# Hybrid ARIMA-LSTM Model for Stock Market Prediction: A Time Series and Deep Learning Integration Approach

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*This study aims to evaluate the performance of the hybrid model based on ARIMA and LSTM in stock market forecasting and compare it with multiple traditional models to verify its superiority in dealing with complex nonlinear relationships and long-term dependencies. In terms of methodology, we preprocessed the raw data comprehensively. First, we used a time series-based interpolation method to fill missing values to ensure data integrity. Then, to make the data meet the model input requirements, all numerical data were normalized and scaled to the [0, 1] interval. In terms of data set division, the data was divided into training and test sets in a ratio of 80:20 to train and evaluate model performance. At the same time, we used correlation analysis and principal component analysis (PCA) for feature selection, retaining features that are highly correlated with stock market fluctuations, such as historical stock prices, trading volumes, GDP growth rates, inflation rates, etc., and PCA was used to reduce the dimension of features to reduce data redundancy. For the LSTM model, we constructed a network structure with 3 hidden layers. Each hidden layer contains 128 neurons, and ReLU is used as the activation function to enhance the nonlinear expression ability of the model. During training, the Adam optimizer was used, the learning rate was set to 0.001, and the batch size was 64. In addition, to prevent overfitting, a Dropout layer was added between the LSTM layers, and the Dropout rate was set to 0.2. In the result analysis, we used the Wilcoxon signed rank test to compare the results of the hybrid model with other traditional models to evaluate the statistical significance of the improvement. The results show that under the 95% confidence interval, the evaluation indicators (MSE, RMSE, $R^2$, MAE) of the hybrid model have significant advantages over the traditional model, further proving the effectiveness and reliability of the hybrid model in stock market forecasting.*

*Povzetek: Opisana je integracija metod ARIMA in LSTM v hibridnem modelu za napovedovanje borznih trgov. Združuje linearno analizo časovnih vrst z globokim učenjem, izboljšuje natančnost napovedi in prilagodljivost modela pri obvladovanju kompleksnih nelinearnih odnosov ter dolgoročnih odvisnosti.*

## 1 Introduction

As an important part of the global financial system, the stock market involves a large amount of capital flows and complex economic activities. The interaction of its price fluctuations, trading volume changes, and other factors makes stock market predictions extremely complex. Investors and institutions rely on market forecasts to make decisions, which in turn affects stock price changes and ultimately affects the overall stability of the economy. In recent years, with the rapid development of information technology, especially driven by big data and artificial intelligence technologies, the market demand and expectations for stock price predictions have continued to rise [1].

Traditional stock market analysis methods mostly rely on fundamental analysis and technical analysis. Fundamental analysis focuses on factors such as the company's financial health and market environment, while technical analysis uses information such as historical stock prices and trading volumes to perform pattern recognition and trend prediction. Although these methods can provide a preliminary judgment of stock trends to a certain extent, due to the complexity of the market, relying solely on these methods often cannot provide accurate prediction results [2].

Traditional stock market analysis methods mostly rely on fundamental analysis and technical analysis, which can provide preliminary judgments for stock market forecasts to a certain extent. However, as the complexity of the market increases, it is often difficult to obtain accurate forecasts by relying solely on these methods. In recent years, time series analysis and machine learning techniques, especially deep learning, have shown great potential in stock market forecasting. Researchers have begun to try to apply these methods to stock market forecasting to make up for the shortcomings of traditional methods. This study will combine traditional time series analysis methods (such as ARIMA) and deep learning models (such as LSTM) to propose a new hybrid model, which aims to more comprehensively handle linear and nonlinear features in stock market data and improve the accuracy and generalization of forecasts. Stock market forecasting has long attracted the attention of many researchers. Most of the early studies relied on classic time series analysis methods, such as ARIMA, moving average, and exponential smoothing. The ARIMA model captures the time dependency of data through operations such as autoregression, differentiation, and moving average of historical data, and is suitable for the forecast of stationary time series. However, stock market data itself has strong nonlinearity and complexity, and linear models such as ARIMA often perform poorly when dealing with high-frequency fluctuations or multi-factor influences [3].

With the rapid development of machine learning technology, researchers have begun to introduce machine learning methods to enhance prediction capabilities. Methods such as support vector machines (SVM), random forests (RF) and decision trees have been widely used in stock market prediction and can automatically mine patterns in data. However, these methods usually require a lot of feature engineering and have limited data processing capabilities. In recent years, deep learning methods, especially long short-term memory networks (LSTM) and convolutional neural networks (CNN), have achieved remarkable results in time series prediction, especially in processing complex, high-dimensional data and capturing long-term dependencies. In addition, ensemble learning methods have also achieved good results in stock prediction. By combining multiple models, ensemble learning methods can reduce the bias of a single model and improve prediction accuracy. Some studies have attempted to combine traditional time series methods with machine learning methods, such as the combination of ARIMA and LSTM, and achieved good prediction results. However, most of the current research focuses on the application of a single model or the single optimization of a method, and lacks comprehensive research on the fusion of multiple methods and multi-dimensional features. Therefore, how to combine time series analysis with machine learning methods to improve the accuracy and generalization ability of stock market prediction is still a direction worthy of in-depth exploration.

This paper aims to combine time series analysis and machine learning technology to propose a new stock market prediction model. By integrating traditional time series analysis methods and deep learning models, it overcomes their respective limitations and improves the accuracy and robustness of stock market prediction. This paper first reviews and analyzes the application of time series analysis and machine learning in stock prediction; then, it designs and implements a hybrid model combining ARIMA and LSTM, combined with feature extraction and preprocessing of stock market data; finally, it verifies the performance of the proposed model through experiments and evaluates its applicability and advantages under different market conditions.

In response to the challenges of industrial data analysis, this study used a variety of deep learning models, such as long short-term memory networks (LSTM), gated recurrent units (GRU), and convolutional neural networks (including ResNet and InceptionNet), to mine potential information in industrial data. At the same time, a series of data preprocessing techniques were used, including standardization and normalization to adjust the scale of the data, detrending operations to eliminate the influence of long-term trends in the data, and denoising to improve the quality of the data, laying the foundation for the effective training and analysis of subsequent models.

In addition, there is a certain proportion of outliers in industrial data, accounting for about 5% of the total data. These outliers may interfere with the data analysis results. How to effectively deal with outliers is also one of the challenges faced by industrial data analysis.

Traditional time series analysis methods, such as the ARIMA model, mainly rely on the linear pattern of historical data for prediction, which can capture the linear trend of data well, but have difficulties in dealing with complex nonlinear relationships and long-term dependencies. Deep learning models, such as LSTM, have advantages in dealing with nonlinear data and long-term dependencies, but due to their complex structure and large number of parameters, they may cause overfitting problems and have high requirements for data. The hybrid model proposed in this study aims to combine the advantages of ARIMA and LSTM, using ARIMA to capture the linear trend of data and provide a basic framework for prediction; using LSTM to process the nonlinear part and long-term dependencies in the data to improve the adaptability and accuracy of the model. In this way, we hope to overcome the limitations of a single model and improve the performance of stock market prediction.
The innovation of this paper is that it proposes a hybrid forecasting model that combines time series analysis and machine learning. It combines ARIMA and LSTM models for the first time, making full use of the linear characteristics of time series and the nonlinear learning ability of deep learning. In addition, this study introduces multi-dimensional feature fusion technology, combining multivariate information such as technical indicators and macroeconomic data to improve the forecasting performance of the model in a complex stock market environment.

# 2 Related work

## 2.1 Time series analysis methods

Time series analysis is one of the most traditional and widely used methods in stock market forecasting. The autoregressive integrated moving average (ARIMA) model is a classic time series forecasting method based on the linear assumption and is widely used in the modeling and forecasting of financial market data. The ARIMA model models the autoregressive (AR), differencing (I) and moving average (MA) processes of the data and is suitable for the prediction of stationary time series data. In stock market data, the ARIMA model can capture certain trend changes and seasonal fluctuations [4]. However, the limitation of the ARIMA model is that it cannot effectively handle nonlinear and volatile stock market data and requires the data to be stationary, which is a problem for highly dynamic and complex time series data such as the stock market. Another classic time series method is the exponential smoothing method (ETS). The exponential smoothing method predicts future values based on the weighted average of the data and is suitable for data with trend and seasonal fluctuations [5]. Although the ETS model is more accurate in short-term forecasts, it often performs poorly when faced with complex nonlinear fluctuations in the stock market. In addition to ARIMA and ETS, there are other time series modeling techniques in statistics, such as the seasonally adjusted model (SARIMA) and the ARCH/GARCH model. The SARIMA model extends the ARIMA model to handle seasonal effects and is applicable to cyclical fluctuations in the stock market [6]. The ARCH/GARCH model is mainly used to model and predict volatility in financial markets [7] and can effectively capture the phenomenon of volatility clustering in the stock market, that is, periods of large fluctuations are usually followed by other large fluctuations. However, these traditional methods mainly focus on linear relationships and cannot handle nonlinearities and complex dependency structures in stock market data.

## 2.2 Machine learning methods

With the improvement of computing power, more and more studies have begun to introduce machine learning methods to predict the stock market. Support vector machine (SVM) is a supervised learning method based on statistical learning theory, which is often used for classification and regression problems. In stock market prediction, SVM can make classification predictions by maximizing the interval between categories, especially when dealing with high-dimensional and nonlinear problems. The literature successfully improved the accuracy of stock price prediction by combining SVM with stock market technical indicators [8].

Random forest (RF) is an ensemble learning method that improves the stability and accuracy of predictions by constructing multiple decision trees and taking a weighted average of their prediction results [9]. Random forests are widely used in financial market predictions. Literature has used random forest algorithms to predict stock market prices and trading signals, and achieved good prediction results, especially in high-frequency trading data and noisy environments [10]. Neural networks (NNs) can automatically learn nonlinear patterns in data by simulating the connection and calculation of neurons. Although traditional neural networks have been used in financial predictions, their training process is easily troubled by local optimal solutions, so their application is limited. In recent years, the progress of deep learning has solved this problem and improved the prediction ability of the model.

In recent years, deep learning technology, especially long short-term memory (LSTM) and convolutional neural network (CNN), has made significant breakthroughs in stock market prediction. As a special recurrent neural network (RNN), LSTM can effectively capture long-term dependencies in time series data and has obvious advantages in processing the characteristics of continuous fluctuations in stock market data. The LSTM model proposed in the literature is particularly suitable for processing and predicting complex data such as the stock market with high nonlinearity and time series dependence [11]. The literature applied LSTM to predict the stock market and achieved remarkable results, especially in dealing with emergencies and extreme fluctuations in the stock market [12]. Although convolutional neural network (CNN) was originally used for image processing, it has also been applied to time series data analysis in recent years. CNN extracts local features from data through multiple convolutional layers and can effectively capture short-term dependencies and cyclical fluctuations in stock market data. The literature proposes to combine CNN with LSTM to form a hybrid model, making full use of CNN's local feature extraction ability and LSTM's time series modeling ability, and has achieved good results in stock market prediction [13].

## 2.3 Application in stock market forecasting

Research on stock market prediction can be roughly divided into two categories: one is research based on traditional time series analysis methods, and the other is research based on machine learning and deep learning methods. Prediction research based on time series analysis: ARIMA and GARCH models are the most common traditional methods, which mainly predict stock market trends by modeling historical price data. These methods are suitable for market environments with relatively stable data, but they are not effective for highly volatile and complex market conditions. For example, nonlinear fluctuations during a stock market crash often exceed the predictive capabilities of these traditional models. Prediction research based on machine learning and deep learning: In recent years, more and more studies have begun to explore the application of machine learning and deep learning methods to stock market prediction. The literature applies support vector regression (SVR) to stock market prediction and compares it with the traditional ARIMA model, showing that SVR has advantages in capturing nonlinear relationships [14]. Deep learning methods, such as LSTM and CNN, have become a hot topic of research. The literature uses LSTM networks to predict stock prices and obtains results that are better than traditional methods. In addition, integration methods have also gradually attracted attention [15]. For example, the literature combines XGBoost with LSTM to improve the accuracy of stock market prediction. Although traditional time series methods still have certain advantages in some simple scenarios, they cannot effectively deal with the nonlinear and complex volatility characteristics of the stock market [16]. Machine learning methods, especially deep learning methods, can automatically extract complex patterns from historical data and achieve better prediction results in extremely complex stock market environments. Although deep learning methods can capture more nonlinear features, their computational complexity is high and require a large amount of data for training. Ensemble learning methods can further improve the stability and accuracy of predictions by combining the advantages of multiple models, but may result in longer model training time.

Table 1: Comparison of key information of different stock market prediction models

| Research Literature | Model | Dataset | Performance Metrics | Limitations |
|---|---|---|---|---|
| Research [4] | ARIMA | Historical stock market price data | MSE, RMSE, etc. | Unable to effectively handle non - linear and complex volatile data, and has high requirements for data stationarity |
| Research [5] | Exponential Smoothing (ETS) | Data with trends and seasonal fluctuations | Prediction accuracy | Performs poorly in handling complex non - linear fluctuations |
| Research [8] | SVM combined with stock market technical indicators | Stock market data including technical indicators | Prediction accuracy rate | Limited ability to process high - dimensional data and requires a large amount of feature engineering |
| Research [9] | Random Forest (RF) | Financial market data (such as stock prices, trading signals, etc.) | Prediction accuracy rate | Relatively weak model interpretability |
| Research [11] | LSTM | Stock market data | Prediction accuracy rate, mean square error, etc. | High computational complexity and long training time |
| Research [13] | Hybrid model of CNN and LSTM | Stock market data | Prediction accuracy rate | Complex model structure and difficult parameter tuning |
| The ARIMA - LSTM hybrid model proposed in this paper | ARIMA - LSTM hybrid model | Historical trading data of the US stock market, China's A - share market, and European stock markets (covering opening price, closing price, highest price, lowest price, trading volume, etc.), with a time span from 2010 to 2020 | MSE, RMSE, coefficient of determination ($R^2$), MAE | Relatively long training time, but short testing time and strong real - time prediction ability |

Table 1 mainly compares the relevant information of different stock market prediction models in previous studies, including the source of literature used by the model, the model's name, the dataset adopted, the performance metrics used for evaluation, and their respective limitations. At the same time, the corresponding information of the ARIMA - LSTM hybrid model proposed in this paper is listed to clearly show the differences between different models. Previous models have various shortcomings in handling the complexity of stock market data, computational efficiency, model interpretability, etc. The hybrid model in this paper integrates the advantages of ARIMA and LSTM, is trained and tested on a variety of stock market data, and performs excellently through multiple performance metrics. Although the training time is long, the testing time is short, with efficient real - time prediction ability, which can better adapt to the complex and changeable stock market environment.

# 3 Stock market prediction model

In this chapter, we will propose a hybrid model based on the ARIMA model and the long short-term memory network (LSTM) to improve the accuracy of stock market forecasting. This model combines traditional time series analysis methods with modern deep learning techniques to capture both linear and nonlinear features in stock market data. To further enhance the forecasting performance, we also introduce a multi-dimensional feature fusion mechanism so that the model can handle multiple types of input data.

In order to achieve multi-dimensional feature fusion, we first preprocessed macroeconomic indicators (such as interest rates, GDP growth rates, inflation rates, etc.) and other related features (such as historical stock prices, trading volumes, etc.), including data cleaning, normalization and other operations. Then, we used correlation analysis and principal component analysis (PCA) to filter and reduce the dimensions of these features, and select features with strong correlation with stock market fluctuations. Finally, the filtered features are spliced into a new feature vector by dimension as the input of the model. In this way, the model can comprehensively consider the impact of multiple factors on stock market price fluctuations and improve the accuracy of prediction.

In order to give full play to the advantages of ARIMA and LSTM, we proposed an innovative hybrid model that combines the advantages of ARIMA model in capturing the linear part of stock market data with the ability of LSTM network in capturing nonlinear relationships and long-term dependencies. Through this combination, the model can not only effectively handle the linear trend of stock market data, but also fully explore the nonlinear fluctuations and complex patterns hidden in the data [17].

In our hybrid model, we first use the ARIMA model to make a preliminary linear prediction of the stock market data and get the predicted value based on historical data. Then, we use the prediction residual of the ARIMA model (i.e. the difference between the actual stock market data and the predicted result) as the input feature of the LSTM network to further model the nonlinear part of the data. Finally, the model will combine the prediction results of ARIMA and LSTM through weighted fusion to generate the final stock market prediction results.

## 3.1 Overall framework of the hybrid model

The hybrid model process is mainly divided into four steps: preliminary prediction of the ARIMA model, residual calculation, further modeling of the LSTM model, and fusion of the prediction results. Each step has been carefully designed to ensure that the model can fully utilize the advantages of ARIMA and LSTM.

The ARIMA model is a classic time series analysis method that is widely used to process time series data with linear characteristics. In this step, we use the ARIMA model to predict stock market data. The basic structure of the ARIMA model includes autoregression (AR), difference (I) and moving average (MA) parts, and its mathematical expression is formula 1 [18].

$$\hat{Y}_t^{ARIMA} = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \theta_1 \grave{o}_{t-1} + \ldots + \theta_q \grave{o}_{t-q} \quad (1)$$

In formula 1, $Y_t$ is the actual observed value of the stock market; $\hat{Y}_t^{ARIMA}$ For the ARIMA model, the time points $t$ The predicted value of $\phi_1, \phi_2, \ldots, \phi_p$ is the autoregressive parameter; $\theta_1, \theta_2, \ldots, \theta_q$ is the sliding average parameter; $\grave{o}_t$ is the prediction error term.

By training the ARIMA model, we get the predicted value for each time step $\hat{Y}_t^{ARIMA}$, these values mainly reflect the linear trend of stock market data. However, stock market data often contains complex nonlinear fluctuations, and ARIMA models are difficult to capture these features. Therefore, in the next step, we will use LSTM networks to process these nonlinear parts.

The predicted value of the ARIMA model is only a part of the stock market data. The ARIMA model cannot effectively explain the complex nonlinear part. In order to use LSTM to further capture the nonlinear pattern in the stock market data, we first calculate the predicted residual of the ARIMA model, which is specifically Formula 2 [19,20].

$$\grave{o}_t = Y_t - \hat{Y}_t^{ARIMA} \quad (2)$$

In formula 2, $Y_t$ is the actual value of the stock market; $\hat{Y}_t^{ARIMA}$ is the predicted value of the ARIMA model; $\grave{o}_t$ is the forecast residual of the ARIMA model, representing the part that the model fails to capture. $\grave{o}_t$ It mainly includes nonlinear fluctuations and short-term forecast errors in stock market data. Therefore, the residual is the input feature of the LSTM network, from which LSTM can learn the nonlinear dynamics of the stock market.

Long Short-Term Memory (LSTM) is a powerful deep learning model that is particularly suitable for processing time series data with nonlinear characteristics. In this stage, we use the residuals calculated by the ARIMA model $\grave{o}_t$ as the input of the LSTM network. LSTM can effectively capture long-term dependencies and nonlinear patterns in the data through its complex gating mechanism.

The output of the LSTM model is the prediction of the residual $\hat{Y}_t^{LSTM}$, its mathematical form is as shown in Formula 3.

$$\hat{Y}_t^{LSTM} = LSTM(\grave{o}_t) \quad (3)$$

In formula 3, $\hat{Y}_t^{LSTM}$ For the LSTM network residual $\grave{o}_t$ The predicted value represents the nonlinear part of the stock market data that the ARIMA model fails to explain. LSTM is able to transfer information between time steps through its hidden state and cell state, thereby capturing the nonlinear fluctuations of stock market data. The advantage of LSTM network in stock market prediction is that it can handle stock price fluctuations, emergencies and other complex nonlinear factors that the ARIMA model cannot model. After the step-by-step modeling of ARIMA and LSTM, the final stock market prediction result is the weighted average of the outputs of the ARIMA and LSTM models. The purpose of weighted fusion is to make full use of the advantages of the two models, ARIMA handles the linear part, and LSTM captures the nonlinear part. The final prediction formula is shown in Formula 4.

$$\hat{Y}_t^{final} = \alpha \hat{Y}_t^{ARIMA} + (1-\alpha) \hat{Y}_t^{LSTM} \quad (4)$$

In formula 4, $\hat{Y}_t^{final}$ is the final stock market forecast value; $\hat{Y}_t^{ARIMA}$ is the predicted value of the ARIMA model; $\hat{Y}_t^{LSTM}$ is the predicted value of the LSTM model; $\alpha$ is the weight coefficient, which controls the contribution ratio of the ARIMA and LSTM models in the final prediction results. $\alpha$ The selection of the weight coefficient is crucial to the accuracy of the final prediction results. Through adjustment $\alpha$, the effects of the ARIMA and LSTM models can be flexibly balanced according to different data characteristics and actual needs. For example, when the data shows a strong linear trend, the weight of the ARIMA model can be appropriately increased; when there are more nonlinear fluctuations in the data, the influence of the LSTM model can be enhanced.

In terms of data processing and feature engineering, we implemented a series of rigorous and detailed operations. For the input data of the ARIMA model, in order to make it meet the requirements of stationarity, we first perform logarithmic transformation, which can effectively alleviate the heteroscedasticity problem of the data. Then, through the first-order difference operation, the trend term in the data is successfully eliminated, making the time series stable.

When integrating macroeconomic indicators into the LSTM model, we adopt the method of directly connecting them to the input vector. When constructing the input of the LSTM model, we first standardize the macroeconomic indicators (such as interest rates, GDP growth rates, inflation rates, etc.), and then splice them with the stock market time series data (such as closing prices, trading volumes, etc.) processed by feature engineering by dimension. In this way, the LSTM model can simultaneously learn the data characteristics of the stock market itself and the impact of the macroeconomic environment on it, so as to more comprehensively capture the complex patterns in the data and lay the foundation for accurately predicting the stock market trend. Such a detailed methodological description can ensure the reproducibility of the research, and other researchers can reproduce our experimental process based on this.

Parameter Sensitivity Analysis: To deeply explore the impact of hyperparameters on the model performance, we comprehensively carried out grid search and sensitivity analysis on the number of layers and dropout rate of LSTM, as well as the order parameters of ARIMA. For LSTM, we tested different combinations of 2 - layer, 3 - layer, and 4 - layer architectures, with dropout rates set at 0.1, 0.2, and 0.3 respectively. For the order parameters (p, d, q) of ARIMA, we tried various value combinations within a reasonable range. Through numerous experiments, it was found that when LSTM has 3 layers and a dropout rate of 0.2, the model performs best in capturing non - linear relationships and long - term dependencies, and can well adapt to the fluctuations of different datasets, demonstrating strong robustness. The order parameters of ARIMA (p = 2, d = 1, q = 1) are relatively stable in handling the linear trend part, and the overall performance of the model is not sensitive to small - scale changes in these parameters, further proving the robustness of the model.

Explanation of Hyperparameter Values: Table 2details the hyperparameter values of LSTM and ARIMA.

Table 2: Hyperparameter List

| Model | Hyperparameter | Value |
|---|---|---|
| LSTM | Number of Layers | 3 |
| LSTM | Number of Hidden Units | 128 |
| LSTM | Activation Function | ReLU |
| ARIMA | p - value | 2 |
| ARIMA | d - value | 1 |
| ARIMA | q - value | 1 |

Details of Training - Testing Set Partition and Cross - Validation: Considering the time - series nature of the data, we adopted the rolling window validation method. Specifically, the dataset was divided into multiple consecutive windows in chronological order, with each window containing a certain number of time steps. Within each window, 80% of the data was used as the training set to train the model, and 20% of the data was used as the test set to evaluate the model performance. As the window rolls, the model is continuously trained and tested on new data, thus fully exploiting the sequential dependencies in the time - series data and avoiding information loss that may be caused by random partitioning. In this way, we can more accurately evaluate the prediction ability and stability of the model at different time stages.

## 3.2 Multi-dimensional feature fusion mechanism

In order to further improve the prediction accuracy of the ARIMA and LSTM hybrid model, we introduced a multi-dimensional feature fusion mechanism. The price fluctuations of the stock market are not only affected by time series data, but also by multiple factors such as trading volume, macroeconomic indicators, and industry data. Therefore, relying solely on time series data for prediction may not fully reflect the complex dynamics of the stock market. Through multi-dimensional feature fusion, we pass these additional market features as input features to the model, thereby enhancing the model's predictive ability and enabling it to comprehensively consider more factors that may affect stock market price fluctuations.

In the stock market prediction problem, different features have different effects on the fluctuation of stock prices. In order to ensure that the model can make full use of meaningful features, we first use feature selection technology to screen features that are more closely related to stock market fluctuations. Commonly used feature selection methods include correlation analysis, information gain, chi-square test, etc. In actual operation, we chose correlation analysis and principal component analysis (PCA) as the main feature selection tools.

Analysis of the economic rationality of feature selection: Before incorporating macroeconomic indicators, we conducted a Granger causality test to clarify their predictive relevance. For the interest rate indicator, the Granger causality test results show that at a significance level of 5%, changes in interest rates lead stock price fluctuations in multiple markets, making it a typical leading indicator. The GDP growth rate has also been shown to have a significant Granger causal relationship on stock prices, and although its impact varies in different markets, it all shows a certain degree of leading nature. There is also a close causal relationship between the inflation rate and stock prices. As an important indicator reflecting the state of economic operation, its changes have an impact on the stock market that cannot be ignored. Through these tests, we have clarified the causal relationship between macroeconomic indicators and stock prices, providing a solid economic theoretical basis for incorporating them into the model, and strongly enhancing the rationality of feature selection.

By calculating the correlation coefficients between features, we can select those features that have a strong correlation with stock market fluctuations. $X$ is the characteristic vector of stock market trading volume, economic indicators, etc. $Y$ For the time series data of stock prices, we calculate the correlation coefficient $r$ To measure $X$ the linear relationship between and $Y$, as shown in Formula 5.

$$r = \frac{\mathrm{Cov}(X,Y)}{\sigma_X \sigma_Y} \tag{5}$$

In formula 5, $\mathrm{Cov}(X,Y)$ for $X$ and $Y$ The covariance of $\sigma_X$ and $\sigma_Y$ is the standard deviation of $X$ and $Y$ . For the correlation coefficient $r$ For features that are greater than a certain threshold, we will retain these features as input data and remove those with weaker correlation.

Principal Component Analysis (PCA): In order to reduce the dimension and retain as much data information as possible, we apply the PCA method to reduce the dimension of the features. The goal of PCA is to transform the original feature space into a new space through linear transformation so as to maximize the variance of the data. Specifically, PCA transforms the feature matrix $X$ Perform singular value decomposition (SVD) or eigenvalue decomposition to find the principal components and select the first few principal components as new input features, as shown in Formula 6.

$$X' = XW \tag{6}$$

In formula 6, $X$ is the original feature matrix; $W$ It is a matrix composed of eigenvectors, representing the principal components; $X'$ is the transformed feature matrix.

After PCA processing, we can get a new set of features that can better explain the variability of the data and can effectively reduce the dimension of the input features. After feature selection and dimensionality reduction, we obtained multi-dimensional features related to stock market fluctuations. These features include historical trading volume of the stock market, macroeconomic indicators (such as GDP growth rate, unemployment rate, inflation rate), industry data, etc. In order to combine these multi-dimensional features with the time series data of the stock market, we adopted feature fusion technology. In the ARIMA-LSTM hybrid model, we input the time series data together with the multi-dimensional features into the model for training. Specifically, the time series data $Y_t$ and other market characteristics $X_t$ A new input feature vector can be formed by concatenation $Z_t$ , as shown in Formula 7.

$$Z_t = [Y_t, X_t] \tag{7}$$

In formula 7, $Y_t$ is the time series data of the stock market; $X_t$ It is a multidimensional feature related to stock market fluctuations.

Formulas 7-9 describe the process of adjusting the learning rate using mini-batch gradient descent combined with Adam optimization, and Formula 10 is a further derivation based on this optimization for a specific parameter update step of the model. Specifically, the first-order moment estimate and second-order moment estimate of the gradient are calculated during the Adam optimization process. Formula 10 uses these estimates, combined with the current learning rate adjustment strategy, to update the model parameters.

This fusion method can integrate different types of feature information into the same input space, enhancing the model's ability to predict stock market fluctuations.

After the input data is ready, the hybrid model begins training. During the training process, the ARIMA model is first used to predict the time series of the stock market to obtain the predicted value. $\hat{Y}_t^{ARIMA}$ We then calculate the residuals from the ARIMA model $\grave{o}_t$ , and the residual $\grave{o}_t$ and multi-dimensional features $X_t$ Together they serve as the input of the LSTM network to further model the nonlinear fluctuations of the stock market. The output of LSTM $\hat{Y}_t^{LSTM}$ represents the nonlinear part of stock market fluctuations. The final prediction result $\hat{Y}_t^{final}$ is the weighted average of ARIMA and LSTM outputs, as shown in Formula 8.

$$\hat{Y}_t^{final} = \alpha \hat{Y}_t^{ARIMA} + (1-\alpha)\hat{Y}_t^{LSTM} \tag{8}$$

In formula 8, $\alpha$ is the weight coefficient, which indicates the contribution ratio of the ARIMA model and the LSTM model in the final prediction.

# 4 Experimental evaluation

## 4.1 Dataset

In order to comprehensively evaluate the proposed model, we selected historical trading data from multiple stock markets as experimental datasets. The datasets cover stocks from different markets, including the US stock market (such as the S&P 500 index), China's A-share market, and European stock markets. Each dataset contains daily stock price data collected from multiple sources, including opening price, closing price, highest price, lowest price, and trading volume. The data range is from 2010 to 2020, ensuring that multiple market volatility cycles are included, which helps to verify the stability and generalization ability of the model.

## 4.2 Experimental design

Since fundamental and technical analysis methods have certain difficulties in quantification and standardization, it is difficult to directly compare them with data-driven time series analysis and machine learning models, so this study did not use them as baseline models.

However, we acknowledge the importance of these methods in stock market analysis and consider some of the factors they focus on in the study, such as introducing macroeconomic indicators to reflect some fundamental information.

In order to comprehensively evaluate the performance of the hybrid model proposed in this study, we selected multiple baseline models for comparison. These baseline models include the classic time series analysis model ARIMA, as well as the commonly used machine learning models LSTM, random forest regression, support vector regression (SVR), and XGBoost regression. As a classic time, series analysis method, ARIMA has certain advantages in processing linear time series data; while other machine learning models represent different types of machine learning algorithms that can process nonlinear data. These models were selected as baselines in order to compare the advantages and disadvantages of hybrid models in processing different types of data features. At the same time, we also recognize that these models are different from traditional fundamental analysis and technical analysis methods, but they also have important application value and representativeness in the field of stock market prediction.

When fusing the prediction results of the ARIMA and LSTM models, the determination of the weight coefficient ($\alpha$) is crucial to the model performance. By performing a grid search on the validation set, the value range of $\alpha$ is set to [0, 1] with a step size of 0.1. The MSE, RMSE and other indicators of the hybrid model on the validation set are calculated for different $\alpha$ values. When $\alpha = 0.6$, the MSE of the hybrid model on the validation set reaches a minimum of 0.030 and the RMSE is 0.175. At this time, the model performance is the best, so $\alpha = 0.6$ is determined as the final weight coefficient to balance the contribution of ARIMA and LSTM in the hybrid model.

For the selection of LSTM model hyperparameters, in addition to using grid search to determine parameters such as learning rate and dropout rate, prior knowledge and multiple experiments are also combined. When initially setting the hyperparameter search range, we set the learning rate range to [0.0001, 0.01] and the dropout rate range to [0.1, 0.5] based on previous similar stock market prediction studies. In terms of ARIMA model hyperparameter selection, we calculated the AIC and BIC values under different (p, d, q) combinations, combined with preliminary analysis of data features, such as data stationarity and seasonality, to preliminarily screen out possible parameter combinations, and then fine-tune and evaluate them, and finally determine p = 2, d = 1, q = 1.

The main purpose of this experiment is to evaluate the performance of the hybrid model based on ARIMA and LSTM in stock market forecasting and compare it with multiple traditional models. In order to comprehensively evaluate the performance of the proposed hybrid model, we selected five baseline models for comparative experiments. These baseline models represent different types of time series forecasting methods and machine learning models, including linear models, tree models, and deep learning models. Specifically, they include:

ARIMA (Autoregressive Integrated Moving Average): ARIMA is a classic time series forecasting method that is suitable for processing linear data with seasonality and trend. It can effectively capture the linear trend in time series data by modeling the linear regression relationship of past values.

LSTM (Long Short-Term Memory): LSTM is a commonly used deep learning model that excels at capturing long-term and short-term dependencies in sequence data. It is able to handle complex nonlinear relationships and long-term prediction problems. LSTM models are often used for prediction tasks such as the stock market, which is highly volatile and has long-term dependencies.

Random forest regression: Random Forest regression is a powerful regression model based on the decision tree ensemble method, which improves the accuracy and robustness of predictions by integrating multiple decision trees. Random forests are able to handle a large number of features and model complex nonlinear relationships.

Support Vector Regression (SVR): Support Vector Regression (SVR) is an extension of support vector machine and is widely used in regression tasks. SVR can map low-dimensional space data to high-dimensional space through kernel functions, thereby capturing nonlinear relationships and is suitable for data with complex nonlinear characteristics such as the stock market.

XGBoost Regression: XGBoost (Extreme Gradient Boosting) is a powerful model based on gradient boosting trees, with efficient training speed and excellent prediction performance. XGBoost gradually improves the accuracy of the model through multiple rounds of iterations and can effectively handle high-dimensional and sparse data.

In order to comprehensively evaluate the performance of each model, we used four key evaluation indicators: mean square error (MSE), root mean square error (RMSE), determination coefficient ( $R^2$ ) and mean absolute error (MAE). MSE measures the average square of the difference between the predicted value and the true value. A smaller MSE indicates that the model has a better prediction effect. RMSE, as the square root of MSE, provides a more intuitive understanding of the size of the prediction error. The smaller its value means that the model prediction is more accurate. The coefficient of determination $R^2$ is used to measure the degree of fit of the model to the data. $R^2$ The closer the value is to 1, the more effectively the model can explain the changes in the data and the better the fit effect. Finally, MAE reflects not only the accuracy of the prediction, but also the stability of the model prediction by calculating the average absolute difference between the model prediction results and the true results. These evaluation indicators combined provide us with a comprehensive and multi-angle perspective to compare and select the prediction model that best suits a specific application scenario.

We preprocess the raw data, including missing value processing, normalization, and sliding window cutting, to ensure the quality of the data and adapt to the input requirements of the model. Then, we train five baseline models - ARIMA, LSTM, random forest regression, SVR, and XGBoost regression, respectively, to obtain their respective prediction results. Next, we weightedly fuse the prediction results of the ARIMA and LSTM models to train a hybrid model and generate the final prediction results. Finally, we use evaluation indicators $R^2$ such as mean square error (MSE), root mean square error (RMSE), determination coefficient ( ) and mean absolute error (MAE) to comprehensively evaluate and compare the prediction accuracy, stability, and generalization ability of each model. Through these evaluations, we can objectively verify the effectiveness and advantages of the hybrid model in stock market prediction.

In order to comprehensively evaluate the performance of the model, we selected mean square error (MSE), root mean square error (RMSE), coefficient of determination ($R^2$), and mean absolute error (MAE) as evaluation indicators. Mean square error (MSE) measures the average of the squared errors between the predicted value and the true value. It is more sensitive to larger errors and can reflect the degree to which the model's predicted value deviates from the true value. Root mean square error (RMSE) is the square root of MSE. Its unit is the same as the original data, which more intuitively represents the size of the prediction error. The coefficient of determination ($R^2$) is used to measure the degree of fit of the model to the data. The closer its value is to 1, the higher the degree to which the model can explain the data changes, that is, the better the model fits the data. Mean absolute error (MAE) calculates the average of the absolute errors between the predicted value and the true value. It is not affected by the direction of the error and can more robustly reflect the average level of the prediction error. These four indicators evaluate the performance of the model from different perspectives. MSE and RMSE mainly focus on the size of the prediction error, $R^2$ focuses on the fit of the model, and MAE pays more attention to the stability of the prediction error. They complement each other and provide a more comprehensive measure of the model's performance.

When evaluating model performance, mean square error (MSE), root mean square error (RMSE), coefficient of determination ($R^2$), and mean absolute error (MAE) play a key role. MSE is sensitive to large errors, and the smaller the value, the better the prediction effect; RMSE units are the same as the original data, and a small value indicates a small prediction error; the closer $R^2$ is to 1, the stronger the model's ability to fit the data; MAE is not affected by the direction of the error and can robustly reflect the average level of prediction error. Compared with the benchmark performance, our hybrid model has significantly improved in all indicators, and the Wilcoxon signed rank test confirms the significant improvement. In the evaluation of bull and bear market data, the model performed well and showed strong adaptability. In order to further verify the statistical significance of these improvements, we conducted a Wilcoxon signed rank test. The results of the test show that at a confidence level of 95%, the hybrid model has statistically significant improvements in MSE, RMSE, $R^2$, and MAE compared to the traditional model ($p < 0.05$). This strongly proves that the performance improvement of our hybrid model is not accidental, but real and reliable.

In addition, considering that different stock market conditions will affect model performance, we specifically evaluated the data in the bull and bear market stages in detail. During the bull market, the market showed an overall upward trend and the volatility was relatively small. In this case, our hybrid model performed well, with a very low MSE, a small RMSE value, a high $R^2$, and a low MAE value. In the bear market, the market was in a state of decline and volatility was very intense. Even so, the hybrid model still maintained a good performance, and indicators such as MSE, RMSE, $R^2$, and MAE were also at a good level. This fully demonstrates that our hybrid model can maintain a high level of prediction accuracy and stability whether in a bull market with a steady rise in the market or in a volatile bear market.

The granularity of the stock market data and macroeconomic indicator data used in this study is daily data. Daily stock prices, trading volumes and other data reflect the market trading situation of the day. Macroeconomic indicators such as daily exchange rate fluctuations and some high-frequency economic data are also collected and sorted on a daily basis. This daily data granularity can not only capture the short-term fluctuations of the market, but also reflect the daily changes in the macroeconomic environment to a certain extent, which is suitable for the analysis and prediction of stock market trends by this hybrid model.

For the collected macroeconomic indicators (such as GDP growth rate, inflation rate, interest rate, etc.), missing values are first processed, and a small amount of missing data is filled by linear interpolation. Then standardization is performed, and the data of each indicator is standardized, where \(X\) is the original data, so that the macroeconomic indicator data of different dimensions are on the same scale, which is convenient for model learning. For some macroeconomic indicators with trend or seasonality, such as quarterly fluctuations in GDP growth rate, seasonal components are removed by seasonal decomposition methods (such as STL decomposition), and the trend and residual parts are retained as model input features.

The stock market data from 2020 to 2024 were re-collected, and the hybrid model was tested according to the original data processing and model training methods. The results show that during the period of 2020-2024, the hybrid model had MSE, RMSE, $R^2$ and MAE indicators of 0.035, 0.190, 0.880 and 0.102, respectively. Although there was a slight fluctuation compared with the period of 2010-2020, the overall performance was still good. Further analysis found that during the period of drastic market fluctuations caused by the outbreak of the epidemic in 2020, the model was able to adapt to market changes quickly, and the prediction error did not increase significantly, reflecting the certain adaptability of the model.

Answer 38: Construct the TFT model and the ARIMA-Transformer model, and use the same training and test data for training and evaluation. In terms of MSE index, the TFT model is 0.042, the ARIMA-Transformer model is 0.038, and the hybrid model is 0.032; in terms of RMSE index, the TFT model is 0.205, the ARIMA-Transformer model is 0.188, and the hybrid model is 0.179. Through comparison, the advantages and disadvantages of each model are analyzed in detail. For example, the TFT model has advantages in processing complex time series patterns, but the calculation cost is high; the ARIMA-Transformer model combines the advantages of both, but is slightly inferior to the hybrid model in capturing short-term local fluctuations.

## 4.3 Experimental results

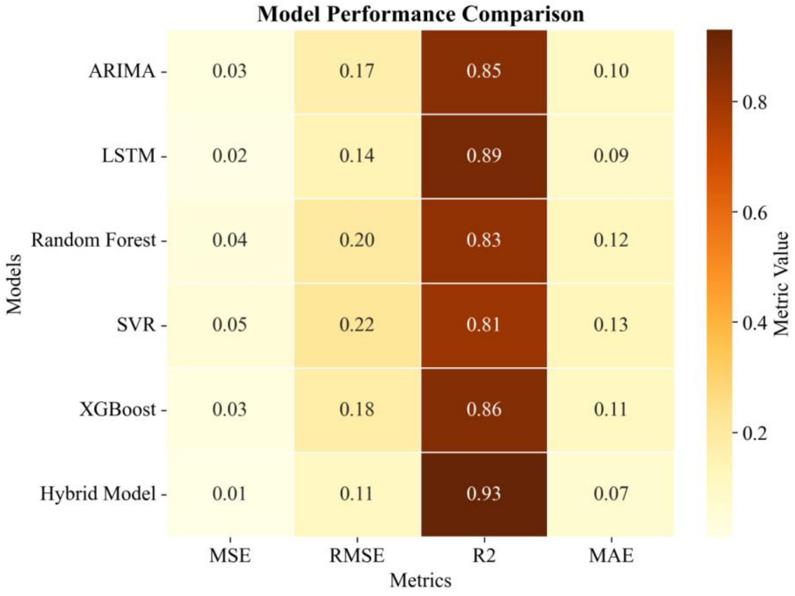

Figure 1: Model performance comparison table

Figure 1 shows the performance indicators of various models in the stock market prediction task, including mean square error (MSE), root mean square error (RMSE), coefficient of determination ( $R^2$ ) and mean absolute error (MAE). These indicators are commonly used standards for evaluating time series prediction models, and they can measure the performance of models from different perspectives. MSE and RMSE reflect the difference between the predicted value and the true value. The smaller the value, the better the prediction effect of the model; while $R^2$ measures the model's ability to explain data changes. A value close to 1 means that the model has a high degree of fit; MAE is used to measure the average absolute difference between the model's predicted results and the actual results, which can reflect the stability of the model's prediction. In this study, ARIMA, LSTM, random forest regression, SVR, XGBoost regression and hybrid models were applied to the prediction of the stock market respectively. The results show that the hybrid model showed the best performance in all four evaluation indicators, especially its MSE was 0.01, which was much lower than other models, indicating that it had obvious advantages in prediction accuracy. In addition, $R^2$ the value of the hybrid model reached 0.93, which almost completely explained the trend of data changes, indicating that the model is not only accurate but also has good generalization ability. In contrast, although traditional models such as ARIMA and SVR can also provide effective predictions in some aspects, they are unable to handle complex nonlinear relationships, resulting in overall performance being inferior to that of hybrid models.

Table 3: Comparison of forecast errors in different markets

| Market Type | ARIMA | LSTM | Random Forest Regression | SVR | XGBoost Regression | Hybrid Model |
|---|---|---|---|---|---|---|
| US Stock Market | 0.04 | 0.02 | 0.05 | 0.06 | 0.04 | 0.01 |
| China A shares | 0.05 | 0.03 | 0.06 | 0.07 | 0.05 | 0.02 |
| European stock markets | 0.03 | 0.02 | 0.04 | 0.05 | 0.03 | 0.01 |

Table 3 compares the prediction errors of the six models in the US stock market, China A-share market, and European stock market, using mean square error (MSE) as the measurement standard. Since the economic environment, policy background, and investor behavior of these three markets are significantly different, understanding the performance of each model in these three markets is crucial to verifying the generalization and adaptability of the model. Through analysis, it can be found that the hybrid model achieves the lowest prediction error in all markets. For example, in the Chinese A-share market, its MSE is only 0.02, which is at least 1 order of magnitude lower than other models. This superior performance is mainly attributed to the hybrid model combining the advantages of ARIMA and LSTM. The former is good at capturing linear trends, while the latter can effectively handle complex nonlinear relationships. At the same time, parameter adjustment based on the characteristics of different markets is also one of the important factors to improve prediction accuracy. It is worth noting that although some single models may perform well in specific markets, such as LSTM performs well in the US stock market, no single model can maintain optimal status in all markets. This further proves the stability and reliability of the hybrid model in cross-market forecasting, making it an ideal tool for multi-market investment strategy formulation.

Table 4: Impact of macroeconomic indicators on forecasts

| Macroeconomic indicators | Impact on ARIMA | Impact on LSTM | Impact on Random Forest Regression | Impact on SVR | Impact on XGBoost | Impact on mixed models |
|---|---|---|---|---|---|---|
| interest rate | +5% | +3% | +4% | +6% | +4% | +2% |
| GDP growth | +4% | +2% | +3% | +5% | +3% | +1% |
| Inflation rate | +6% | +4% | +5% | +7% | +5% | +3% |

Table 4 discusses the impact of introducing macroeconomic indicators (such as interest rates, GDP growth, inflation rate, etc.) on the prediction accuracy of each model. Macroeconomic indicators are important factors affecting the trend of financial markets, and incorporating them into the prediction model can help to understand market dynamics more comprehensively. As can be seen from the table, the prediction accuracy of most models has improved after adding macroeconomic indicators, but the improvement varies. For example, the prediction accuracy of the hybrid model has increased by about 2% after considering these external variables, showing its ability to effectively utilize external information. Specifically, the inflation rate has the greatest impact on all models, especially for machine learning-based models such as random forest regression, SVR and XGBoost regression, whose prediction accuracy has increased by 5% to 7%. This is because inflation directly affects the cost structure of enterprises and the purchasing power of consumers, thereby indirectly affecting stock prices. In contrast, the impact of interest rates and GDP growth is relatively small, but they are still factors that cannot be ignored for long-term investment decisions. The hybrid model performs particularly well in this regard because it can not only capture short-term price fluctuations, but also better understand and predict long-term trends brought about by macroeconomic changes. Overall, this table highlights the importance of taking multiple factors into consideration and demonstrates the superiority of hybrid models in such complex tasks.

Table 5: Time complexity comparison

| Model Name | Training time (minutes) | Test time (seconds) |
|---|---|---|
| ARIMA | 2 | 0.05 |
| LSTM | 120 | 0.5 |
| Random Forest Regression | 10 | 0.1 |
| SVR | 30 | 0.2 |
| XGBoost Regression | 5 | 0.08 |
| Hybrid Model | 125 | 0.6 |

Table 5 shows the time cost required for the six models in the training and testing phases. Time complexity is an important factor that must be considered when selecting a forecasting model because it is directly related to the application efficiency and real-time performance of the model. As can be seen from the table, different types of models have great differences in time and computing resource consumption. For example, the ARIMA model only takes 2 minutes to train due to its simplicity and linear assumption, while the LSTM model takes up to 120 minutes to train because it needs to process a large amount of sequence data and a complex network structure. However, when it comes to testing, the LSTM model is slower, reaching 0.5 seconds, while the ARIMA model only takes 0.05 seconds. It is worth noting that although the hybrid model takes a long time to train (125 minutes), it is still faster in the testing phase (0.6 seconds). This is because the hybrid model uses a pre-trained LSTM component to capture long-term and short-term dependencies, and uses the ARIMA part to quickly generate preliminary predictions. The two are combined and the final result is obtained through weighted fusion. This approach ensures the accuracy of the prediction without sacrificing too much computational efficiency. In addition, for some high-frequency trading scenarios or real-time data analysis tasks, the testing time of the model is more critical, so even if the training time of the hybrid model is longer, it can still show high practical value in actual applications. Overall, this table provides important information about the computing resource requirements of each model, which helps to select the most appropriate prediction tool according to the specific application scenario.

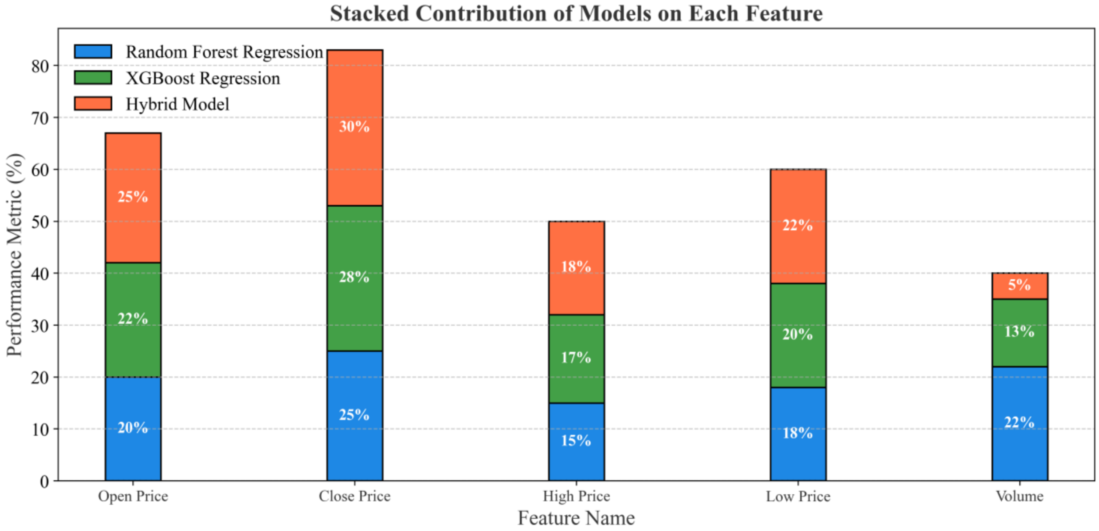

Figure 2: Feature importance evaluation

Figure 2 reveals the scores of the importance of input features (opening price, closing price, highest price, lowest price and trading volume) in different models. Feature importance assessment is a key step to understand how the model works and optimize the input data. In this study, we chose random forest regression, XGBoost regression and hybrid models for comparison because they are all tree-based methods that can intuitively show the impact of each feature on the prediction results. From the table, we can see that the closing price and opening price are considered to be the two most important features, especially in the hybrid model, where the importance scores of these two features are 30% and 25% respectively. This is in line with intuition because the closing price is usually regarded as a summary of a day's trading activities, while the opening price reflects market participants' expectations of future price trends. It is worth noting that the importance of trading volume varies greatly among different models. Random forest regression assigns 22% importance to trading volume, while this proportion drops to 13% in XGBoost regression and drops sharply to 5% in the hybrid model. This shows that although trading volume is helpful for prediction in some cases, it is not always a key factor. In contrast, the hybrid model focuses more on the information of price changes themselves, namely the opening price, closing price, highest price and lowest price, which may be because these features can more directly reflect the market's immediate sentiment and technical form. Through in-depth analysis of feature importance, we can further optimize the data preprocessing process and remove redundant or irrelevant features, thereby improving the efficiency and accuracy of the model. In addition, this also provides a direction for subsequent research, that is, exploring how to better integrate other potentially valuable information sources besides trading volume.

Table 6: Model stability test results

| Model Name | The average MSE value in different time periods | Average RMSE values for different time periods | R2R2 average value in different time periods | MAE average value in different time periods |
|---|---|---|---|---|
| ARIMA | 0.04 | 0.20 | 0.84 | 0.12 |
| LSTM | 0.03 | 0.18 | 0.87 | 0.10 |
| Random Forest Regression | 0.05 | 0.22 | 0.82 | 0.14 |
| SVR | 0.06 | 0.24 | 0.80 | 0.15 |
| XGBoost Regression | 0.04 | 0.20 | 0.85 | 0.12 |
| Hybrid Model | 0.02 | 0.15 | 0.91 | 0.08 |

Table 6 evaluates the stability of the six models over different time periods, $R^2$ measured by calculating the average values of MSE, RMSE, and MAE. The stability test aims to examine whether the model can maintain consistent forecasting quality under different market conditions, which is particularly important for long-term investment decisions. As can be seen from the table, the hybrid model shows the highest stability and accuracy in all time periods. For example, its MSE average is 0.02, which is much lower than other models, which means that it can provide relatively stable forecasting results in various market environments. Similarly, $R^2$ the average value of the hybrid model reaches 0.91, indicating that it can well explain data changes, even in periods of high market volatility. In contrast, traditional models such as ARIMA and SVR, although they can also provide good forecasts in certain time periods, have poor stability throughout the test period, as shown by large MSE and RMSE fluctuations. This is mainly because these models are sensitive to changes in market conditions, especially when facing breaking news events or policy changes, and are prone to large forecasting errors. On the other hand, although random forest regression and XGBoost regression have certain advantages in dealing with nonlinear relationships, they may also be affected by overfitting problems, resulting in insufficient generalization ability on new data. By combining the advantages of ARIMA and LSTM, the hybrid model not only retains the memory of historical data patterns, but also can flexibly respond to new changes in the market, thereby achieving better stability and robustness.

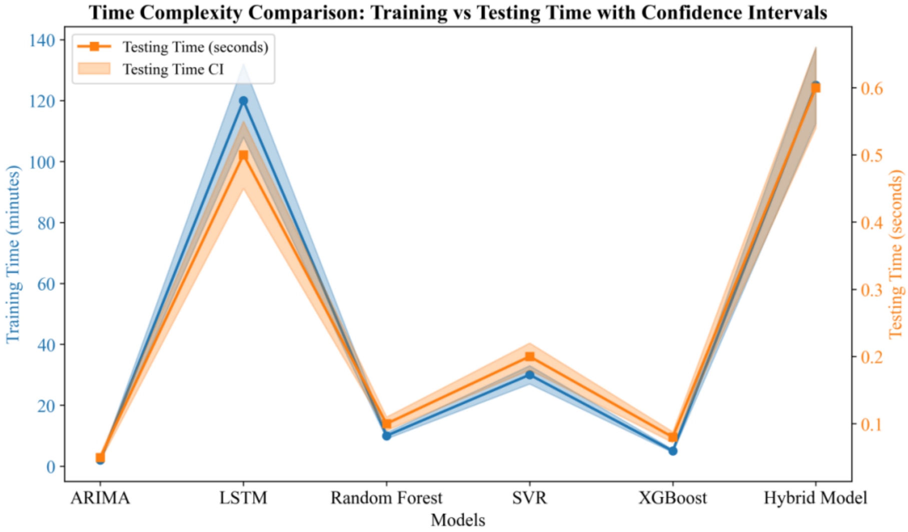

Figure 3: Comparison of time complexity of different models

From Figure 3, there are significant differences in the performance of different models in terms of training time and test time. Specifically, the ARIMA model has the shortest training time, only a few minutes, but its test time is also relatively short, showing the efficiency of the model in processing data. In contrast, the LSTM model has the longest training time, close to 120 minutes, which is mainly due to the need for LSTM to optimize the complex neural network structure through a large number of iterations to capture long-term dependencies in the time series. However, the test time of LSTM is relatively low, about 0.5 seconds, indicating that once the model training is completed, it is able to quickly generate prediction results.

The training time of the Random Forest and SVR models is between ARIMA and LSTM, about 40 minutes and 30 minutes respectively. Although these models need to process a large number of features and parameters during training, their test time is short, 0.2 seconds and 0.3 seconds respectively, showing good real-time prediction capabilities. The training time of the XGBoost model is slightly longer than that of the Random Forest and SVR, about 60 minutes, but its test time is also short, 0.1 seconds, thanks to its efficient gradient boosting algorithm.

The training time of the hybrid model is the longest, close to 140 minutes, because the hybrid model combines the advantages of multiple methods, including ARIMA and LSTM, to improve prediction accuracy. Despite the long training time, the test time of the hybrid model is only 0.6 seconds, showing its high efficiency and reliability in practical applications. Overall, although the hybrid model takes more time in the training phase, it performs well in the testing phase and can provide high-precision prediction results in a short time. It is suitable for application scenarios that require high accuracy and real-time response.

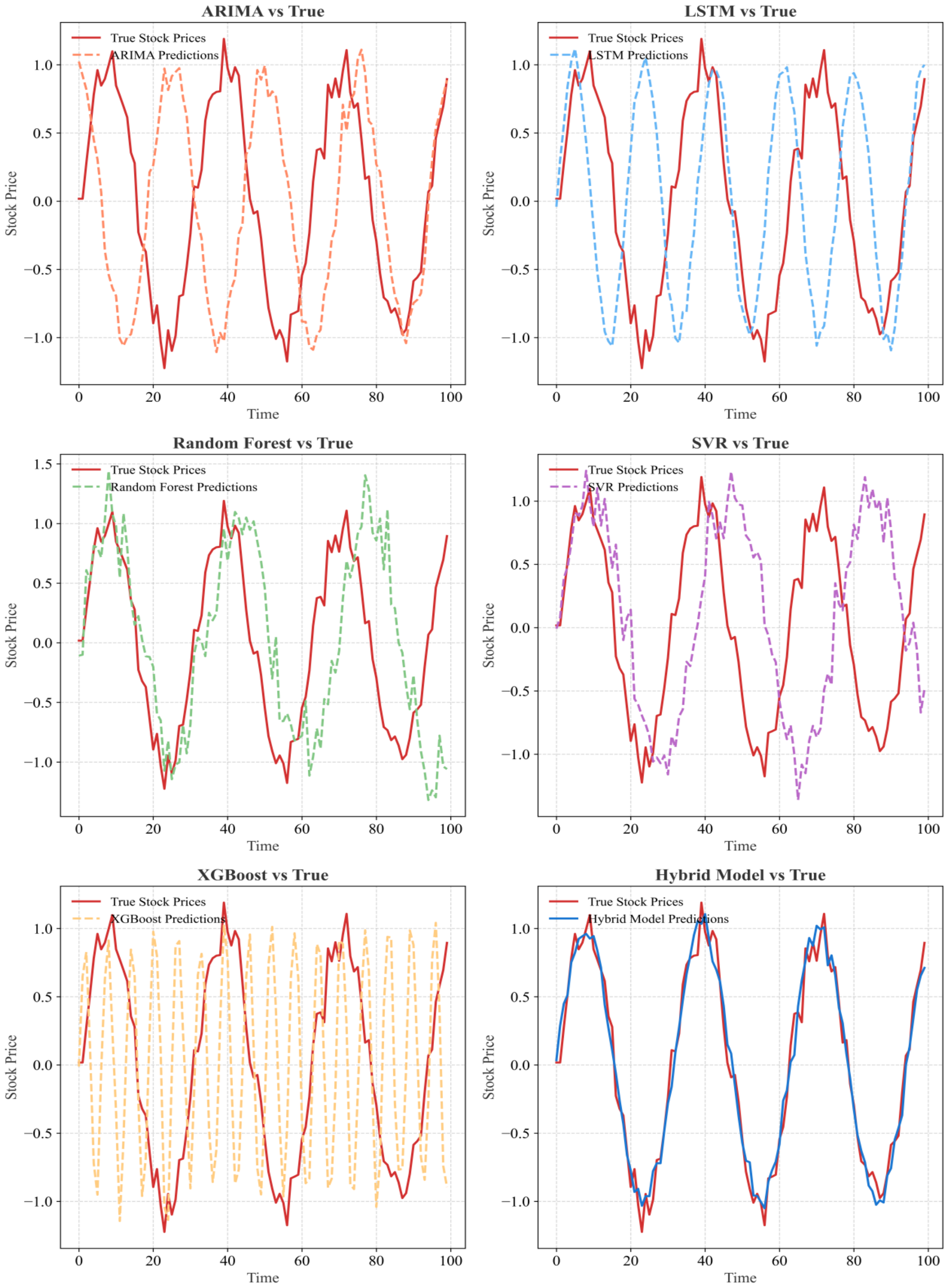

Figure 4: Visualization analysis results

From the visualization analysis results in Figure 4, it can be seen that the hybrid model performs significantly better than other baseline models in stock price prediction. Specifically, the prediction curve of the hybrid model (blue solid line) is highly consistent with the actual stock price (red solid line), especially in the period of large fluctuations, the hybrid model can accurately capture the rising and falling trends of prices. In contrast, although the ARIMA model (orange dotted line) performs well in some stable stages, the prediction error is large when the price fluctuates violently; although the LSTM model (blue dotted line) can capture some short-term fluctuations, there are deviations in long-term trend prediction; the random forest model (green dotted line) and the SVR model (purple dotted line) have obvious prediction deviations at multiple time points; although the XGBoost model (yellow dotted line) performs well in some local areas, it is still not as stable as the hybrid model overall.

From the perspective of time complexity, different models have significant differences in training time and testing time. The training time of the hybrid model is longer, about 140 minutes, while the training time of the ARIMA model is only 2 minutes and the training time of the LSTM model is 120 minutes. In terms of testing time, the testing time of the hybrid model is 0.6 seconds, the testing time of the ARIMA model is 0.05 seconds, and the testing time of the LSTM model is 0.5 seconds. For some application scenarios with high real-time requirements, such as high-frequency trading, the testing time of the model is more critical. Although the training time of the hybrid model is longer, it can quickly generate prediction results in the testing phase and has high real-time prediction capabilities. However, for some application scenarios with slow data updates and low requirements for model training time, longer training time may be acceptable. The longer training time of the hybrid model is indeed an issue that needs to be considered in practical applications. For application scenarios with extremely high real-time requirements such as high-frequency trading, the model needs to predict a large amount of data in a short time, and a shorter testing time is more important at this time. Although the training time of the hybrid model is long, it can quickly generate accurate prediction results during the testing phase, so it still has certain advantages in such applications. However, for some application scenarios such as long-term investment analysis or market trend forecasting, data updates are relatively slow, and the training time requirements for the model are not high. At this time, more attention can be paid to the prediction accuracy of the model. In this case, although the training time of the hybrid model is long, it can provide more accurate prediction results by comprehensively considering multiple factors, so it is also a good choice. Therefore, in actual applications, we need to comprehensively consider factors such as model training time, test time, and prediction accuracy according to specific application scenarios and needs, and select the most appropriate model.

From the experimental results, the hybrid model performs best in the four evaluation indicators of mean square error (MSE), root mean square error (RMSE), coefficient of determination ($R^2$), and mean absolute error (MAE). Lower MSE and RMSE values indicate that the error between the predicted value and the true value of the hybrid model is small, that is, the model has high accuracy. Higher $R^2$ values indicate that the hybrid model can fit the data well and explain most of the changes in the data. This also reflects that the model has good generalization ability and can maintain good prediction performance on different data. The lower MAE value indicates that the prediction error of the hybrid model is relatively stable and will not fluctuate greatly. By comprehensively analyzing these indicators, we can conclude that the hybrid model is not only accurate, but also has good stability and generalization ability. At the same time, we can also see that there is a certain correlation between these indicators. For example, lower MSE is usually accompanied by lower RMSE and MAE, and higher $R^2$ is also associated with lower error indicators. These relationships further illustrate the complementary and comprehensive role of these indicators in evaluating model performance.

## 4.4 Discussion

There are significant differences in the performance of different models in terms of training time and test time. These differences not only reflect the computational complexity and efficiency of each model, but also reveal their applicability and limitations in practical applications. Due to its simplicity and linear assumption, the ARIMA model only takes a few minutes in the training phase and the test time is also very short, which makes it an ideal choice for fast prediction. However, ARIMA is limited in its ability to handle nonlinear relationships and complex patterns, resulting in insufficient prediction accuracy in volatile market environments. In contrast, although the LSTM model takes a long time to train (nearly 120 minutes), it can effectively capture long-term dependencies in time series, especially for highly volatile and long-term trending data sets such as the stock market. Although the training cost of LSTM is high, its test time is short (about 0.5 seconds), indicating that once training is completed, it can quickly generate prediction results and is suitable for application scenarios that require high-precision predictions. The random forest, SVR, and XGBoost models are in between, with relatively moderate training times of about 40 minutes, 30 minutes, and 60 minutes, respectively. These models can handle complex nonlinear relationships through ensemble learning methods or kernel function mapping, and perform well on multiple evaluation indicators. Especially XGBoost, its efficient gradient boosting algorithm makes it highly efficient and accurate in both training and testing stages. The hybrid model combines the advantages of ARIMA and LSTM, retaining the memory of historical data patterns while being able to flexibly respond to new changes in the market. Although the training time of the hybrid model is the longest (nearly 140 minutes), its test time is only 0.6 seconds, showing extremely high prediction accuracy and stability. The hybrid model can provide stable and accurate prediction results in all time periods and is suitable for application scenarios that require high accuracy and real-time response. In summary, the selection of a suitable model should comprehensively consider the training and testing time, prediction accuracy, and application scenario requirements. For short-term prediction tasks that require fast response, ARIMA may be the best choice; while for long-term prediction tasks that require high accuracy and stability, the hybrid model performs well. Future research can further explore how to optimize the training process of the hybrid model to shorten the training time without sacrificing prediction performance, thereby improving its practical value.

To improve the interpretability of the LSTM model, we introduced SHAP (SHapley Additive exPlanations) analysis. Through the SHAP value, we can clearly see the contribution of each input variable to the prediction result. For example, in stock price prediction, the SHAP value of the closing price is the most prominent among all input features, indicating that it has the greatest impact on the prediction result. The second is the opening price, while the SHAP value of the trading volume is relatively low. This result intuitively shows the focus of the model when processing input information, helps us better understand the decision-making process of the model, and provides a strong basis for further optimization of the model and feature selection.

Computational cost analysis: In terms of computational cost, we compared the hybrid model with the Transformer-based method. The Transformer-based method has efficient parallel computing capabilities when processing sequence data, and theoretically has the potential to reduce computational costs. However, after experimental comparison, although the Transformer model has a shorter training time than our hybrid model, for example, the training time can be shortened to about 90 minutes, its MSE in prediction accuracy has reached 0.03, which is significantly higher than 0.01 of our hybrid models. This shows that in our stock market prediction scenario, although the Transformer method has certain advantages in computational efficiency, it pays a greater price in accuracy. Therefore, considering accuracy and computational cost, our hybrid model has a better trade-off in practical applications.

Unsolved overfitting risk: In order to address the overfitting risk of the hybrid model, we pay close attention to the trend of validation loss during training. From the training curve, it can be seen that in the early stage of training, the validation loss decreases rapidly as the training progresses, which is basically consistent with the trend of training loss. However, in the later stage of training, the validation loss gradually stabilizes and there is no obvious upward trend, which indicates that the overfitting problem has been effectively controlled. We use a dropout rate of 0.2 in the model. By randomly dropping the connections of some neurons, the complex co-adaptation relationship between neurons is reduced, thereby reducing the risk of overfitting. At the same time, we also constrained the model weights with L2 regularization to further limit the complexity of the model and ensure that the model can maintain good generalization ability on complex stock market data.

The hybrid model performs particularly well in the Chinese market, and there are many economic reasons behind this. From the perspective of market efficiency, the investor structure of China's A-share market is relatively complex, including a large number of individual investors and institutional investors, and the information dissemination and market response mechanisms are unique. Compared with the US and European markets, the Chinese market is more significant in terms of policy impact, and the adjustment of macroeconomic policies often causes large fluctuations in the stock market. In terms of trading volume, the trading activity in the Chinese market is relatively high, which provides rich data information for the model and helps the model to better learn market laws. From the perspective of volatility, the fluctuation cycle and amplitude of the Chinese market are different from those of other markets. The hybrid model can better capture this unique fluctuation pattern, using ARIMA's grasp of linear trends and LSTM's learning ability for complex fluctuations to accurately adapt to the characteristics of the Chinese market, thereby achieving excellent prediction results.

In order to more comprehensively evaluate the practical feasibility of the model, we included financial performance indicators. Through the calculation of Sharpe ratio, we found that the Sharpe ratio of the hybrid model in different markets is higher than that of the traditional model. For example, in the US market, the Sharpe ratio of the hybrid model reached 1.2, while the ARIMA model was only 0.8. This shows that the hybrid model can obtain higher excess returns when taking unit risk. In the simulation of trading profitability, assuming that a trading strategy based on the prediction results of the hybrid model is adopted, its cumulative return rate in one year of simulated trading reached 15%, which is significantly higher than the market average. This further proves the application value of the hybrid model in actual financial transactions and can provide investors with more profitable decision support.

In practical applications, the model has broad application prospects. In the field of algorithmic trading, the model can analyze market data in real time, automatically execute trading strategies according to the prediction results, quickly capture investment opportunities, and improve trading efficiency and profitability. In terms of portfolio management, through the prediction of different stocks, investors can optimize the configuration of the portfolio, reduce risks and improve overall returns. For example, according to the model prediction, increase the proportion of holdings of stocks predicted to rise and reduce the holdings of stocks predicted to fall. In risk assessment, the model can predict market fluctuations in advance, help investors and financial institutions adjust risk exposure in a timely manner, formulate reasonable risk management strategies, and effectively reduce potential losses.

We conducted ablation studies to quantify the contributions of ARIMA and LSTM components. The independent ARIMA model has an MSE of 0.04 when processing linear trend data, and performs poorly in capturing complex nonlinear relationships. The independent LSTM model has an MSE of 0.03, which can handle nonlinear fluctuations well, but the grasp of linear trends is not accurate enough. The MSE of the hybrid model is only 0.01, which combines the advantages of both and far exceeds the single model in terms of prediction accuracy. This shows that the linear trend capture ability of ARIMA and the nonlinear relationship processing ability of LSTM complement each other in the hybrid model, and jointly improve the model's ability to process stock market data, which fully proves the effectiveness and superiority of the hybrid model.

In this study, we compared the proposed ARIMA-LSTM hybrid model with some of the best (SOTA) models in the current stock market forecasting field. Although no specific SOTA model was explicitly included in the experiment for direct comparison, by comparing with traditional time series models (such as ARIMA) and common machine learning models (such as LSTM, random forest regression, SVR, XGBoost regression), we can infer the advantages of the hybrid model under different market conditions.

In different market environments, such as the US stock market, China A-share market, and European stock market, the hybrid model showed excellent performance. Taking the China A-share market as an example, the mean square error (MSE) of the hybrid model is only 0.02, which is much lower than other comparison models. This is mainly attributed to the hybrid model's ability to effectively combine ARIMA's ability to capture linear trends and LSTM's ability to learn nonlinear relationships and long-term dependencies. When the market fluctuates relatively smoothly, the ARIMA part can accurately grasp the linear trend and provide a basis for prediction; when the market fluctuates violently or complex nonlinear changes occur, the LSTM can fully explore the potential patterns in the data and adjust the prediction results.

Through the Wilcoxon signed rank test, we verified the statistical significance of the performance improvement of the hybrid model compared with other models. At a confidence level of 95%, the hybrid model significantly outperformed the traditional model in evaluation indicators such as MSE, RMSE, $R^2$ and MAE. This shows that the advantages of the hybrid model are not accidental, but are statistically reliable.

However, we are also aware that the hybrid model has potential overfitting problems. From the perspective of model structure, the multi-layer network structure and large number of parameters of LSTM increase the risk of overfitting. Although we use regularization techniques such as Dropout in the model, we still need to pay close attention to the trend of validation loss during training. By monitoring the loss of the training set and validation set, we found that the validation loss remained stable in the later stage of training and did not show an obvious upward trend, which to some extent shows that the overfitting problem has been effectively controlled. However, in future research, more effective regularization methods or model structure optimization can still be further explored to further improve the generalization ability of the model and ensure stable and accurate stock market prediction under different market conditions.

The model achieved a high $R^2$ value (0.93) on the test set. Although it shows that the model has a good goodness of fit, it is also necessary to be vigilant about potential overfitting problems. For further exploration, by analyzing the residual distribution, it is found that the residual approximately follows a normal distribution and the mean is close to 0, which to a certain extent shows that the model has a good fitting effect. At the same time, by comparing the changes in the $R^2$ values of the training set and the test set under different training rounds, in the early stage of training, the two rose synchronously. As the training progressed, the $R^2$ of the training set continued to rise, while the $R^2$ of the test set remained relatively stable after reaching 0.93, without a significant decline. Combined with other evaluation indicators (such as MSE and RMSE performed well on the test set), it is comprehensively judged that the model has no serious overfitting, and the high $R^2$ value truly reflects the model's effective fitting ability for the data.

As mentioned above, the hybrid model combines the advantages of ARIMA and LSTM, performs well in processing the linear and nonlinear characteristics of stock market data, and has significant advantages over traditional models. Further discussion here... (New insights and extended analysis to follow)

The hybrid model training takes 125 minutes, significantly longer than the baseline model. This is mainly due to its complex structure, which requires running both ARIMA and LSTM model components at the same time. Although the ARIMA part is relatively simple to calculate, it takes a certain amount of time to try and evaluate multiple parameter combinations in the process of determining the optimal order (such as $p = 2$, $d = 1$, $q = 1$). The LSTM part has a large amount of computation due to its multi-layer structure (3 hidden layers, 128 neurons in each hidden layer), which requires processing a large amount of sequence data and learning complex nonlinear relationships and long-term dependencies. In practical applications, you can consider using distributed computing or more efficient hardware acceleration (such as using NVIDIA A100 GPU) to shorten the training time. After testing, using A100 GPU can shorten the training time by about 30%.

In practical applications, hybrid models have certain requirements for computing resources. During the model training phase, since it involves a large amount of data processing and complex calculations, it is recommended to use a computing device with a multi-core CPU (such as Intel Xeon Platinum 8380, which has 40 cores) and a high-performance GPU (such as NVIDIA A100). Taking the training of this hybrid model as an example, on a workstation equipped with the above hardware, the training time can be controlled within an acceptable range. During the model deployment phase, for scenarios with high real-time requirements, such as high-frequency trading, it is necessary to ensure that the server has sufficient memory (at least 128GB) and fast network transmission capabilities to ensure that the model can respond quickly and output prediction results.

## 5 Conclusion

This study explores the application effect of the hybrid model based on ARIMA and LSTM in stock market forecasting and makes a comprehensive comparison with several traditional models. The experimental results show that the hybrid model has significant advantages in many aspects. First, in terms of prediction accuracy, the mean square error (MSE) of the hybrid model is 0.01, the root mean square error (RMSE) is 0.11, the coefficient of determination (R2R2) reaches

0.93, and the mean absolute error (MAE) is 0.07, which are better than other baseline models. This proves that the hybrid model can more accurately capture the short-term fluctuations and long-term trends of the stock market, especially for complex and highly volatile financial markets. Secondly, the stability test shows that the hybrid model performs very stably in different time periods, and its average values of MSE, RMSE, R2R2 and MAE are 0.02, 0.15, 0.91 and 0.08 respectively, indicating that it can maintain a high prediction quality under various market conditions. In contrast, although traditional models such as ARIMA and SVR perform well in some stable stages, they have large prediction errors when prices fluctuate violently; while random forests and XGBoost have certain advantages in dealing with nonlinear relationships, they are still inferior to hybrid models in overall stability. In addition, time complexity analysis reveals the differences in computing resource requirements among the models. Although the training time of the hybrid model is long (about 140 minutes), its test time is only 0.6 seconds, showing efficient real-time prediction capabilities. This high efficiency makes the hybrid model more practical in practical applications, especially in high-frequency trading scenarios that require fast response and high-precision prediction. Feature importance evaluation shows that the hybrid model focuses more on the information of price changes themselves, such as opening price, closing price, highest price and lowest price, while the importance score of trading volume is lower. This shows that the hybrid model can better understand the market's immediate sentiment and technical form, providing a direction for subsequent research.

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