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Predicting Stock Prices Using Stacking-Based Ensemble Learning and Seasonal and Trend Decomposition Using Loess

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Abstract: With the development of the economy and the increasing awareness of people to invest in their own assets, stocks have become the most common way for people to manage their money. However, stocks also have strong risk and uncertainty. The emergence of artificial intelligence techniques has contributed to improving the stock forecast stability, so the stock market forecasting through artificial intelligence, in particular, the machine learning algorithms has become a popular research area. In this study, a hyper-parametric stacking-based ensemble learning model based on seasonal and trend decomposition using Loess (SEL-STL) is proposed. Firstly, the normalized preprocessing is performed on the raw data. Then, the preprocessed data is decomposed by means of seasonal and trend decomposition using Loess (STL). Subsequently, the Bayesian optimization algorithm is employed to optimize the hyper-parameters of the base prediction models. After that, the ensemble model is obtained by integrating the optimized base prediction models using the stacking-based ensemble learning method. Finally, the ensemble model is improved by further optimizing the model performance using the Adaptive Boosting. In the experiments, the datasets with three different stock exchange indices are used to evaluate the performance of the proposed model in stock price prediction. The experimental results show that the proposed model outperforms the other baseline prediction models in solving the stock price prediction problem.

Keywords: Seasonal and Trend Decomposition, Stacking-Based Ensemble Model, Bayesian Optimization, Adaptive Boosting, Stock Price Prediction

1. Introduction

With the rapid development of the global economy and the increasing awareness of people at all levels to invest in their own assets, stocks, as the most popular product in the financial field, have become the most common way for people to manage their financial property. However, though the stocks may bring profit, they also have strong risk and uncertainty. The coexistence of high yield and high risk makes more and more stock investors try to find a reasonable forecasting method to avoid risks and increase profit. Researchers have tried to come up with the results of stock price prediction by putting forward various assumptions and conducting experimental analysis. However, due to the nonlinearity and high volatility of the financial market, it is unrealistic to accurately predict the stock market, but the prediction of the general trend of the stock market is optimistic.

The emergence of artificial intelligence techniques, in particular, machine learning algorithms, has made great contributions to reducing risk volatility and improving forecasting stability, and therefore become a hot research field for stock forecast. Machine learning methods, including deep learning methods, continue to improve, which are very effective in solving a series of predictive problems in the financial market. Some machine learning methods have achieved acceptable results in stock market forecasting, but their prediction accuracy still needs to be improved.

With the continuous progress of artificial intelligence technology and machine learning methods, the ensemble learning models have been applied to more and more research fields, including the field of stock investment. This study proposes a hyper-parametric stacking-based ensemble learning model based on seasonal and trend decomposition using Loess (SEL-STL). Firstly, to eliminate the adverse effects of raw data with different order of magnitude and improve the data quality, the data is normalized through preprocessing. Secondly, to deal with the data vulnerability to periodic and seasonal changes, a time series decomposition method, namely seasonal and trend decomposition using Loess (STL) [1] is employed to decompose the normalized data. Thirdly, to reduce the impact of the hyper-parameter setting of the base prediction models on the prediction accuracy, the Bayesian optimization algorithm is employed to optimize the hyper-parameters of the base prediction models, including ridge regression (Ridge) [2], k-nearest neighbor algorithm (KNN) [3], multi-layer perceptron (MLP) [4], support vector regression (SVR) [5], and Gradient Boosting Decision Tree (GBDT) [6]. After that, the stacking-based ensemble learning method is used to combine the optimized base prediction models to obtain the ensemble model, which is further optimized through the Adaptive Boosting method (AdaBoost) [7]. In the experiment, the performance of the proposed model is compared with that of the other baseline models on the stock price prediction using datasets with three different stock exchange indices. The experimental results show that the proposed ensemble model is superior to other baseline prediction models in the prediction of stock prices.

The rest of this study is organized as follows: Section 2 reviews previous studies on stock price prediction, stacking-based ensemble model and Bayesian optimization. Section 3 illustrates the proposed ensemble model. Section 4 demonstrates and compares the experimental results. Section 5 describes the conclusions and provides future research directions.

2. Related Work

2.1. Stock Price Prediction

The high-yield and high-risk of stocks in the financial market encourage people to explore the stock price prediction models. Although the linear models may achieve the acceptable prediction results in the financial market in the early stage, its limitations are very obvious. The stock price prediction has strong instability, and the relationship between variables will fluctuate with time, which makes it difficult for the ordinary linear models to achieve accurate prediction results.

In recent years, with the rapid development of deep learning technology in machine learning, it has gradually become the main research method. For example, Patel et al. [8] employed four prediction models, including artificial neural network (ANN), support vector machine (SVM), random forest and primitive Bayes, to predict the movement direction of stocks and stock price indexes in the Indian stock market. Long et al. [9] realized the importance of feature learning in implementing the purposefully designed learning networks, and proposed the deep learning-based feature engineering for stock price movement prediction. Janiesch et al. [10] proposed to go beyond technological aspects and highlight issues in human-machine interaction and artificial intelligence servitization. The deep learning models have not only been employed in this study, but also been integrated with other machine learning models to solve the stock price prediction problem collaboratively.

2.2. Stacking-Based Ensemble Model

A single machine learning method is often restricted by various objective conditions, resulting in poor model performance, while the ensemble learning method of multiple machine learning models tend to improve the model performance and output the more accurate results. The ensemble model method adopted in this paper is stacking integration. Its flexible structure and stability can well hedge the high volatility in different fields and make a good early prediction. For example, Cui et al. [11] proposed a comprehensive earthquake casualty prediction system by combining an overlay ensemble model and improved swarm intelligence algorithm to predict the number of casualties Khoei et al. [12] enhanced the stacking-based ensemble models with Genetic Algorithm to detect early stages of Alzheimer's disease, which can better distinguish healthy people (with normal cognition), people with mild cognitive impairment and patients with Alzheimer's disease. Wang et al. [13] proposed a stacking-based integrated learning of decision trees for interpretable prostate cancer detection, which showed the classification performance of this method is superior to the other advanced methods in terms of classification accuracy, sensitivity and specificity.

The stacking integration method has achieved good results in different fields and improved the prediction performance of the model. It is also applicable in the stock price prediction market, and therefore integrated with other artificial intelligence-based methods in this study to predict the stock prices more accurately.

2.3. Bayesian Optimization

In the base prediction models, their hyper-parameter setting will affect the prediction accuracy of the base prediction models and further the performance of the ensemble model, so it is necessary to optimize these hyper-parameters. Bayesian optimization [14] is a promising technique, which can effectively optimize multiple continuous parameters. Its effectiveness has been well proved with two real-world experiments carried out on Facebook: optimizing the ranking system and optimizing the server compiler flag [15].

Bayesian optimization method also plays a significant role in the machine learning models. For example, Sameen et al. [14] combined one dimensional convolution network (1D-CNN) with Bayesian optimization to evaluate the landslide sensitivity in Yangyang Province, South Korea, indicating that the Bayesian optimization has improved the accuracy of CNN by

3%, compared with the default configuration. Abbasimehr and Paki [16] combined three deep learning models, including multi-head attention, long short term memory (LSTM), and convolutional neural network (CNN), with Bayesian optimization to predict the COVID-19 confirmed cases. In this study, the stacking integration method will be enhanced with Bayesian optimization to not only improve the prediction accuracy of the base prediction models, but also to improve the overall performance of the ensemble model.

3. Methodology

3.1. Introduction and Preprocessing of Data Sets

This study utilizes the trading index records observed by three stock exchanges as its data sets. The first is the Shanghai Stock Exchange valuation index, which includes 2431 records from January 4, 2012 to December 31, 2021 and is referred to as SSEC in this study; the second is the Shanghai and Shenzhen Stock Exchange valuation index, which includes 2431 records from January 4, 2012 to December 31, 2021 and is referred to as CSI in this study; and the third is the Shenzhen Stock Exchange valuation index, which is referred to as SZI in this study. Because different orders of magnitude of data input variables in the original data set will affect the model's performance, the valuation indexes in the data sets are preprocessed using the normalization technique to improve the availability and standardization of valuation indexes and reduce the impact on model performance.

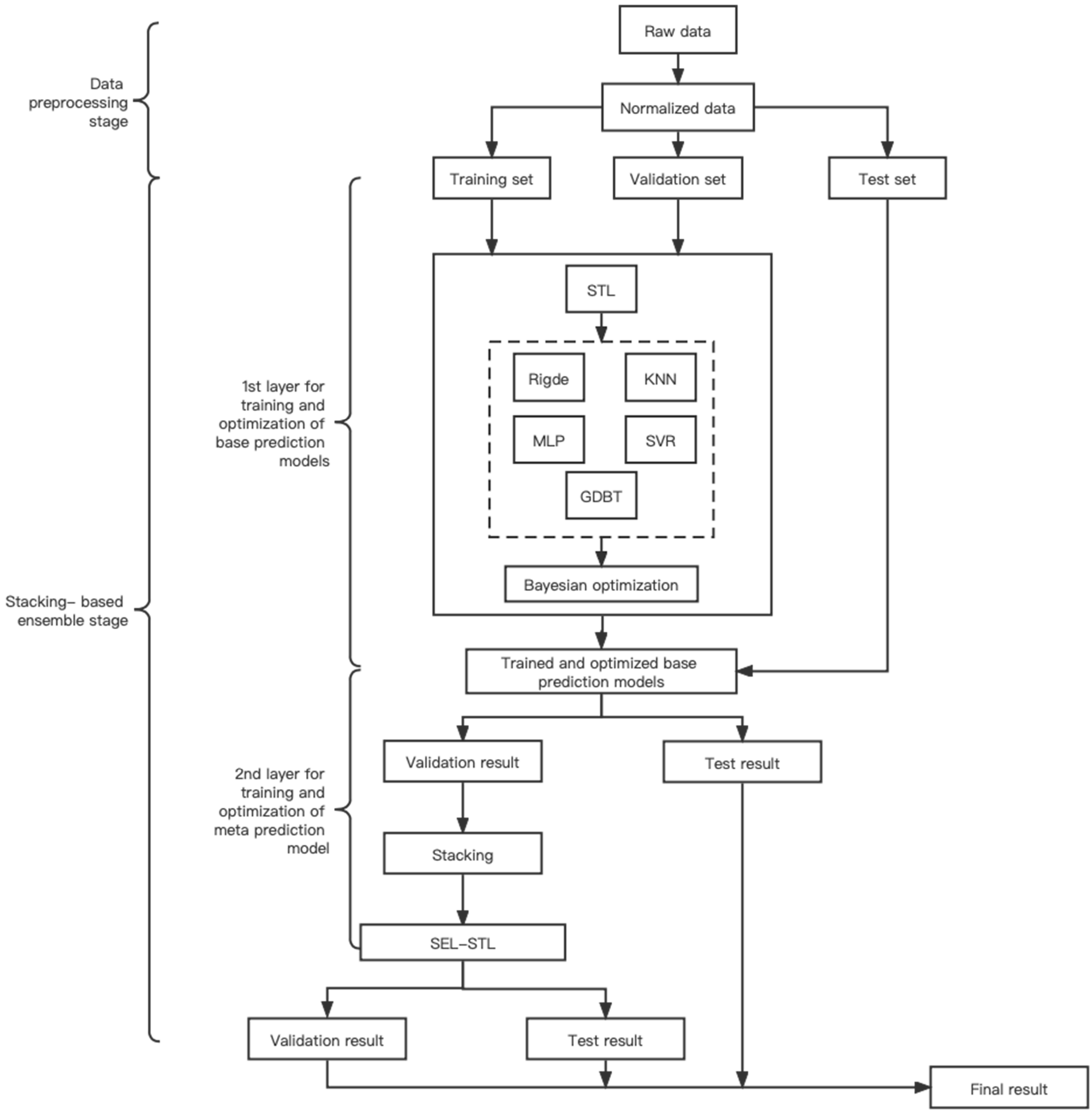

***Figure 1.** Flow chart of the proposed model.*

3.2. The Proposed SEL-STL Model

The flowchart of the proposed SET-STL model is shown in figure 1, and detailed as follows:

(1) Employ STL method to decompose the preprocessed data, augmenting the normalized stock price valuation data with additional fine-grained features for better training the base prediction models Ridge, KNN, MLP, SVR, and GBDT.

(2) Use the Bayesian optimization algorithm to optimize the hyper-parameters of the base prediction models, addressing the problem that the machine learning models tend to have too many hyper-parameters to be adjusted.

(3) Apply the two-layer stacking-based ensemble learning method to integrate the base prediction models to obtain the ensemble model. The first layer is responsible for training and optimization of base prediction models, while the second layer is responsible for training and optimization of the meta prediction model. The output of optimized base prediction models are used as the input of the meta prediction model.

(4) Use the AdaBoost method to optimize the ensemble model to obtain the final SEL-STL model.

3.2.1. Stacking Integration

The stacking integration method is a machine learning method with numerous benefits. It integrates multiple base learning models into an ensemble model to achieve more comprehensive benefits. In this study, a stacking-based ensemble learning model based on STL is proposed to predict stock prices in order to improve prediction accuracy. The Ridge, KNN, MLP, SVR, and GBDT are used as the base prediction models. The stacking integration procedure consists of two layers: training and optimization of the base prediction models, followed by training and optimization of meta prediction model.

In the 1st layer, the Bayesian optimization algorithm is employed to optimize the five base prediction models using the training set and validation set. In the 2nd layer, five trained and optimized base prediction models are employed to predict the validation set during the training of the meta prediction model. The five validation results obtained from the optimized base prediction models are then connected and formed into a characteristic matrix that serves as the input for training the meta prediction model that will be further optimized through AdaBoost method. On the test set, five optimized base prediction models are evaluated to test the optimized meta prediction model and obtain the final prediction results.

3.2.2. Boosting Method

Boosting model is a serial algorithm that continuously serializes the weak learner models to increase the ensemble model's prediction accuracy. This study employs one of the most prominent boosting algorithms, the adaptive lifting model AdaBoost. The AdaBoost algorithm will modify the data weight based on the effect of the previous classification. If data is misclassified this time, its weight will be increased next time. Greater weight means that the subsequent tree will pay closer attention to this information and strive to make more accurate predictions. Each base model calculates its individual prediction accuracy for the final results. The greater a base model's accuracy, the better and more trustworthy it is, so it needs contribute more to the final prediction results. Consequently, when calculating the final prediction results, a greater weight will be assigned to the base models with greater precision before recombining the prediction results.

In this study, AdaBoost algorithm is employed to adjust the model weight in order to reduce model prediction error, enhance model performance, and obtain the effective SEL-STL ensemble model.

4. Experiment

This section introduces the evaluation indicators of all prediction models and discusses the experimental results of all models in predicting the stock price valuation index. The Python programming language is used to implement all models and methods.

4.1. Evaluation Indicators

Three widely used credible statistical indicators are employed for performance evaluation of models, including determination coefficient (R^2), mean absolute error (MAE), and root mean square error (RMSE), as shown in Eqs. (1) - (3).

$$R^2 = \left[1 - \frac{\sum_{i=1}^{N} (\hat{x}_i - x_i)^2}{\sum_{i=1}^{N} (\overline{x}_i - x_i)^2} \right] \tag{1}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} \left| \hat{x}_i - x_i \right| \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{x}_i - x_i)^2} \tag{3}$$

where N is the size of the test sample, x_i ($1 \le i \le N$) represents the real stock price at time i, $\hat{x}_i$ represents the predicted stock price at time i. $\overline{x}_i$ represents the average stock price of N test samples. The lower the MAE and RMSE, the better the prediction performance. For R^2 value, the greater its value is, the better the prediction performance.

4.2. Analysis of Experimental Results

Table 1 shows the evaluation results of SEL-STL and other seven models (i.e., STL-Ridge, STL-KNN, STL-MLP, STL-SVR, STL-GDBT, STL-Stacking and Bstacking) on SSEC, CSI, and SZI datasets. STL-Ridge refers to the Ridge model based on STL, STL-KNN refers to the KNN model based on STL, STL-MLP refers to the MLP model based on

STL, STL-SVR refers to the SVR model based on STL, and STL-GDBT refers to the GDBT model based on STL. STL-Stacking refers to the ensemble model integrating STL-Ridge, STL-KNN, STL-MLP, STL-SVR and STL-GDBT. Bstacking refers to stacking model enhanced with AdaBoost method but without STL processing.

In order to show the evaluation results more clearly, Figure 2 shows the evaluation results of all models.

Table 1. *Evaluation results of models on SSEC, CSI and SZI data sets.*

Dataset	Method	R^2	MAE	RMSE
SSEC	STL-Ridge	0.9962	0.0098	0.0002
	STL-KNN	0.9946	0.0121	0.0003
	STL-MLP	0.9808	0.0233	0.0011
	STL-SVR	0.9775	0.0293	0.0013
	STL-GDBT	0.996	0.0104	0.0002
	STL-Stacking	0.9963	0.0098	0.0002
	Bstacking	0.9953	0.0127	0.0003
	SEL-STL	1	0.0009	0
CSI	STL-Ridge	0.9964	0.0093	0.0002
	STL-KNN	0.9941	0.0123	0.0003
	STL-MLP	0.9789	0.0241	0.0012
	STL-SVR	0.9681	0.0363	0.0018
	STL-GDBT	0.9962	0.0097	0.0002
	STL-Stacking	0.9965	0.0092	0.0002
	Bstacking	0.9944	0.0141	0.0003
	SEL-STL	1	0.0009	0
SZI	STL-Ridge	0.9929	0.0112	0.0003
	STL-KNN	0.9897	0.0142	0.0004
	STL-MLP	0.9754	0.0214	0.001
	STL-SVR	0.967	0.0265	0.0013
	STL-GDBT	0.9928	0.0116	0.0003
	STL-Stacking	0.9932	0.0111	0.0003
	Bstacking	0.9899	0.0154	0.0005
	SEL-STL	0.9999	0.0011	0

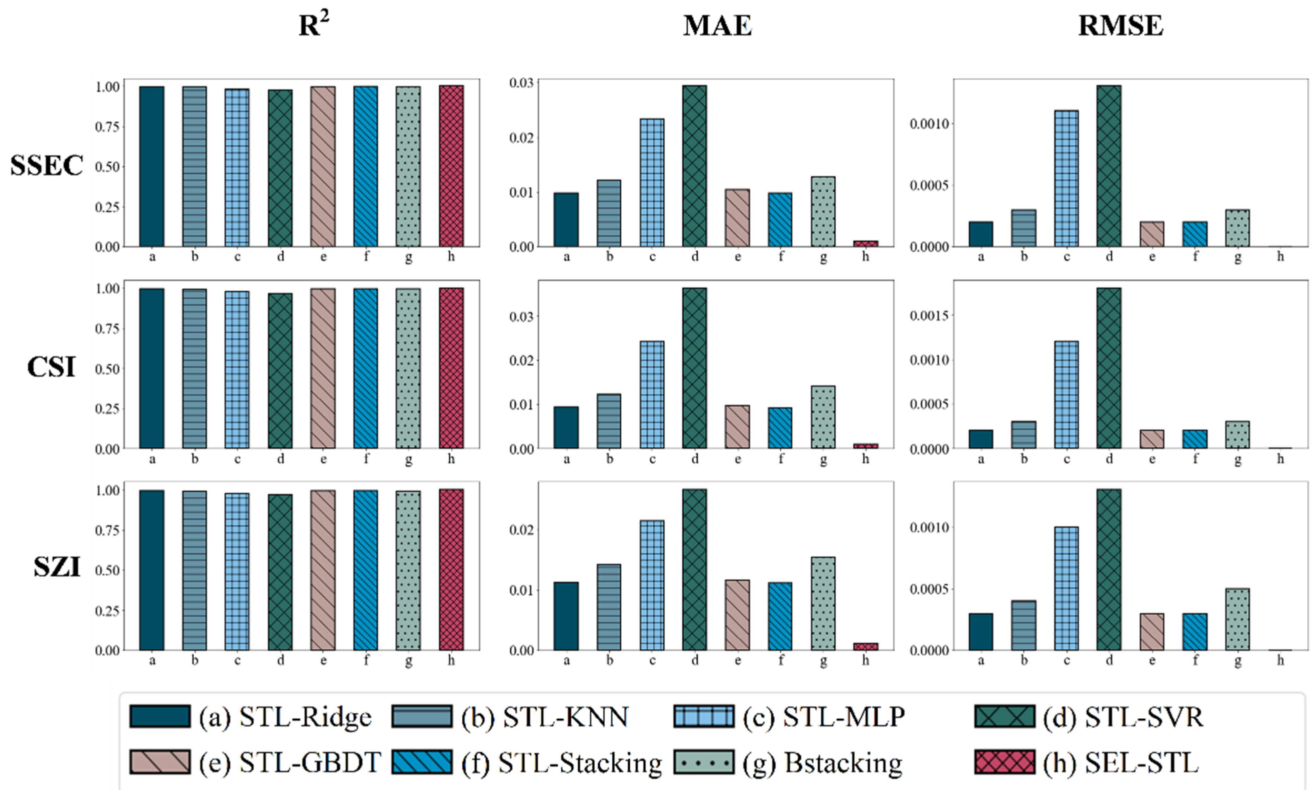

Figure 2. *Evaluation results of models on SSEC, CSI and SZI data sets.*

The outcomes presented in table 1 and figure 2 can be summed up as follows.

It is observed that the proposed SEL-STL ensemble model is superior to the individual prediction models, i.e., STL-Ridge, STL-KNN, STL-MLP, STL-SVR and STL-GBDT models.

(1) The MAE values of STL-Ridge, STL-KNN, STL-MLP, STL-SVR and STL-GBDT models for SSEC dataset are 0.0098, 0.0121, 0.0233, 0.0293 and 0.0104, respectively, which are significantly higher than that of SEL-STL, i.e., 0.0009. The RMSE values of STL-Ridge, STL-KNN, STL-MLP, STL-SVR and STL-GBDT models are 0.0002, 0.0003, 0.0011, 0.0013, and 0.0002, respectively, whereas RMSE value of SEL-STL is zero. STL-Ridge, STL-KNN, STL-MLP, STL-SVR and STL-GBDT models yield R^2 values of 0.9962, 0.9946, 0.9808, 0.9775, and 0.996, respectively, which are lower than that of SEL-STL, i.e., 1.

(2) The MAE values of STL-Ridge, STL-KNN, STL-MLP, STL-SVR and STL-GBDT models for CSI dataset are 0.0093, 0.0123, 0.0241, 0.0363, and 0.0097, respectively, which are higher than that of SEL-STL, i.e., 0.0009. The RMSE values of STL-Ridge, STL-KNN, STL-MLP, STL-SVR and STL-GBDT models are 0.0002, 0.0003, 0.0012, 0.0018 and 0.0002, respectively, whereas RMSE value of SEL-STL is zero. STL-Ridge, STL-KNN, STL-MLP, STL-SVR and STL-GBDT models yield R^2 values of 0.9964, 0.9941, 0.9788, 0.9681, and 0.9962, respectively, which are lower than that of SEL-STL, i.e., 1.

(3) The MAE values of STL-Ridge, STL-KNN, STL-MLP, STL-SVR and STL-GBDT models for SZI dataset are 0.0112, 0.014, 0.0265 and 0.0116, respectively, which are higher than that of SEL-STL, i.e., 0.0011. The RMSE values of STL-Ridge, STL-KNN, STL-MLP, STL-SVR and STL-GBDT models are 0.0003, 0.0004, 0.001, 0.0013 and 0.0003, respectively, whereas RMSE values of SEL-STL is zero. STL-Ridge, STL-KNN, STL-MLP, STL-SVR and STL-GBDT models yield R^2 values of 0.9929, 0.9897, 0.9754, 0.967 and 0.9928, respectively, which are lower than that of SEL-STL, i.e., 0.9999.

It is also observed that the proposed SEL-STL ensemble model is superior to the general ensemble models, i.e., STL-Stacking (without AdaBoost processing) and Bstacking (without STL processing) models.

(1) The MAE values of STL-Stacking and Bstacking models for SSEC dataset are 0.0098 and 0.0127, which are higher than that of SEL-STL, i.e., 0.0009. The RMSE values of STL-Stacking and Bstacking models are 0.0002 and 0.0003, respectively, whereas RMSE value for SEL-STL is zero. STL-Stacking and Bstacking models yield R^2 values of 0.9963 and 0.9953, respectively, which are lower than that of SEL-STL, i.e., 1.

(2) The MAE values of STL-Stacking and Bstacking models for CSI dataset are 0.0092 and 0.0141, which are higher than that of SEL-STL, i.e., 0.0009. The RMSE values of STL-Stacking and Bstacking models are 0.0002 and 0.0003, respectively, whereas RMSE value of SEL-STL is zero. STL-Stacking and Bstacking models yield R^2 values of 0.9965 and 0.9944, respectively, which are lower than that of SEL-STL, i.e., 1.

(3) The MAE values of STL-Stacking and Bstacking models for SZI dataset are 0.0111 and 0.0154, respectively, which are higher than that of SEL-STL, i.e., 0.0011. The RMSE values of STL-Stacking and Bstacking models are 0.0003 and 0.0005, respectively, whereas RMSE value for SEL-STL is zero. STL-Stacking and Bstacking models yield R^2 values of 0.9932 and 0.9899, respectively, which are lower than that of SEL-STL, i.e., 0.9999.

In summary, the MAE and RMSE values of SEL-STL are lower than those of other models, indicating that SEL-STL has a higher prediction performance. Additionally, the R^2 value of SEL-STL is higher than those of other models, indicating that the prediction performance of SEL-STL is more accurate. By using the above evaluation indicators, it can be concluded that SEL-STL obtains better prediction performances of stock prices.

As demonstrated in [17, 18], the Bayesian optimization algorithm and stacking ensemble method can effectively improve the prediction accuracy for stock price prediction. However, there are some shortcomings in references [17, 18]. Ghosh and Datta [17] simplified the stock price prediction problem as a binary classification problem and used classification models to predict the stock trend. Instead, in this study, the stock price is predicted through regression methods. The comparison results show that the stacking ensemble method can significantly improve the prediction accuracy and reduce the prediction error in both classification and regression models. Huang et al. [18] combined Bayesian optimization algorithm with LSTM model for stock prediction. However, the advantages of ensemble methods are not considered. Therefore, to further prove the Bayesian optimization algorithm and stacking ensemble method can boost the prediction accuracy and minimize the prediction error, the performance of proposed SEL-STL model is compared with that of base prediction models (i.e. STL-Ridge, STL-KNN, STL-MLP, STL-SVR and STL-GBDT). The results presented in table 1 and figure 2 show that the combination of Bayesian optimization algorithm and the two-layer stacking-based ensemble learning method can integrate the advantages of different base prediction models and obtain superior prediction accuracy.

5. Conclusion

This study proposes a hyper-parametric stacking-based ensemble model for predicting stock prices, analyzes its prediction effect on SSEC, CSI, and SZI data sets, and contributes to the improvement of the stock market's prediction accuracy.

Firstly, to deal with the different order of magnitude in the original data set, the data is normalized to enhance the efficiency and quality of data processing. Secondly, to address the data vulnerability to periodic and seasonal changes, STL method is employed to reduce the impact of abnormal data in a more reasonable manner. Thirdly, to reduce the influence of the hyper-parameter setting of the base prediction models on their prediction accuracy, which further affects the performance of the ensemble model, the Bayesian optimization method is employed to optimize the hyper-parameter of the base prediction models. Then, the stacking-based ensemble learning method enhanced with AdaBoost method is utilized to obtain the optimal ensemble model SEL-STL.

In the experiment, the proposed model has been compared with five base prediction models and two general ensemble models. Despite the fact that the proposed SEL-STL model is capable of producing the more accurate predictions, there are still some aspects that can be improved in the future. For the experimental evaluation of this model, only three kinds of evaluation indicators were chosen. Given that the MAPE and other evaluation indicators are excluded from the evaluation due to the small difference of performance between the proposed model and other models, it is worthwhile to investigate whether the proposed model can be further optimized to outperform the other models in all evaluation indicators. In addition, the experiments can be conducted to check whether the proposed model can be extended to solve the prediction problems well in other fields.

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