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Stock Price Forecasting: Hybrid Model of Artificial Intelligent Methods

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Predicting the price of stock is very helpful and can attract the interest of researchers and investors who make subjective investment judgments based on objective technical indicators. We propose a new hybrid forecasting model utilizing the combined prediction's principle as well as the artificial intelligence's technique. First, the new method presented combines the single models in series. Next, we present the principle of hybrid prediction which is a foundation of our model, and its validity is proven and carefully illustrated in this paper. According to this principle, the combined model consists of three sole prediction models and demonstrates greater forecast accuracy than the single model. The new model also owns the qualitative prediction, as well as the quantitative prediction. Furthermore, a clear introduction of the three sole prediction models is given, and the comprehensive forecasting rules are introduced. The comparison analysis is included in this paper to validate the new method, and the multi-agent simulation, including different investment strategies, is given in complex situations, such as the stock market. According to the results of the multi-agent simulation and theoretical proofs, the combined model owns the highest accuracy of stock price prediction and results in more profits than other single models. Accordingly, we can conclude that this model would be a suitable and powerful method in directing investment decisions. This newly presented model functions similarly to the prediction system, which not only exhibits a high accuracy rate but also has an effect on guiding operations in the stock market due to the introduction of intelligent agents.

Keywords: *stock price, Hybrid model; artificial intelligence; multi-agent simulation; Engineering Economics.*

Introduction

In recent years, numerous studies have been done in the area of forecasting the stock market due to forecasting's commercial applications, high stakes, and attractive benefits (Yazdani-Chamzini *et al.*, 2012; Zavadskas & Turskis, 2011; Li *et al.*, 2014). Consequently, a variety of predicting algorithms have been proposed. As one of the most important artificial intelligence models, the support vector machine (SVM) method is widely used in stock market predictions (Yang *et al.*, 2002; Tian *et al.*, 2012). For example (Yu *et al.*, 2009) have studied an evolving least squares support vector machine learning paradigm with a mixed kernel, which is used to predict the trend of the stock market. The artificial neural network

(ANN) is also a widely used method in stock market forecasting (Guresen *et al.*, 2011; Mostafa, 2010; Cheng *et al.*, 2012; Cimpoeru, 2011). A newly method integrated by the genetic fuzzy systems and the artificial neural networks is presented by (Hadavandi *et al.*, 2010) to forecast stock prices. There are also many other methods that are used to predict the stock market, such as the hidden Markov model (HMM), the probabilistic neural network (PNN) and the autoregressive moving average model (ARMA). (Gupta & Dhingra, 2012) have studied a new method to forecast the stock index using the hidden Markov model. Additionally, the probabilistic neural network (PNN) (Khashei *et al.*, 2012) model is also used to forecast the stock index.

Among all of the stock market predicting methods, the fusion model obtains better forecasts than does the single model (Zhang & Wu, 2009). Many studies have tested the performance of fusion models, which yield better results (Hassan, 2009; Li *et al.*, 2014). A three-stage prediction system of stock market, including the neural networks, the fuzzy type-2 clustering and the multiple regression, is proposed by (Enke *et al.*, 2011).

(Gunasekaran & Ramaswami, 2011) have given a new approach integrating the artificial immune algorithm and adaptive neuro fuzzy inference system to predict the Indian stock market. In this paper, we present a novel model that follows the idea of the fusion model but uniquely utilizes independent model components. We present three different combination models, "ARMA+SVM" fusion model, "ARMA+PNN" fusion model, and back-propagation PNN model. Thus, our model is called the Combination Prediction Model to distinguish it from the fusion model or hybrid model, and we demonstrate its reasonability in this paper. Another feature of our model lies in the design and introduction of intelligent agents (Smeureanu *et al.*, 2012; Sakalas & Virbickaite, 2012) who can reflect the transaction strength and guide operations in a real stock market. As a result, a dynamic combination model will be established and is different from the existing static model. The new model not only enjoys a high accuracy rate but also has an effect on guiding operations.

The paper proceeds in the following order to present the above work and contributions clearly. Section 2 demonstrates the principle of combining models with the theoretical proofs in detail. Section 3 introduces the three combined models. Section 4 tests the correctness and effectiveness of our model with comparison analysis and multi-agent simulation. Section 5 presents the conclusions.

The Principle of Hybrid Forecasting Model

None of the existing prediction models is omnipotent; therefore, each model has its own merits and demerits, and each model has its own scope of application. To reduce the systematic risk of prediction and employ the role of every adopted model fully, we use a hybrid forecasting model which is based upon the majority voting rule, and the reasons are explained by the following lemma.

[Lemma 1] When we adopt the majority voting rule and n is an odd number, the accuracy rate of the hybrid model's prediction is bigger than that of any single model if the each model's forecasting accuracy rate is no less than 0,5 and the prediction models' results are independent.

Proof. Based on the lemma 1's condition, we can gain that $\theta = \theta_i$ for $i \in \{1, 2, \cdots, n\}$ and the θ_i denotes the prediction accuracy rate of the i-th model. Then, according to the fact that results of single model are independent with that of the other model, we can obtain the accuracy rate of the combined model's prediction

$$\tilde{\theta} = \sum_{\{\sum_{i=1}^{n} \sigma_i > \frac{n}{2}\}} \prod_{i=1}^{n} \theta_i^{\sigma_i} (1-\theta_i)^{1-\sigma_i} \tag{1}$$

where σ_i is the indicator variable of the i-th model, and when it equals 1, the i-th model gives the correct prediction. Otherwise, the model gives the wrong prediction, according to the majority voting rule. As the combined model provides the correct prediction if and only if the above condition holds, the formula $\sum_{i=1}^{n} \sigma_i > n/2$ employs the condition of summing. Next, we have to prove that $\tilde{\theta} \geq \theta$. In fact, we can obtain the following formula according to formula (1).

$$\tilde{\theta} = \theta^n + C_n^1 (1-\theta)^1 \theta^{n-1} + \cdots + C_n^{(n-1)/2} (1-\theta)^{(n-1)/2} \theta^{(n+1)/2} \tag{2}$$

from which we can next have:

$$f(\theta) = \frac{\tilde{\theta}}{\theta} - 1 = \theta^{n-1} + C_n^1 (1-\theta)^1 \theta^{n-2} + \cdots + C_n^{(n-1)/2} (1-\theta)^{(n-1)/2} \theta^{(n-1)/2} - 1 \tag{3}$$

We can calculate that if θ is 1 or 0,5, the result of formula (3) is 0. Furthermore, based on the mathematical analysis, we get that :

$$\frac{\partial^2 f(\theta)}{\partial \theta^2} < 0 \text{, for any } \theta \in [0.5,1] \quad (4)$$

which indicates that $f(\theta) \geq 0$ for any $\theta \in [0.5,1]$.

The above steps induces that $\tilde{\theta} \geq \theta$, when the value of θ is between 0,5 and 1. Thus, the whole lemma 1 holds.

However, the lemma 1's conditions cannot always be meted, especially given the requirement that each single model has the same accurate rate of prediction. Fortunately, the formula (1), expressed by $\tilde{\theta}(\theta_i)$, is a continuous one about θ_i, so when $|\theta_i - \theta| < \delta$, we have that $\exists\ \delta, \varepsilon$, the inequality $|\tilde{\theta}(\theta_i) - \tilde{\theta}(\theta)| < \varepsilon$ based on the definition of a continuous function. Based on the above analysis, the following corollary can be derived.

[Corollary 1] For any $\theta_i \in (0.5,1)$, when $\max\theta_i - \min\theta_i < \delta$, where $i \in \{1,2,\cdots,n\}$, $\exists\ \delta$, the inequality $\tilde{\theta} \geq \max\theta_i$ holds.

According to the above Corollary and Lemma, we can know that the accurate rate of the hybrid model's prediction can be greater than that of each single model under certain conditions. Thus, the theoretical outcome describes the reason why we select the combining model as part of the agent's intelligence to predict stock index.

As shown in Table 1, an example of a hybrid model consisting of three single models is given to explain the rules of the above lemma and corollary.

Table 1

Exemplifications of Lemma 1 and Corollary 1

The predication's accurate value	Example 1	Example 2	Example 3	Example 4
Model 1	60 %	70 %	60 %	65 %
Model 2	60 %	70 %	65 %	70 %
Model 3	60 %	70 %	70 %	80 %
Combination	64,8 %	78,4 %	71,9 %	80,7 %

The validity of the above Lemma and Corollary are demonstrated in Table 1. The first two examples show the results of Lemma 1, and the rest two examples reflect Corollary 1 with δ equaling 0,1 in example 3 and 0,15 in example 4. Thus, Lemma 1 and Corollary 1 are correct and are important foundations of the following parts because they explain why we need the combination prediction model, rather than the single one with the highest accuracy rate.

Three Single Models Constituting the Hybrid Model

We will introduce the hybrid model which is composed of ARMA + SVM, ARMA + PNN, and BP-PNN (Perry et al., 2001). In the three single models, the first two models (ARMA + SVM, ARMA + PNN) can produce quantitative and qualitative outcomes simultaneously. However, the BP-PNN model is a qualitative model that functions to forecast three trends of a stock: increase, decrease, and flat. The first two models are combination models which employ the same principle grasping the non-linear characteristic of the stock, and thus help to improve their prediction accuracy. In more detail, the principle of AMRA+SVM and ARMA+PNN lies in decomposing the stock index in the following:

$$\begin{aligned}&\textit{Stock index} = \textit{Linear explainable part} + \\ &\textit{Non-linear explainable part} + \textit{White noise}\end{aligned} \quad (5)$$

In the above formula, AMRA is a linear model, and both PNN and SVM are non-linear models so they are non–linear explainable part. The white noise reflects the random interferences and cannot be explained by the former two parts. In many existing papers, the merits of these combining models are validated, such as the work by (Kim, 2003; Khashei & Bijari, 2012; Zhang & d Wu, 2009) and others. The mathematical expression of Formula (5) can be written as follows:

$$y_t = \bar{y}_t + \tilde{y}_t + w_t, \quad (6)$$

where the white noise, the non–linear explainable part and the linear explainable part are donated by w_t $\tilde{y}_t$ and $\bar{y}_t$, respectively. Understandably, $\bar{y}_t$ is the result from ARMA, and $\tilde{y}_t$ comes from SVM or PNN. Next, the above three models and implementation procedures are introduced as follows.

(1) Single Model 1: ARMA+SVM.

Firstly, ARMA (Wang et al., 2012; Shen & Ding, 2014) is constructed as below;

$$\begin{aligned}\bar{y}_t &= \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots + \alpha_p y_{t-p} \\ &+ \varepsilon_t - \gamma_1\varepsilon_{t-1} - \gamma_2\varepsilon_{t-2} - \cdots - \gamma_q\varepsilon_{t-q}\end{aligned} \quad (7)$$

where y_{t-j} ($j = 1,2,\cdots,p$) donates the stock index at the time $t-j$, ε_{t-i} ($j=0,1,\cdots,q$) represents the white noise at the time $t-i$, and the rest parameters in the above equation (7) are identified through fitting the model.

Next, we can obtain Δy_t which is defined as:

$$\Delta y_t = y_t - \bar{y}_t = \tilde{y}_t + w_t \quad (8)$$

In fact, the Δy_t ($t=1,2,\cdots$) is the part that cannot be explained by the linear part, ARMA, and forms the input variables of SVM. Then, we can obtain the samples as follows:

$(\mathbf{x}_t, \Delta y_t)$, with $t=1,2,\cdots$, (9)

where the vector $\mathbf{x}$ is the input variables and can be decribed as follows: $\mathbf{x}=(x_1,x_2,x_3,x_4,x_5,x_6)^T$, and x_i, $i=(1,2,\cdots,4)$ donates the 5-Day average of closing price, 20-Day average of closing price, 60-Day average of closing price, and 5-Day average trading volume, respectively. x_5 reflects the difference between the average of long-term and the average of short-term and is expressed by x_1-x_3. x_6 is the average of x_5 within nine trading days. The samples are SVM's inputs, i.e., the learning samples. Then, the SVM and these samples are utilized to forecast $\tilde{y}_t$. The regression method of SVM (Orru et al., 2012; Qi, et al., 2013) is described as follows.

The regression equation can be written as:

$$f(\mathbf{x}_t) = w\phi(\mathbf{x}_t) + b, \quad (10)$$

where $\phi(\cdot)$ is a function satisfying that $K(x,y)=\phi(x)\cdot\phi(y)$, and $K(x,y)$ can be a Gauss function as the SVM regression model's kernel function.

Next, we introduce the following optimization problem to decide the value of w and b in the Formula (10).

$$\min_{w,b} \quad C\frac{1}{n}\sum_{t=1}^{n} L_\varepsilon(\Delta_t) + \frac{1}{2}\|w\|^2$$
$$s.t.\ L_\varepsilon(\Delta_t) = \begin{cases} |f(\mathbf{x}_t)-\Delta_t|-\varepsilon, & |f(\mathbf{x}_t)-\Delta_t| \geq \varepsilon \\ 0, & |f(\mathbf{x}_t)-\Delta_t| < \varepsilon \end{cases} \quad (11)$$

where ε represents the precision coefficient, C denotes the penalty coefficient. These two values can be set to gain the best forecasting outcomes by comparing many times. The codes of the model can be obtained in this paper's supplement materials.

(2) Single Model 2: ARMA+PNN.

The part of ARMA is the same to that in the single model 1 and shares the equations (7), (8) and (9). Then, we can obtain the samples described in equation (9).

Next, the non–linear explainable ($\tilde{y}_t$) is forecasted by probabilistic neural network, PNN (Sankari & Adeli, 2011; Lin *et al.*, 2013; Qi *et al.*, 2013).

As shown in Figure 1, the structure of PNN includes an input layer, a pattern layer, a summation layer, and an output layer. The input layer contains six nodes (corresponding to $\mathbf{x}_t$), and one node (corresponding to Δy_t) constitutes the output layer. The pattern layer has several groups of pattern units and the pattern unit estimates a particular pattern's contribution to the function of probability density. The summation layer summarizes the density estimate on each pattern of each group.

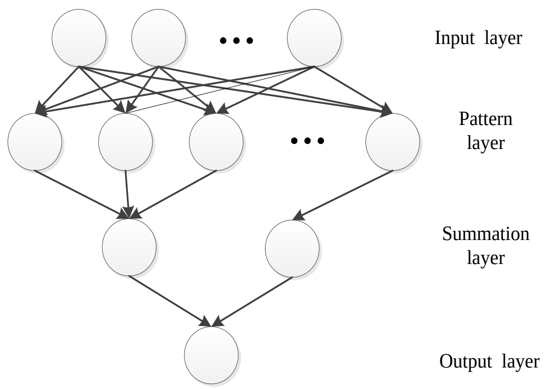

Figure 1. Structure Chart of probabilistic neural network

The last step is identical to the single model 1. The corresponding detailed programs can be found in the supplemental materials of this paper.

(3) Single Model 3: BP-PNN

The BP-PNN (PNN with back-propagation algorithm) is proposed with the foundation of PNN model, and introduces the framework of the back-propagation algorithm. The topological structure of BP-PNN is shown as the following figure.

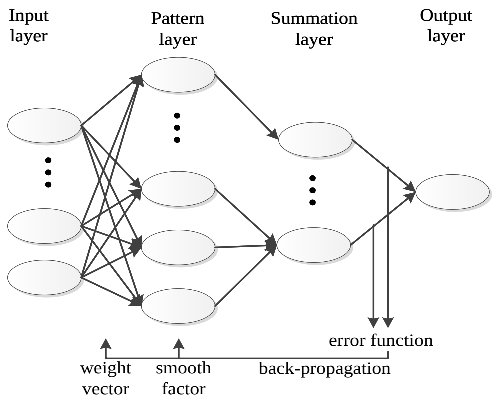

Figure 2. Topological Structure of the BP-PNN

The two variables, that is, the smooth factor and the weight vector, can be adjusted by the back-propagation algorithm to enhance the prediction accuracy of the formula. We can define a specific error function E which is expressed by input variable and weight vector.

$$E = 1 - \frac{F(X \cdot W) \cdot T \cdot \left(C^{real}\right)^T}{F(X \cdot W) \cdot T \cdot E^T}$$

(12)

In the formula, F expresses the non–linear operator of the pattern layer node, T denotes attribute matrix from the pattern layer to the summation layer, the vector of correct classification could be represented by C^{real}, H denotes one row vector which is constituted by smooth factor of any pattern layer node;, and W is the weighted matrix from input layer to pattern layer. The error function can be trained with the sample by adjusting the value of H and W to enhance the performance of BP-PNN.

Comprehensive Predicting Rules Based on Combination Model

The quantitative results can be obtained by the first two single models and are denoted by ${}_1p_t$ and ${}_2p_t$, respectively, where p_t is the average of the comprehensive quantitative result. Next, the predicting volatility, represented by r_t, is defined in the following:

$$r_t = \frac{p_t - y_{t-1}}{y_{t-1}} = \frac{{}_1p_t + {}_2p_t - 2y_{t-1}}{2y_{t-1}} \quad (13)$$

Meanwhile, g_t are the qualitative results and can be acquired by the third single model introduced in section 3.1. Based on the above denotations, the comprehensive predicting rules are listed in Table 2 which also presents the suggestions about how to operate the corresponding stock.

Table 2

Forecasting rules and corresponding operations

gt	rt	Decisions	Operations
–1	$< -1.5\%$	strong bearish	sell at a large amount
	$(-0.5\%, -1.5\%]$	bearish	sell at a proper amount
	$(-0.5\%, 0.5\%]$	little bearish	sell at a small amount
	$(0.5\%, 1.5\%]$	unclear	no operations
	$> 1.5\%$	unclear	no operations
0	$< -1.5\%$	little bearish	sell at a small amount
	$(-0.5\%, -1.5\%]$	unclear	no operations
	$(-0.5\%, 0.5\%]$	unclear	no operations
	$(0.5\%, 1.5\%]$	unclear	no operations
	$> 1.5\%$	little bullish	purchase at a small amount
1	$< -1.5\%$	unclear	no operations
	$(-0.5\%, -1.5\%]$	unclear	no operations
	$(-0.5\%, 0.5\%]$	little bullish	purchase at a small amount
	$(0.5\%, 1.5\%]$	bullish	purchase at a proper amount
	$> 1.5\%$	strong bullish	purchase at a large amount

It is easy to observe that these suggested operations are given only when the result of quantitative model is in accordance with that of the qualitative model and when the presented model is a robust one. The operation's direction is decided by the qualitative model, and the operation is done according to the results of the quantitative model. According to this opinion, the method can not only forecast the outcomes much more correctly, but would also make more moderate investment advices. Moreover, the Table 2 can also be helpful in designing the intelligences of the Agent in the following section.

Data and Comparison Results

We choose the Shanghai Stock Exchange Composite Index (Ticker code: 000001) and select the closing prices from August 24th, 2011 to January 20th, 2012 as the sample for validating the model. The number of trading days within the period is 100. By using the above models, the results of different models can be obtained and showeded in Figure 3.

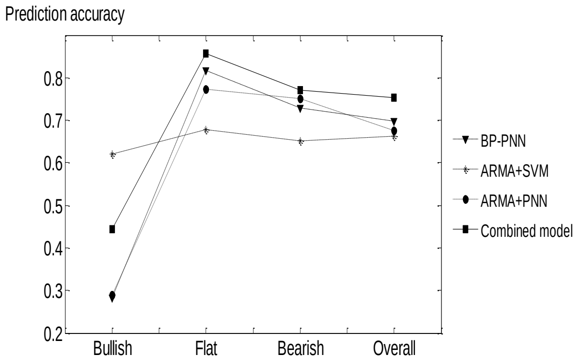

Figure 3. The basic results of predicting

Figure 3 presents the forecasting accuracy rates of three different models as well as the hybrid model, where the accuracy rates are further divided into three categories: "Bullish", "Flat", and "Bearish". Although the ARMA+SVM model and ARMA+PNN model produce the quantitative results, the qualitative outcomes are also contained, from which we can know the stock's trend. Therefore, the results of the two quantitative models are comparable with that of the BP-PNN. According to the comparison of the values showed in the above figure, we can easily obtained that the combined model owns the highest overall accuracy rate. The results of this comparison are consistent with the Lemma and the Corollary demonstrated in part 2.

Multi-Agent Simulation

The above section 4.1 only offers a comparison of which models have the highest accuracy rate, and we cannot make investments in a stock market according to it. Thus, we give a multi-agent simulation (Dion et al., 2011; Li et al., 2010;) for validating the presented models comprehensively by comparing the designed agents' profits.

Four types of agents have been constructed: the hybrid model which operates according the combined model, quantitative model which operates according to the average result of two quantitative models (ARMA+SVM, ARMA+PNN), qualitative model which operate according to the result of BP-PNN, and random strategy which decide to buy or sell randomly. The detailed intelligence corresponded to the four types of agents can be obtained from Li et al., 2014.

Furthermore, the trading constraints are made based on the real stock market in the following: (1) the purchased stocks cannot be sold on the same trading day and vice versa, (2) the short-sell is not allowed, (3) the transaction fees account for 7‰ of the turnover and are charged when the stock is purchased. Meanwhile, the above constructed four different agents are allocated 10,000 units of money initially. Based on the whole intelligences and the trading constraints, the final results are presented in Figure 4 which have undergone 100 simulation cycles.

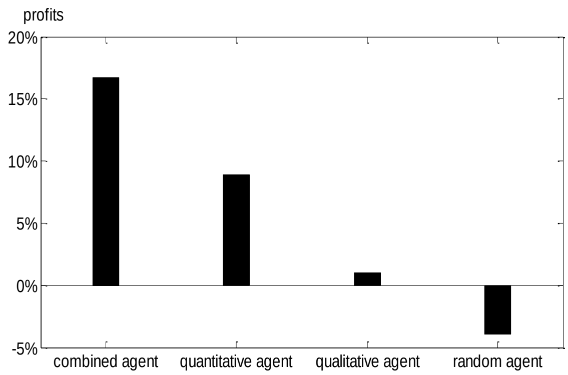

Figure 4. The profits of four types of agents

After 100 trading days, the final profits of four agents are shown in Figure 4, and it is easily found that the profit of the combined agent is the highest one. All in all, the combined agent, which is directed by the hybrid model proposed by our method, get satisfactory profits and do better than other agents. Accordingly, this newly presented forecasting model is practical and meaningful from this viewpoint.

Conclusions

The primary contributions of our research are as follows. Firstly, we present a novel method to integrate the prediction methods. The method through which many hybrid models combine two models is in series, which means the second model's input is the first model's output. We combine the forecasting methods in parallel rather than in series. Next, a new combined forecast model is presented, the reason for choosing the method of combined forecast is explained by proving a corresponding principle, and the model is proved according to a simulation of multi-agent. Among the multi-agent simulation, we should provide the forecast rules. The existing single or fusion models have a few easy forecasting rules or may even have no rules. Accordingly, the complex situations cannot be dealt with by these models, and the wrong prediction results can be increased by these models without sound forecasting rules. Based on the features of our combined model, we give operation suggestions only when the quantitative model is consistent with the qualitative model. The operation's direction is decided by the result of quantitative model, and the quantitative model's result decides the operation's strength. Furthermore, the specialty of this paper lies in the using of a multi-agent simulation in order to compare the combined model with the single ones.

In the comparison with the sole models, we select the real market data and obtain the forecasting accuracy of the three single models and our combined model. Through comparison of the results, the hybrid model gains the highest overall accuracy rate, and the value of the prediction accuracy reaches up to 75,3%. In addition, the multi-agent simulation also demonstrates our hybrid model's superiority. We construct four different types of agents that take advantage of our hybrid model, the qualitative model, the quantitative model, and the random strategy, respectively. The profitability of the hybrid model exceeds 16,7%, which is much higher than the other three agents. All in all, the comparison test and simulation analysis confirm that our hybrid model proposed in this paper can obtain higher prediction accuracy and satisfactory profits and is preferred over other models.

In the field of prediction of a stock composite index, the research on forecasting methods is ongoing and useful, especially on the models' application in the stock market. As the hybrid model owns the sole model's advantage and makes up the shortcomings of the other models, the combined model is becoming a trend in stock prediction. In this paper, we propose a novel hybrid forecasting method according to the technique of artificial intelligence and the forecasting principle. The new hybrid model consists of three classical forecasting methods according to the prediction principle. The comparison analysis and multi-agent simulation are used to validate the new hybrid model. Based on the results experiments, the hybrid model can be useful in guiding our investment decisions in the real stock market.

This paper has some limitations which may be subjects to study in the future. There are many different artificial intelligence methods used to forecast the stock composite index. Therefore, it may be our first questions to answer which models are suitable to combine, and compare the differences of these combined models. Additionally, the research on utilizing hybrid models to predict the stock price is very rich. It is necessary for us to compare our hybrid models with many other combined models proposed in existing papers, and the two different combining methods may be applied to construct more powerful prediction models. In addition, the research idea of combined models can be used in many other fields such as commodity recommendation models, weather forecasting models, and others. We deeply hope the model proposed in this paper will be helpful in other aspects.

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