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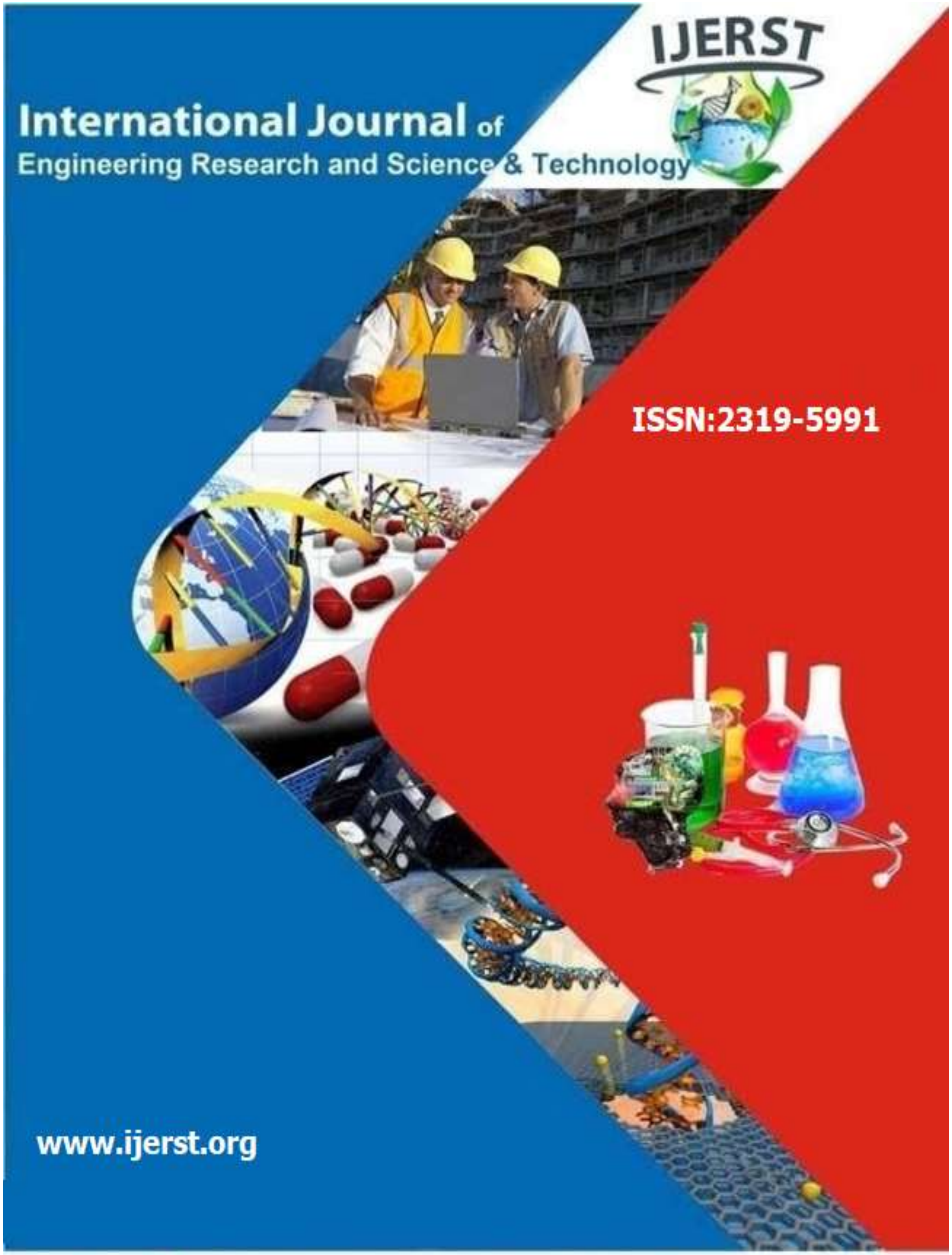

E-mail: editor@ijerst.org or ijerst.editor@gmail.com

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A DEEP LEARNING–OPTIMIZED HYBRID ARCHITECTURE FOR PREDICTIVE STOCK MARKET MODELING USING SENTIMENT INDICATORS

K.Neelakanteswara Prasad M.Tech
Associate Professor
Bapatla Engineering College
Bapatla, Andhra Pradesh

Thatha.Gowri Priya
Department of MCA
Bapatla Engineering College
Bapatla,Andhra Pradesh

Policharla.Bhavya Sri
Department of MCA
Bapatla Engineering College
Bapatla,Andhra Pradesh

Shaik.Neeha Sulhtana
Department of MCA
Bapatla Engineering College
Bapatla,Andhra Pradesh

Patnana.Venkata Reddy
Department of MCA
Bapatla Engineering College
Bapatla,Andhra Pradesh

ABSTRACT

Because of the inherent volatility, non-linearity, and the impact of both quantitative and qualitative elements, accurately predicting the stock market is still a difficult task. In order to improve forecasting accuracy, this research suggests a hybrid architecture optimised for deep learning that combines historical stock data with market sentiment indices. The model combines sophisticated deep learning algorithms, like Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN), for temporal and feature pattern recognition with Natural Language Processing (NLP) techniques to extract sentiment scores from financial news and social media platforms. The hybrid methodology aligns sentiment-driven insights with conventional market signals by using feature fusion and hyperparameter tweaking techniques to maximise forecast performance. The suggested model performs noticeably better than baseline methods in terms of prediction accuracy and resilience, according to experimental findings on benchmark datasets. This study highlights the possibility of combining artificial intelligence with human behavioural signals to provide more accurate and timely stock market predictions.

I. INTRODUCTION

With the maturity of China's stock market and the rapid growth of Internet finance, many people realize the importance of investment and choose to enter the financial market. However, the stock market is characterized by massive data and enormous volatility. Many retail investors need more data-mining skills to make money. Therefore, accurate stock price prediction can reduce investment risks and improve investment returns for investors and enterprises.

Early scholars used statistical methods to construct a linear model to fit the stock price time series trend. The traditional methods contain ARMA, ARIMA, GARCH, etc. The ARMA is established to conduct a time series stock analysis [1]. The ARIMA model is developed based on the ARMA and predicts the trend of stock price changes [2]. The ARIMA model can also introduce wavelet analysis to improve the fitting accuracy of the Shanghai Composite Index [3]. The GARCH model provides innovative ideas for stock time series prediction through a time window [4]. At the same time, some scholars have combined ARMA and GARCH to build a new prediction model, which provided theoretical support for

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the volumetric price analysis of multivariate stocks [5]. Generally speaking, these classical methods only capture regular and structured data. However, traditional forecasting methods require assumptions that are uncommon in real life. Therefore, It is challenging to describe nonlinear financial data using statistical methods.

Subsequently, many researchers attempt to anticipate stock prices using machine learning approaches such as Support Vector Machines (SVM) and Neural Networks. Machine learning's core idea is to use algorithms to parse data, learn from it, and make predictions about new data. Because the SVM shows unique benefits in dealing with limited samples, high-dimensional data, and nonlinear situations, many scholars use it in stock forecasting. Hossain and Nasser [6] found that the SVM method is superior to the statistical ones in stock prediction accuracy. Chai et al. [7] suggested a hybrid SVM model to anticipate the HS300 index's ups and downs and found that the least squares SVM combined with the Genetic Algorithm (GA) performed better. However, when the SVM applies to large-scale training samples, much memory and computing time will be consumed, which may limit its development space in predicting a large amount of stock data. Then, Artificial Neural Networks (ANN) and multi-layer ANN address financial time series issues. According to the experimental data, ANN has the benefits of quick convergence and high accuracy [8], [9], [10]. Moghaddam and Esfandyari [11] evaluated the effect of several feed forward artificial neural networks on the market stock price forecast through experiments. Liu and Hou [12] improved the BP (Back Propagation) neural network using the Bayesian regularization method. Nevertheless, the traditional neural network method has the following areas for improvement. Generalization ability is not strong, quickly leads to over fitting, and falls into local optimization. Since many samples need to be trained, better models must be found to solve these problems.

A new model for predicting stock prices is proposed in this paper (MS-SSA-LSTM), which matches the characteristics of multi-source data with LSTM neural networks and uses the Sparrow Search Algorithm. The MS-SSA-LSTM stock price forecast model can forecast the stock price in advance and help investors and traders make more informed investment decisions. Investors and traders obtain the data of individual stocks they want to invest in, including historical transaction data and comment information of stock market shareholders, and input them into the MS-SSA-LSTM model. The model automatically outputs a stock price trend chart and forecasts the stock price for the next day.

Here, we can get the motivation for this paper.

(1) Adding sentiment indicators to the model features will improve prediction accuracy. However, applying a general dictionary in the financial field cannot achieve good results. Therefore, We need to construct a sentiment dictionary specific to individual stocks.

(2) Stock price series has complicated characteristics such as nonlinearity, high noise, and strong time-variability. LSTM is effective at handling comprehensive time series data. So LSTM network, a deep learning method, is adopted.

(3) In the LSTM network, hyper parameter variation directly affects the model's prediction accuracy. Artificial selection of appropriate hyper parameters for the network model will cost many resources. Therefore, LSTM can be optimized using the Sparrow Search Algorithm proposed in 2020.

Here are the main contributions of this paper.

(1) The SSA-LSTM model incorporates multi-source data that affects stock prices, such as historical trade data and stock forum comments.

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The MS-SSA-LSTM model outperforms the single data source model regarding prediction accuracy.

(2) Analyze the stock forum comments text information. Then, we construct a sentiment dictionary based on authoritative dictionaries in the financial investment field suitable for individual stock sentiment analysis and sentiment indicator calculation.

(3) A Sparrow Search Algorithm-optimized LSTM model can acquire better hyper parameter values and forecast stock prices than a single LSTM network.

II. LITERATURE SURVEY

''Investigation of market efficiency and financial stability between S&P 500 and London stock exchange: Monthly and yearly forecasting of time series stock returns using ARMA model,''

M. M. Rounaghi and F. N. Zadeh,

We investigated the presence and changes in, long memory features in the returns and volatility dynamics of S&P 500 and London Stock Exchange using ARMA model. Recently, multifractal analysis has been evolved as an important way to explain the complexity of financial markets which can hardly be described by linear methods of efficient market theory. In financial markets, the weak form of the efficient market hypothesis implies that price returns are serially uncorrelated sequences. In other words, prices should follow a random walk behavior.

The random walk hypothesis is evaluated against alternatives accommodating either unifractality or multifractality. Several studies find that the return volatility of stocks tends to exhibit long-range dependence, heavy tails, and clustering. Because stochastic processes with self-similarity possess long-range dependence and heavy tails, it has been suggested that self-similar processes be employed to capture these characteristics in return volatility modeling. The present study applies monthly and yearly forecasting of Time Series Stock Returns in S&P 500 and London Stock Exchange using ARMA model. The statistical analysis of S&P 500 shows that the ARMA model for S&P 500 outperforms the London stock exchange and it is capable for predicting medium or long horizons using real known values. The statistical analysis in London Stock Exchange shows that the ARMA model for monthly stock returns outperforms the yearly. A comparison between S&P 500 and London Stock Exchange shows that both markets are efficient and have Financial Stability during periods of boom and bust.

''Gold price forecasting using ARIMA model,'' G. Bandyopadhyay

This study gives an inside view of the application of ARIMA time series model to forecast the future Gold price in Indian browser based on past data from November 2003 to January 2014 to mitigate the risk in purchases of gold. Hence, to give guideline for the investor when to buy or sell the yellow metal. This financial instrument has gained a lot of momentum in recent past as Indian economy is curbed with factors like changing political scenario, global clues & high inflation etc, so researcher, investors and speculators are in search of different financial instrument to minimize their risk by portfolio diversification. Gold earlier was only purchased at the time of marriage or other rituals in India but now it has gained importance in the eyes of investors also, so it has become necessary to predict the price of Gold with suitable method.

''Stock return prediction under GARCH—An empirical assessment,''

H. Herwartz,

The GARCH model and its numerous variants have been applied widely both in the

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financial literature and in practice. For purposes of quasi maximum likelihood estimation, innovations to GARCH processes are typically assumed to be identically and independently distributed, with mean zero and unit variance (strong GARCH). Under less restrictive assumptions (the absence of unconditional correlation, weak GARCH), higher order dependency patterns might be exploited for the ex ante forecasting of GARCH innovations, and hence, stock returns. In this paper, rolling windows of empirical stock returns are used to test the independence of consecutive GARCH innovations. Rolling p-values from independence testing reflect the time variation of serial dependence, and provide useful information for signaling one-step-ahead directions of stock price changes. Ex ante forecasting gains are documented for nonparametric innovation predictions, especially if the sign of the innovation predictors is combined with independence diagnostics (p-values) and/or the sign of linear return forecasts.

‘‘International evidence on crude oil price dynamics: Applications of ARIMA-GARCH models,’’

H. Mohammadi and L. Su,

We examine the usefulness of several ARIMA-GARCH models for modeling and forecasting the conditional mean and volatility of weekly crude oil spot prices in eleven international markets over the 1/2/1997–10/3/2009 period. In particular, we investigate the out-of-sample forecasting performance of four volatility models — GARCH, EGARCH and APARCH and FIGARCH over January 2009 to October 2009. Forecasting results are somewhat mixed, but in most cases, the APARCH model outperforms the others. Also, conditional standard deviation captures the volatility in oil returns better than the traditional conditional variance. Finally, shocks to conditional volatility dissipate at an exponential rate, which is consistent with the covariance-stationary GARCH models than the slow hyperbolic rate implied by the FIGARCH alternative.

‘‘Recurrent support and relevance vector machines based model with application to forecasting volatility of financial returns,’’

A. Hossain and M. Nasser,

In the recent years, the use of GARCH type (especially, ARMA-GARCH) models and computational – intelligence – based techniques -Support Vector Machine (SVM) and Relevance Vector Machine (RVM) have been successfully used for financial forecasting. This paper deals with the application of ARMA – GARCH, recurrent SVM (RSVM) and recur-rent RVM (RRVM) in volatility forecasting. Based on RSVM and RRVM, two GARCH methods are used and are com-pared with parametric GARCHs (Pure and ARMA -GARCH) in terms of their ability to forecast multi-periodically. These models are evaluated on four performance metrics: MSE, MAE, DS, and linear regression R squared. The real data in this study uses two Asian stock market composite indices of BSE SENSEX and NIKKEI225. This paper also ex-amines the effects of outliers on modeling and forecasting volatility. Our experiment shows that both the RSVM and RRVM perform almost equally, but better than the GARCH type models in forecasting. The ARMA-GARCH model is superior to the pure GARCH and only the RRVM with RSVM hold the robustness properties in forecasting.

‘‘A hybrid least square support vector machine model with parameters optimization for stock forecasting,’’

J. Chai, J. Du, K. K. Lai, and Y. P. Lee,

This paper proposes an EMD-LSSVM (empirical mode decomposition least squares support vector machine) model to analyze the CSI 300 index. A WD-LSSVM (wavelet denoising least squares support machine) is also

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proposed as a benchmark to compare with the performance of EMD-LSSVM. Since parameters selection is vital to the performance of the model, different optimization methods are used, including simplex, GS (grid search), PSO (particle swarm optimization), and GA (genetic algorithm). Experimental results show that the EMD-LSSVM model with GS algorithm outperforms other methods in predicting stock market movement direction.

III. EXISTING SYSTEM

In addition, Yan et al. [16] developed a high-precision prediction model based on the LSTM deep neural network in a short-term financial market. LSTM neural network has a higher prediction accuracy than BP neural network and standard RNN and can successfully forecast stock prices. Nabipour et al. [17] selected ten technical indicators as the prediction model's input. The experiment revealed that LSTM outperformed other algorithms in terms of model-fitting abilities, including decision tree, random forest, Adaboost, XGBoost, ANN, and RNN. Aksehir and Kilic [18] suggested a CNN-based model predicting the nextday trading behavior of Dow Jones 30 Index equities. Technical indicators, gold, and oil price data are fed into the model. The accuracy of the results is 3-22% higher than other models based on CNN.

However, scholars usually need to artificially set the hyperparameter values of the LSTM network, which is intensely subjective. The setting of hyperparameters directly controls the topology of the network model, which will affect the model's prediction performance. Artificial selection of the appropriate hyperparameters for the network model will consume many human and computing resources. To solve the above problems, scholars try to use some Swarm Intelligence (SI) algorithms to optimize the hyperparameters of neural networks. SI can search globally to a certain extent and find the approximate value of the optimal solution. Ji et al. [19] demonstrated that the LSTM optimized by the Improved Particle Swarm Optimization model (IPSO) is superior to the LSTM model. Zeng et al. [20] optimized LSTM by adopting an Adaptive Genetic Algorithm (AGA) and improved the prediction accuracy. At the same time, other intelligent algorithms are also widely used in optimizing neural networks. Sparrow Search Algorithm (SSA) was put forward and inspired by the sparrows' foraging and anti-predation behavior [21]. Compared with the traditional particle swarm and gray wolf optimization algorithms, the SSA algorithm is relatively novel and has a robust optimization ability in price prediction. In addition, the algorithm considers the randomness of individuals in the search process, so it has a solid global search capability. At the same time, the algorithm can also adaptively adjust the search parameters to meet the needs of different problems.

The content of the stock forum is updated in real-time, and the information mined from it is closer to the actual state of investor sentiment than other data sources. However, it will significantly affect investors' investment propensities and a subsequent linkage effect on stock price fluctuations. So it is crucial to analyze the text information of stock forums for our research. Scholars mainly adopt machine learning and semantic analysis methods regarding sentiment classification methods. The machine learning method has high classification accuracy but relies on financial personnel to manually classify training sets, which leads to increased time costs. The semantic analysis method is easier to use in economic and financial analysis, but the standard dictionary is challenging to apply to the economic context [34]. The key lies in constructing a unique financial dictionary.

Disadvantages

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• The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets to detect Stock Price Prediction.

• Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.

• Incorrect labeling: The existing machine learning models are only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions.

IV. PROPOSED SYSTEM

A new model for predicting stock prices is proposed in this paper (MS-SSA-LSTM), which matches the characteristics of multi-source data with LSTM neural networks and uses the Sparrow Search Algorithm. The MS-SSA-LSTM stock price forecast model can forecast the stock price in advance and help investors and traders make more informed investment decisions. Investors and traders obtain the data of individual stocks they want to invest in, including historical transaction data and comment information of stock market shareholders, and input them into the MS-SSA-LSTM model. The model automatically outputs a stock price trend chart and forecasts the stock price for the next day. Here, we can get the motivation for this paper.

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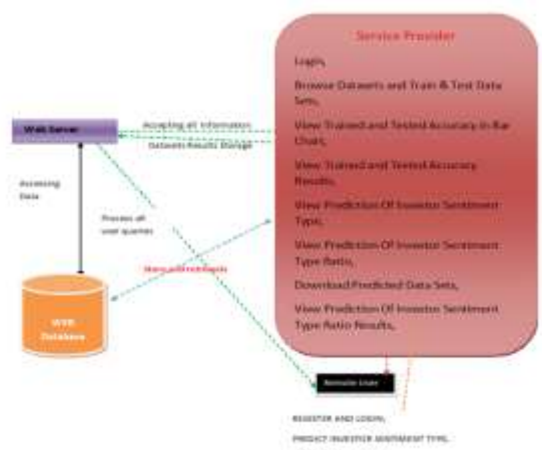
Advantages

(1) The SSA-LSTM model incorporates multi-source data that affects stock prices, such as historical trade data and stock forum comments. The MS-SSA-LSTM model outperforms the single data source model regarding prediction accuracy.

(2) Analyze the stock forum comments text information. Then, we construct a sentiment dictionary based on authoritative dictionaries in the financial investment field suitable for individual stock sentiment analysis and sentiment indicator calculation.

(3) A Sparrow Search Algorithm-optimized LSTM model can acquire better hyper parameter values and forecast stock prices than a single LSTM network.

V. SYSTEM ARCHITECTURE



VI. SYSTEM IMPLEMENTATION MODULES

Service Provider

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In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Predicted Job Title Identification Type, View Job Title Identification Type Ratio, Download Predicted Data Sets, View Job Title Identification Type Ratio Results, View All Remote Users.

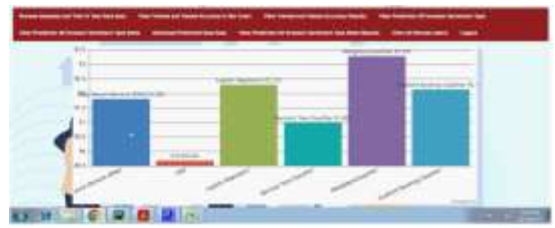
View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, Predict Job Title Identification Type, VIEW YOUR PROFILE.

VII. RESULTS



VIII. CONCLUSION

The stock price is affected by shareholder emotion, and the hyper parameters in the LSTM network are frequently chosen based on subjective experience. Therefore, this paper proposes the MS-SSA-LSTM model of stock price prediction. Six representative data sets of individual stocks in the Chinese financial market are selected to train and test the model. Moreover, four assessment indicators are employed to check the model's prediction performance. Through comparative analysis, we can draw the following results.

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First of all, the MS-SSA-LSTM model considers multiple data sources. On the one side, the data source is the characteristics of the historical transaction data, including the previous closing price, opening price, closing price, etc. On the other side, the data source is the sentiment of shareholders in the market. Adding a sentiment indicator enhances the model's predictive performance compared with only using fundamental stock trading indicators as input. Thus, the stock bar can be used as a guiding platform for investor sentiment. The platform managers can conduct public opinion management and early warning, reasonably guide shareholders to invest rationally and take countermeasures in advance for possible panic or riot. Ultimately, we should establish a good and orderly stock market environment.

Secondly, the parameters of LSTM need to be adjusted artificially, which challenges obtaining the best prediction results. Therefore, the SSA is chosen to optimize the LSTM model's hyper parameters. This approach not only objectively explains the network structure and parameter setting of the model but also improves the model's adaptability and forecasting capabilities. In a challenging financial market, the LSTM model optimized by SSA can quickly and precisely comprehend data properties, provide high-precision price prediction, and decrease investors' risk.

Thirdly, the comparative experiments of six individual stocks in different models verify that the MS-SSA-LSTM model has high accuracy, reliability, and adaptability to the stock market. In the experiment, 5-10 time steps can make the prediction effect of the model reach optimal, indicating that the enormous volatility of China's financial market is more suitable for short-term prediction. Meanwhile, this model can be applied to other time series problems.

Finally, the MS-SSA-LSTM model is universal. Although we tested the model only on China's financial market, it is also suitable for foreign stock markets. The input values to the model are multi-source data, one is the technical stock data, and the other is the sentiment index of shareholders. These multi-source data exist in both Chinese and foreign financial markets. Social media platforms for discussing stock prices are diversified and open. As long as we can dig out the comments on the stock, we can calculate the sentiment index and use it as one of the model's input features. In addition, establishing a comment platform for the stock market helps us collect comments easily and quickly.

FUTURE SCOPE

In the MS-SSA-LSTM model, our multi-source data still have limitations. Regarding sentimental analysis, this paper only divides emotions into positive and negative. In addition, other variables, such as macroeconomic conditions and policy shifts, will also impact the stock price forecast. In the future, sentimental analysis needs to be further refined. We should extract different emotional indicators into our research, such as sadness, fear, anger, and disgust. Meanwhile, more data sources, such as Weibo and WeChat official accounts, may be introduced to estimate market sentiments. In addition, we should use mining techniques to find other factors that predict stock prices.

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