets, this capability holds significant importance for predicting long-term asset price trends.

The Wavelet Transform (WT) is a powerful tool for analyzing signals, as it decomposes a given signal into a series of fundamental components or functions that effectively capture its defining characteristics [5]. The Wavelet transform has recently proven to be a highly effective tool in a wide range of disciplines, including engineering, physics, signal processing, and financial time series analysis, due to its robust ability to extract meaningful features from data [2]. This technique is particularly well-suited for non-stationary data, where both the mean and autocorrelation of the signal vary dynamically over time. In the realm of finance, where the majority of time series data exhibits non-stationarity, the application of the wavelet transform becomes particularly advantageous and pertinent [12]. By transforming the original financial data into a collection of frequency elements, each with a resolution tailored to its specific scale, the wavelet transform presents a captivating alternative to conventional time series and frequency domain methods. This feature is invaluable when dealing with signals that exhibit changes in their frequencies over time, a common occurrence in financial market analyses. It enables analysts to gain deeper insights into the intricate dynamics of financial time series, thus facilitating more informed decision-making processes [13]. The wavelet LSTM methodology represents a fusion of the wavelet transform and the long short-term memory architecture [6]. Reducing data instability through wavelet decomposition enables the LSTM model to more easily identify features within the data, thereby enhancing prediction accuracy. This model excels in processing highly noisy, non-linear, and non-stationary stock data.

The ARIMA-GARCH model, LSTM, and Wavelet-LSTM each exhibit unique advantages in the field of financial analysis. The ARIMA-GARCH model is suitable for capturing both the trend and volatility of time series data simultaneously. LSTM, on the other hand, excels at handling time series data with long-term dependencies and nonlinear characteristics. Meanwhile, Wavelet Transform provides a new perspective and methodology for financial time series analysis through its multi-resolution analysis and noise reduction capabilities. Collectively, these tools and methods have contributed significantly to the advancement of financial analysis, offering investors and decision-makers more accurate and reliable information support.

3. Methodology

3.1. ARIMA-GARCH model

The ARIMA-GARCH model is a complex model that combines the linear ARIMA model with the nonlinear GARCH model; it is capable of capturing both the conditional mean and conditional variance of traffic flow series simultaneously [3]. The ARIMA-GARCH model has extensive applications in financial market forecasting. In the realm of financial research, a myriad of models have been devised to forecast both returns and volatility, yet the most prevalent among them is the combination of Autoregressive Integrated Moving Average (ARIMA) with Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, offering a robust solution for predictive analysis in the financial domain [5].

In 1970, George Box and Gwilym Jenkins introduced the ARIMA (Autoregressive Integrated Moving Average) model, which is also known as the Box-Jenkins methodology. This methodology encompasses a series of steps aimed at identifying, estimating, and diagnosing ARIMA models using time series data [14]. In ARIMA model, the future value of a variable is a linear combination of past values and past errors, expressed as follows:

$$Y_t = \emptyset_0 + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (1)$$

where, $\mathbf{Y_t}$ is the actual value and $\boldsymbol{\varepsilon_t}$ is the random error at t, $\boldsymbol{\emptyset_i}$ and $\boldsymbol{\theta_j}$ are the coefficients, p and q are integers that are often referred to as autoregressive and moving average, respectively.

Tim Bollerslev introduced the foundational GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model in 1986. Each GARCH model is comprised of two key components: a mean equation and a variance equation. The following is the mean equation

$$R_t = \pi + \varepsilon_t \quad (2)$$

where Rt is the stock return at time t, π is the mean stock return, and t ε is the return residual. The variance equation in GARCH model is written as follows.

$$\sigma_t^2 = \alpha + \omega_1 \varepsilon_{t-1}^2 + \lambda_1 \sigma_{t-1}^2 \quad (3)$$

$$\alpha > 0, \omega_1 \geq 0, \lambda_1 \geq 0 \quad (4)$$

where σ_t^2 is the conditional variance and is the weighted term which depends on the volatility of past period ($\boldsymbol{\omega_1 \varepsilon_{t-1}^2}$) and also the past period's conditional variance ($\boldsymbol{\lambda_1 \sigma_{t-1}^2}$). The stationarity is assumed when the coefficients of past period's volatility and conditional variance are equal to one.

3.2. LSTM

The LSTM (Long Short-Term Memory) model, also known as the Long Short-Term Memory network, is a special type of Recurrent Neural Network (RNN) designed to address the issues of gradient vanishing or exploding that traditional RNNs often encounter when processing long sequences of data. LSTM is widely acknowledged as an exceptional variation of RNN that possesses the capability to leverage historical data, enabling it to exhibit a remarkable level of adaptability in the realm of time series analysis [5]. Here is the repeating module in LSTM:

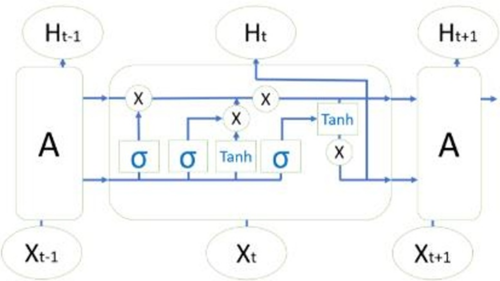

Figure 1. LSTM model [14]

3.3. WT

Wavelet Transform (WT) is a type of transformation that breaks down a signal into a series of fundamental functions that represent the signal [5]. It performs a detailed, multi-scale examination of signals by applying operations like stretching and shifting, enabling the effective removal of noise present in the data while preserving the essential characteristics of the original signals [15]. This approach allows for a refined analysis that captures both temporal and frequency information across different scales [16]. The mathematical formula of the wavelet function ψ(t) is stated as follows:

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \quad (5)$$

According to the following formula, $\psi_{(a,b)}(t)$ is achieved by scale change and mother wavelet delay:

$$\psi_{(a,b)}(t) = |a|^{\frac{-1}{2}} \psi\left(\frac{t-b}{a}\right) \quad (6)$$

$$a, b \ni R \quad a \neq 0 \quad (7)$$

3.4. Model performance evaluation

Mean Squared Error (MSE) is a commonly used method to measure the degree of difference between the predicted values and the actual values of a model. It calculates the average of the squares of the differences between the predicted values and the true values. The formula for MSE is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (8)$$

Where, n is the number of samples. $\boldsymbol{y_i}$ is the true value of the $\boldsymbol{i}$-th sample. $\boldsymbol{\hat{y}_i}$ is the predicted value of the $\boldsymbol{i}$-th sample. $\sum_{i=1}^{n}(\boldsymbol{y_i} - \boldsymbol{\hat{y}_i})^2$ is the sum of the squares of the differences between the predicted values and the true values for all samples.

A smaller MSE value indicates that the predicted values of the model are closer to the actual values, suggesting better predictive performance of the model. MSE is a commonly used indicator for evaluating the performance of regression models because it is sensitive to the size of errors and can effectively reflect the accuracy of the model's predictions.

MAE (Mean Absolute Error) is a commonly used metric to measure the difference between predicted values and actual values. It calculates the average of the absolute values of the differences between predicted values and true values. The formula for MAE is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (9)$$

Where, n is the number of samples. $\boldsymbol{y_i}$ is the true value of the $\boldsymbol{i}$-th sample. $\boldsymbol{\hat{y}_i}$ is the predicted value of the $\boldsymbol{i}$-th sample. $|\boldsymbol{y_i} - \boldsymbol{\hat{y}_i}|$ is the sum of the absolute values of the differences between the predicted values and the true values for all samples.

A smaller MAE value indicates that the prediction errors of the model are smaller, suggesting better predictive performance of the model. One advantage of MAE is that it directly reflects the average size of prediction errors and is relatively straightforward to calculate. However, compared to MSE (Mean Squared Error), MAE penalizes errors uniformly, without giving heavier penalties to larger errors as MSE does.

4. Results

In this article, we use three models to analyze the stock data of four companies - TSLA, JD, MSFT, and TCEHY - over a five-year period in the U.S. stock market and compare their prediction errors. The data is sourced from Yahoo Finance.

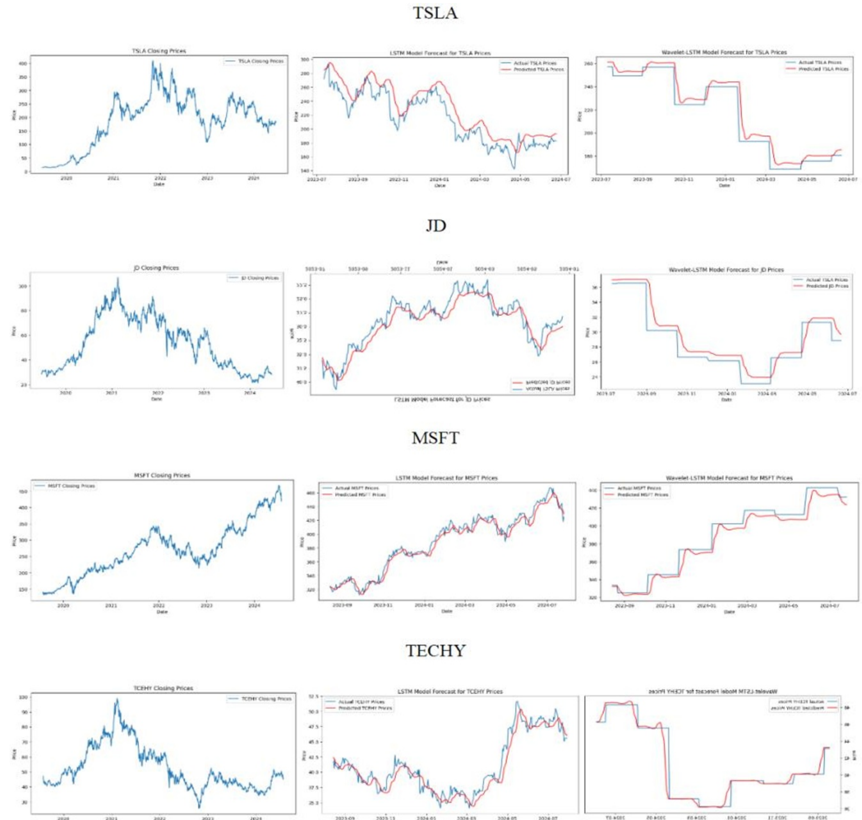

Figure 2. Stock data and model forecast information for four companies over five years

Notes: Figure 2 shows the stock data of four companies and the information of the model forecasts over a five-year period. The first column presents stock price trend charts for four companies spanning five years. The second and third columns respectively display the analysis and prediction results for these four companies using LSTM and Wavelet-LSTM models.

The first line shows the five-year stock price trend of Tesla, starting from the beginning of 2020, the stock price gradually rose, and reached a significant peak in 2021. Afterwards, the stock price began to experience fluctuations and declined. Moving into 2023, the stock price experienced another decline. However, by 2024, Tesla's stock price began to recover and show an upward trend.

The first figure in the second row is a line chart depicting the closing price trend of JD (JD.com) stock from 2020 to 2024. The price line gradually rises from 2020, reaching a significant peak in 2021. However, this positive momentum did not last long, as the price began to gradually decline thereafter. Moving into 2022 and 2023, the price line continued its downward trend, and by 2024, there were still no signs of a recovery in the price.

The third line showcases the closing price trend of Microsoft Corporation from 2020 to 2024. Starting in 2020, the price gradually rose, reaching a notable peak in 2021. Moving into 2022 and 2023, the price line continued to maintain a downward trajectory. Finally, by 2024, the closing price remained at a relatively low level, with no signs of a rebound.

The last row of data displays the closing price trend of TCEHY's stock from 2020 to 2024. Initially in 2020, the stock price was at a relatively low level. Over time, the stock price began to gradually rise, demonstrating a steady growth trend. By 2021, the stock price reached a notable peak. However, entering 2022, the stock price started to gradually decline. This downward trend continued into 2023, and finally, in 2024, TCEHY's stock price still did not show any significant signs of recovery, remaining at a relatively low level.

Here is a table summarizing the relevant data obtained from analyzing the stock data of TSLA, JD, MSFT, and TCEHY using the three models: ARIMA-GARCH, LSTM, and Wavelet-LSTM.

Table 1. The average performance of the three models across the four firms

	TSLA		JD		MSFT		TCEHY	
Model	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
ARIMA-GARCH	4.86	37.67	0.78	0.77	14.66	283.07	1.13	2.40
LSTM	9.34	133.13	1.30	2.41	5.71	47.91	1.03	1.88
Wavelet-LSTM	5.52	66.01	1.16	2.32	5.83	67.24	0.40	1.17

Table 1 presents the mean absolute error (MAE) and root mean square error (MSE) of three models (ARIMA-GARCH, LSTM, and Wavelet-LSTM) for four companies (TSLA, JD, MSFT, TCEHY). These metrics are used to evaluate the accuracy of the models' predictions. From the data in Table 1, we can observe that ARIMA-GARCH, LSTM, and Wavelet-LSTM each demonstrate their respective strengths in analyzing different companies.

For TSLA, ARIMA-GARCH achieves the lowest MAE of 4.86 and MSE of 37.67 among the three models, indicating that it has relatively small errors and higher accuracy in predicting TSLA-related indicators. LSTM, on the other hand, exhibits significantly higher errors with an MAE of 9.34 and MSE of 113.13, particularly in MSE, suggesting that LSTM's performance in predicting TSLA is inferior to ARIMA-GARCH. Wavelet-LSTM, with an MAE of 5.52 and MSE of 66.01, has lower errors than LSTM but still higher than ARIMA-GARCH. For JD, ARIMA-GARCH remains the most precise model with an MSE of 0.78 and MAE of 0.77, demonstrating its suitability for predicting scenarios related to JD. Wavelet-LSTM, with an MAE of 1.16 and MSE of 2.32, performs between ARIMA-GARCH and LSTM, having slightly higher errors than ARIMA-GARCH but lower than LSTM. In contrast, for MSFT, ARIMA-GARCH performs poorly with a high MAE of 14.66 and MSE of 283.07, far exceeding the errors of LSTM and Wavelet-LSTM. LSTM emerges as the most accurate model for MSFT with an MAE of 5.71 and MSE of 47.91.For TCEHY, Wavelet-LSTM achieves the highest accuracy among the three models with an MAE of 0.40 and MSE of 1.17.

In summary, the performance of different models varies across companies' data. While ARIMA-GARCH demonstrates high accuracy for three out of four companies except MSFT, LSTM consistently maintains good performance across various prediction scenarios. Wavelet-LSTM generally shows a slight improvement over LSTM in precision, likely due to Wavelet transform's ability to extract features from time series more effectively, enhancing the prediction accuracy when combined with LSTM.

5. Conclusions

In this study, we evaluated the performance of three predictive models—ARIMA-GARCH, LSTM, and Wavelet-LSTM—in forecasting specific metrics for four companies: TSLA, JD, MSFT, and TCEHY. The models were assessed using mean absolute error (MAE) and root mean square error (MSE) as metrics to quantify prediction accuracy. Our analysis reveals several key insights that have important implications for model selection and application in similar prediction tasks.

Firstly, we found that no single model consistently outperforms the others across all companies. This underscores the need for a tailored approach to model selection, where the choice of model should be based on the characteristics of the specific data and prediction requirements. For instance, ARIMA-GARCH exhibited superior performance for TSLA and JD, indicating its suitability for predicting metrics in these companies. However, it performed poorly for MSFT, highlighting the importance of exploring alternative models when faced with data that does not conform to the assumptions of ARIMA-GARCH.

Secondly, LSTM emerged as a robust model that maintained good performance across different prediction scenarios. Its ability to capture complex temporal dependencies in the data made it particularly suitable for MSFT, where it outperformed both ARIMA-GARCH and Wavelet-LSTM. This suggests that LSTM can be a valuable tool for predictive analytics, especially in domains where the data exhibits high degrees of nonlinearity and temporal dynamics.

Thirdly, Wavelet-LSTM, a hybrid model combining Wavelet transform and LSTM, demonstrated a generally improved performance over LSTM, albeit with some variability across companies. The integration of Wavelet transform allowed for more effective feature extraction from the time series data, leading to enhanced prediction accuracy in many cases. This finding highlights the potential of hybrid modeling approaches that leverage the strengths of multiple techniques to achieve better results.

In conclusion, our study demonstrates the importance of considering multiple predictive models and evaluating their performance on a case-by-case basis. The choice of model should be driven by the specific characteristics of the data and the prediction goals. Furthermore, the results suggest that hybrid models, such as Wavelet-LSTM, offer promising avenues for improving prediction accuracy in complex time series analysis tasks. As future research continues to explore new modeling techniques and optimization strategies, we anticipate that the field of predictive analytics will continue to evolve, enabling even more accurate and insightful predictions for a wide range of applications.

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