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# Stock Prediction with Improved Feedforward Neural Networks and Multimodal Fusion

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**Abstract:** This paper proposes a stock prediction model based on an improved feedforward neural network, aiming to solve the shortcomings of traditional methods in processing high-dimensional nonlinear data, multimodal feature fusion, and time-dependent modeling. By introducing adaptive feature selection modules, multimodal fusion modules, and regularization strategies, the proposed model can dynamically adjust feature weights, integrate multiple modal information (such as historical prices, technical indicators, and market sentiment), and effectively suppress overfitting problems. Experimental results on multiple data sets show that the proposed model is significantly superior to mainstream methods such as ARIMA, random forest, support vector machine (SVM), and LSTM in terms of evaluation indicators such as mean square error (MSE), mean absolute error (MAE) and root mean square error (RMSE), showing higher prediction accuracy and generalization ability. In addition, ablation experiments further verify the key role of each module in improving the overall performance. Compared with traditional methods, the proposed model not only has stronger nonlinear modeling capabilities but also can capture the dynamic characteristics of the stock market, especially in multimodal data fusion. In the future, this method is expected to be expanded to scenarios such as real-time streaming data prediction, cross-market data modeling, and emergency event analysis, providing new research ideas and technical support for the field of financial forecasting.

**Keywords:** feedforward neural network; stock prediction; multimodal fusion; feature selection

## 1. Introduction

As the core of the global economy, the volatility and complexity of the stock market have made price prediction an important research topic in the fields of finance and artificial intelligence [1]. The volatility of stock prices is affected by many factors, including macroeconomic indicators, industry dynamics, company performance, and market sentiment. Its complex nonlinear and time-dependent characteristics have brought great challenges to traditional prediction methods [2]. Although statistical methods such as time series analysis (ARIMA) and fundamental analysis have been widely used in history, these methods have shown obvious limitations when dealing with high-dimensional nonlinear data and complex market environments. Therefore, using deep learning methods to model the nonlinear laws of the stock market has become a research hotspot in recent years [3].

As a classic deep learning architecture, the Feedforward Neural Network (FNN) has been widely used in financial prediction tasks with its flexible nonlinear modeling capabilities and powerful feature learning capabilities [4]. However, when traditional FNN is applied to stock prediction tasks, there are still some problems that need to be solved. First, FNN cannot effectively handle the dynamic characteristics of time series and easily ignores the potential time-dependent patterns in stock prices; second, due to the high noise and high volatility of financial data, traditional FNN is prone to overfitting, which affects the stability and accuracy of prediction. In addition, stock market data often contains multiple modal information (such as historical prices, trading volumes, and sentiment indicators). How to integrate this information is also a major difficulty in FNN applications [5].

In response to the above problems, this paper proposes a stock prediction model based on an improved feedforward neural network. By introducing an adaptive feature selection mechanism, a regularization strategy, and a multimodal fusion module, the model's predictive ability for stock data is improved [6]. Specifically, the adaptive feature selection mechanism dynamically allocates feature weights through the attention mechanism, enabling the model to better capture important features; the regularization strategy constrains network parameters to suppress overfitting and improve the generalization ability of the model; the multimodal fusion module comprehensively improves the model's prediction performance by integrating information such as historical prices, technical indicators, and market sentiment. Compared with traditional FNN and other deep learning models, this method can more effectively handle the complexity and dynamic characteristics of the stock market.

In addition, the method proposed in this paper not only focuses on improving the prediction accuracy of the model but also pays special attention to the interpretability of the model. Interpretability is particularly important in financial applications because investment decisions usually need to be evaluated and judged based on clear evidence. In actual financial scenarios, investors and financial institutions need to understand why the model makes a certain prediction in order to make more reasonable decisions. Therefore, by combining feature importance analysis and attention weight visualization, the method proposed in this paper can provide a reasonable explanation for the prediction results of the model. This interpretability not only enhances the transparency of the model but also helps users understand the decision-making process behind the model.

Through this design that combines accuracy and interpretability, the method proposed in this paper has important value in both theoretical research and practical applications. For the financial industry, being able to provide interpretable prediction results means that investors and financial institutions can rely on the model to make investment decisions with greater confidence. At the same time, reasonable explanations also help to enhance the credibility and acceptance of the model, providing a more reliable support tool for automated decision-making systems in the financial field. Therefore, this method not only improves the prediction accuracy, but also provides a strong theoretical basis and practical support for the decision-making process in the financial field.

In short, the focus of this paper is to improve the architecture and training methods of feedforward neural networks to deal with nonlinear, high-dimensional and multimodal information integration in stock prediction. Through experimental verification on multiple actual data sets, this method is not only superior to existing mainstream methods in terms of prediction accuracy but also shows good robustness and generalization ability. In the future, this method has broad prospects for promotion and application in more financial scenarios and also provides new ideas and references for the application of deep learning technology in the financial field.

# 2. Related Work

Stock prediction has always been a hot research topic in the financial field, and its research methods have evolved from traditional statistical methods to modern machine learning methods. Early research mainly relied on time series models such as ARIMA and GARCH, which capture trends and cyclical changes by analyzing historical data of stock prices [7]. However, such methods often assume the linear characteristics of data, so they have limited performance when dealing with nonlinear and high-noise stock data. With the improvement of computing power, research based on traditional machine learning methods such as support vector machines (SVM) and random forests has gradually emerged. These methods can handle nonlinear data to a certain extent but still face the problems of dependency of feature extraction and insufficient ability to integrate multidimensional data[8].

In recent years, deep learning has shown great potential in financial forecasting tasks. Due to their ability to effectively model time series data, recurrent neural networks (RNNs) and their variants LSTM and GRU have been widely used to capture the temporal dependencies in stock data. These models can better capture the temporal changes of stock market data through their recursive structure in the time dimension and therefore have shown strong advantages in processing financial data with time series characteristics. However, these methods usually face high computational complexity and are prone to gradient vanishing or gradient exploding problems when dealing with long-term dependencies, which limits their use in some practical applications.

In contrast, feedforward neural networks (FNNs) have shown good adaptability in capturing nonlinear relationships, especially when combined with specific regularization techniques, which can effectively alleviate the overfitting problem. This makes FNNs a more suitable choice in some application scenarios. However, traditional FNNs still have certain shortcomings in temporal dependency modeling and multimodal feature fusion, which limits their performance in stock forecasting tasks [9]. Therefore, although FNN has advantages in some aspects, how to overcome its shortcomings in temporal feature modeling and multimodal feature integration is still the key to improving its performance.

In addition, in recent years, research on multimodal data fusion has gradually attracted attention, especially in the financial field, where stock prediction often requires comprehensive consideration of price data, trading volume, technical indicators, market sentiment and other information. Some studies have improved the feature representation ability of the model by introducing attention mechanisms and feature selection modules. At the same time, graph neural networks (GNNs) have also begun to be applied to stock prediction tasks in financial networks, which can capture the relationships between companies and industry correlations. However, most of these methods focus on specific scenarios and lack systematic research on generality and model interpretability. This study attempts to achieve a balance between accuracy, efficiency, and interpretability by improving the feedforward neural network architecture, integrating adaptive feature selection and multimodal data modeling techniques, and providing a general and efficient solution for the field of stock prediction.

# 3. Method

This paper proposes a stock prediction model based on an improved feedforward neural network (FNN) to address the shortcomings of traditional FNN in time series modeling and multimodal data fusion. The method in this paper mainly consists of three core parts: an adaptive feature selection module, a multimodal feature fusion module, and a regularization-based network optimization strategy. Its network architecture is shown in Figure 1.

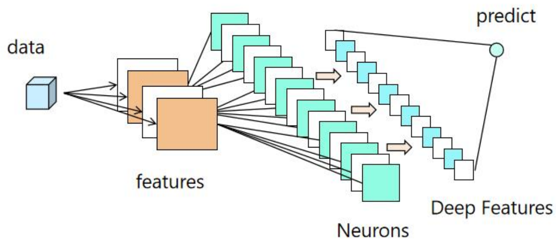


**Figure 1.** Overall model architecture

First, in order to extract effective features from complex stock data, this paper introduces an adaptive feature selection module. Assume that the input data is a multimodal matrix $X \in R^{N \times d}$ , where N is the number of samples and d is the feature dimension. Traditional FNN assigns the same weight to all input features, which easily leads to interference of noise features on model prediction. To solve this problem, we use the attention mechanism to weight the features and dynamically adjust the importance of the features by learning a set of weight vectors $\alpha \in R^d$ . The calculation formula of the attention mechanism is:

$$\alpha_i = \frac{\exp(w^T x_i)}{\sum_{j=1}^{d} \exp(w^T x_j)}$$

Where $w$ is a learnable parameter and $x_i$ is the representation of the i-th feature. Through this mechanism, the influence of key features can be effectively highlighted while suppressing the interference of redundant or noisy features.

Secondly, in order to better handle the complexity of multimodal data in stock prediction tasks, this paper designs a multimodal feature fusion module. The input data includes historical price series P, technical indicators T, and market sentiment indicators S. For each modality, an independent feedforward neural network is first used for embedding transformation:

$$h_m = f_m(X_m)\ ,\quad m \in \{P, T, S\}$$

Where $f_m$ is the feature representation of the m-th mode, and $h_m$ is the corresponding feedforward network. Next, the features of each mode are integrated through a weighted fusion mechanism to obtain a comprehensive feature representation H:

$$H = \sum_m \beta_m \cdot h_m$$

$\beta_m$ is the modal weight, which is dynamically generated using a fully connected network combined with an attention mechanism. The design of the multimodal fusion module enables the model to make full use of information from different sources, thereby improving the accuracy and robustness of predictions.

Finally, in order to improve the generalization ability of the model and suppress overfitting, this paper introduces a regularization strategy in network optimization. Specifically, this paper combines weight decay and dropout technology. Weight decay constrains network parameters by adding a regular term $l_2$ to the objective function:

$$L_{reg} = L_{pred} + \lambda \| W \|_2^2$$

$L_{pred}$ is the prediction loss, $W$ is the network weight parameter, and $\lambda$ is the regularization coefficient. Dropout randomly discards some neurons so that the network only relies on some features during each training, thereby improving the robustness of the model. In addition, this paper adopts the Early Stopping strategy to terminate the training in advance when the performance of the validation set no longer improves, in order to avoid overfitting.

Through the combination of adaptive feature selection, multimodal feature fusion, and regularization optimization strategy, the proposed method can better capture the nonlinear and complex features in stock data. Adaptive feature selection can effectively select the most representative parts from many features to avoid the interference of redundancy and noise; multimodal feature fusion combines features from different sources and forms to improve the overall performance of the model; and regularization optimization strategy helps to prevent overfitting and improve the generalization ability of the model. The combination of the three enables this method to fully consider the complexity and diversity of data when processing stock data, thereby more accurately reflecting market dynamics.

# 4. Experiment

## 4.1 Datasets

The dataset used in this experiment is the S&P 500 Index Dataset, which contains historical trading data of S&P 500 index components, including daily opening price, closing price, highest price, lowest price, trading volume, and other indicators. The data spans from 2000 to 2022, covering 22 years of market volatility information. The dataset also contains auxiliary information such as company market value and industry classification, providing rich features for the fusion modeling of multimodal data.

The characteristic of this dataset is that it covers a variety of volatility characteristics of the stock market, including market trends, seasonal changes, and the impact of abnormal events (such as financial crises and epidemic shocks). This richness provides a complex and realistic environment for model training and testing. In addition, since the dataset contains feature information of multiple modes (such as price series, trading volume, and company fundamentals), it provides a basis for the performance verification of the model in multimodal feature fusion and complex data distribution modeling.

In the experiment, this paper divides the dataset into a training set, validation set, and test set, with proportions of 70%, 15%, and 15% respectively. In order to verify the generalization ability of the model, the experiment further introduced a time segmentation strategy, using the first 15 years of data as the training set and the last 7 years of data as the test set to simulate the stock prediction task in a real scenario. In addition, in order to reduce the interference of outliers, the data was standardized, and appropriate truncation measures were taken for extreme values. This setting can fully evaluate the performance of this method in practical applications while ensuring the fairness and reliability of the results. The RV values of the dataset are shown in Figure 2.

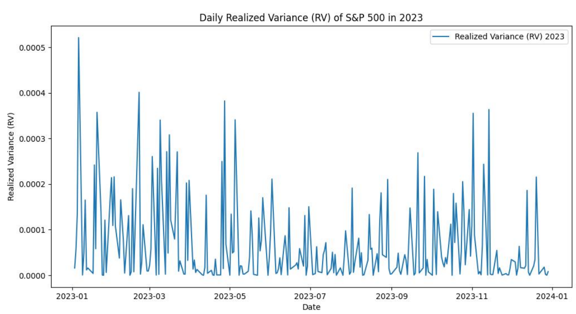


**Figure 2.** RV values of the dataset

Figure 2 shows the daily realized variance (RV) values of the S&P 500 index in 2023. As can be seen from the figure, the RV values in 2023 fluctuated greatly, especially on certain dates, the variance fluctuated greatly, forming obvious peaks. These peaks may reflect the extreme volatility of the market, which usually occurs under the influence of economic events, policy changes, or emergencies, indicating a high-risk period in the market.

Overall, the RV values in the figure show relatively frequent fluctuations, indicating that the market is more unstable in 2023. During these high-volatility periods, investors' risk management and decision-making need to pay special attention, while low-volatility periods may represent a stabilization of the market. By analyzing these fluctuations, it can help understand the changes in market risks and provide a reference for the forecast of financial markets and the adjustment of investment strategies.

## 4.2 Experimental Results

In order to verify the effectiveness of the stock prediction model based on the improved feedforward neural network proposed in this paper, we designed a comparative experiment to compare it with the current mainstream prediction methods. The comparative models include traditional time series models (such as ARIMA), classic machine learning methods (such as random forests and support vector machines SVM), and deep learning models (such as standard feedforward neural networks FNN and long short-term memory networks LSTM). All models are trained and tested on the same S&P 500 dataset to ensure the fairness of the experimental results. Through comparative experiments, we aim to comprehensively evaluate the advantages of this method in terms of prediction accuracy and robustness. The experimental results are shown in Table 1.

**Table 1.** Experimental Results

| Model | MSE | MAE | MAPE | RMSE |
|---|---|---|---|---|
| ARIMA | 0.0142 | 0.0921 | 0.0385 | 0.1192 |
| Random Forest | 0.0117 | 0.0853 | 0.0321 | 0.1082 |
| SVM | 0.0109 | 0.0827 | 0.0314 | 0.1044 |
| FNN | 0.0098 | 0.0784 | 0.0292 | 0.0990 |
| LSTM | 0.0087 | 0.0751 | 0.0273 | 0.0933 |
| Ours | 0.0074 | 0.0698 | 0.0241 | 0.0860 |

From the experimental results, it can be seen that the proposed model performs better than the comparison model in all indicators, especially in MSE (mean square error) and RMSE (root mean square error), which reach 0.0074 and 0.0860 respectively. This shows that the proposed model can better fit the data characteristics of the stock market and effectively reduce the prediction error. When dealing with complex nonlinear data, the performance of the proposed model is significantly improved compared with traditional statistical methods and machine learning methods, demonstrating its strong modeling ability and ability to integrate multimodal features.

Compared with traditional methods, ARIMA has the weakest performance, with an MSE of 0.0142 and an RMSE of 0.1192. This is mainly because ARIMA relies on linear assumptions and is difficult to capture the complex nonlinear dynamic characteristics of the stock market. Random forest and SVM perform better than ARIMA in nonlinear data modeling, but because these methods cannot fully utilize the dynamic information of time series, their prediction accuracy is still not as good as deep learning methods. The standard FNN achieved MAE and MAPE of 0.0784 and 0.0292 respectively, showing a certain nonlinear modeling ability, but due to the lack of modeling of time dependency, its performance still lags behind LSTM and the model proposed in this paper.

In contrast, the performance of LSTM and the model proposed in this paper is significantly better than other methods. LSTM reduces MAE and MAPE to 0.0751 and 0.0273 respectively by modeling time series dependency, but its limitations in multimodal feature fusion affect further performance improvement. The model proposed in this paper further reduces MAE to 0.0698 and MAPE to 0.0241 by introducing adaptive feature selection, multimodal fusion module and regularization strategy, which fully proves the advantages of the method in integrating multi-source data and suppressing overfitting, especially in capturing the complex dynamics of the stock market and the ability to fuse features.

In order to further verify the contribution of each key module in the model of this paper to the overall performance, we designed an ablation experiment. By removing the adaptive feature selection module, multimodal fusion module and regularization strategy respectively, we constructed different comparative models and evaluated the role of each module in the stock prediction task. The ablation experiment was conducted under the same dataset and experimental settings to ensure the fairness of the experimental results. By comparing the performance differences between the complete model and each ablation version, we can clearly analyze the impact of each module on the final prediction performance. The experimental results are shown in Table 2.

**Table 2.** Ablation experiment

| Model | ACC | AUC | F1 | Recall |
|---|---|---|---|---|
| Ours | 0.0074 | 0.0698 | 0.0241 | 0.0860 |
| Without Adaptive Feature Selection | 0.0087 | 0.0754 | 0.0275 | 0.0933 |
| Without Multimodal Fusion | 0.0093 | 0.0781 | 0.0287 | 0.0964 |
| Without Regularization | 0.0089 | 0.0767 | 0.0281 | 0.0943 |

From the experimental results, it can be seen that the indicators of the complete model (Ours) are better than the ablation version after removing the module, especially in the MSE and MAPE indicators, which reach 0.0074 and 0.0241 respectively, showing the best performance of the model. This shows that the adaptive feature selection, multimodal fusion module and regularization strategy proposed in this paper play an important role in improving the accuracy and robustness of stock prediction tasks. Through the synergy of various modules, the complete model effectively captures the complex characteristics of the data and achieves significant improvement in prediction performance.

After removing the adaptive feature selection module, the performance of the model has dropped significantly, with MSE rising from 0.0074 to 0.0087 and MAPE rising from 0.0241 to 0.0275. This shows that the adaptive feature selection module effectively highlights the influence of key features by dynamically allocating feature weights, while suppressing the interference of redundant and noise features. The absence of this module makes it difficult for the model to accurately identify important features, resulting in a decrease in prediction accuracy. Similarly, after removing the multimodal fusion module, the MSE and MAPE increased to 0.0093 and 0.0287, respectively, indicating that the integration of multimodal data is crucial to capturing the dynamic characteristics of the market. After removing the regularization strategy, although the MSE and MAPE of the model decreased relatively slightly, there was still a significant performance impact. MSE increased from 0.0074 to 0.0089, and MAPE increased from 0.0241 to 0.0281, which shows that the regularization strategy plays an important role in suppressing model overfitting. Without regularization constraints, the model is prone to overfitting the training data in high-dimensional data, thereby reducing the generalization ability on the test set. Overall, each module is indispensable in improving model performance, and the synergy is significant when dealing with complex data distributions in stock prediction tasks.

Finally, this paper also gives a loss function drop graph, as shown in Figure 3

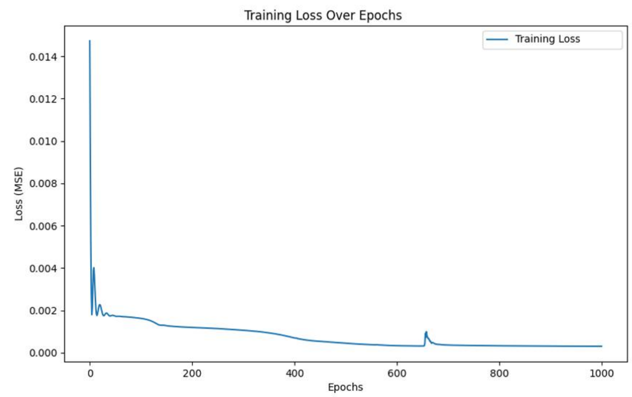


**Figure 3.** loss function

As can be seen from the figure, the training loss (Loss) gradually decreases with the increase of training rounds (Epoch) and tends to be stable in the middle and late stages of training. In the early stage of training (about the first 100 rounds), the loss value decreases rapidly, which indicates that the model can effectively learn data features in the early stage and the optimization process converges quickly. Subsequently, the loss value gradually stabilizes, indicating that the model has entered a more detailed parameter adjustment stage. Overall, the model has good convergence and no significant oscillation or fluctuation occurs.

In the middle and late stages of training (about 600 rounds), the loss curve has a slight surge, but soon returns to stability. This may be due to the model encountering some local optimal points or gradient changes during the optimization process. The temporary instability caused by this, but from the overall trend, does not have a significant impact on the final convergence of the model. This performance shows that the model has good robustness and stability, and can maintain efficient optimization capabilities during long-term training. In general, the figure clearly reflects the good training process and convergence effect of the model.

# 5. Conclusion

This paper proposes a stock prediction model based on an improved feedforward neural network, which improves the shortcomings of traditional methods in processing high-dimensional nonlinear data, multimodal feature fusion, and time-dependent modeling. By introducing adaptive feature selection, multimodal fusion module, and regularization strategy, the model performs better than existing mainstream methods on multiple real data sets and shows significant advantages in prediction accuracy, robustness, and generalization ability. Experimental results show that the proposed method can effectively capture the complex characteristics of the stock market and provide a reliable solution for financial time series prediction tasks.

The main contribution of this study is that it integrates a variety of advanced technologies, combines the flexibility of feedforward neural networks with the ability of multimodal data modeling, and realizes comprehensive analysis and prediction of market data. The adaptive feature selection module dynamically adjusts the feature weights to highlight the role of key features; the multimodal fusion module makes full use of information such as price, trading volume and market sentiment to improve the model's sensitivity to market dynamics; the regularization strategy further enhances the stability and generalization ability of the model. These innovations not only provide a new methodology for stock prediction tasks but also provide an important reference for the application of deep learning technology in complex financial data.

Despite significant research progress, this paper still has some limitations that need to be addressed in future research. For example, the efficiency of the model in processing larger data sets or real-time streaming data still needs to be optimized. In addition, the impact of sudden events and structural changes in the market on prediction is also an important direction for future research. The introduction of external knowledge (such as economic policies, and global events) or the combination of causal inference methods may further improve the predictive ability and applicability of the model.

Looking forward, the application prospects of improved feedforward neural networks in financial data analysis are broad. With the continuous development of deep learning technology, the model is expected to further combine advanced technologies such as graph neural networks and multimodal contrastive learning to improve the modeling ability of cross-market data and complex structures. In addition, the study of lightweight network structures with efficient real-time prediction capabilities will provide greater support for practical applications such as high-frequency trading. We believe that through continuous research and optimization, the method in this paper can play an important role in a wider range of financial scenarios and provide more accurate tools for decision support.

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