Forecasting China's Consumer Price Index with a Double-Layer Attention-Enhanced LSTM Model

MANRU DONG[1], and XIAOBIN TANG[2]
[1]School of Systems Science and Statistics, Beijing Wuzi University, Beijing 101149, China
[2]School of Statistics, University of International Business and Economics, Beijing 100029, China

ABSTRACT Against the backdrop of an increasingly complex and volatile domestic and international economy, timely and accurate forecasting of the consumer price index (CPI) is important for strengthening consumer confidence, implementing the strategy of expanding domestic demand, and supporting macroeconomic management. To address the multidimensional dynamics of CPI movements and the lag in official data release, this study constructs a CPI forecasting dataset by combining official statistics with text-mined online search indicators. A double-layer attention-enhanced long short-term memory model, denoted ATT-LSTM-ATT, is then developed by integrating Multi-Representational Attention and Soft Attention into the LSTM architecture. The first attention layer adaptively weights input features, while the second emphasizes critical temporal states. The proposed model is compared with ATT-LSTM, standard LSTM, support vector regression (SVR), random forest (RF), XGBoost, and LightGBM (LGBM). The empirical results show that: (1) the double-layer attention mechanism substantially improves the ability of the LSTM model to capture key features and critical time points, especially signals associated with real estate policy, shopping festivals, and holidays; (2) compared with six benchmark models, ATT-LSTM-ATT delivers the best overall forecasting accuracy and exhibits stronger stability across long-, medium-, and short-horizon prediction tasks; and (3) the text-mining-based forecasting framework can generate monthly CPI estimates about three weeks earlier than the official release. These findings suggest that combining big-data text signals with an attention-enhanced deep learning architecture provides a useful approach for timely CPI nowcasting and macroeconomic decision support.

INDEX TERMS consumer price index; inflation nowcasting; LSTM; attention mechanism; online search data

I. INTRODUCTION

Since the reform and opening-up period, China has achieved a historic transition from high-speed growth to high-quality development. At the current stage, however, the economy continues to face the combined pressures of demand contraction, supply shocks, and weakening expectations. Among these issues, sluggish consumption and weak household demand are particularly important. Strengthening consumption vitality, restoring consumer confidence, and upgrading the consumption structure have therefore become central to the strategy of expanding domestic demand and sustaining high-quality growth. In this context, timely and accurate forecasting of the consumer price index (CPI) is essential. Reliable CPI forecasts help policymakers monitor the dynamics of household consumption, optimize resource allocation, improve industrial coordination, and formulate more effective macroeconomic policy [25].

As one of the most important macroeconomic indicators, CPI has long attracted attention in both economic theory and policy practice. However, as economic activity becomes more complex, consumption patterns evolve, and statistical indicators remain low-frequency and lagged, CPI has become more difficult to forecast accurately in real time. Traditional forecasting methods are often constrained by restrictive assumptions, low-frequency data, and limited ability to capture nonlinear relationships [1-4]. Under the conditions of the big-data era, conventional approaches no longer fully satisfy the needs of economic monitoring and policy design [24].

Existing studies on CPI forecasting can be broadly divided into two strands. The first relies on traditional econometric methods, such as GARCH, ARIMA, and exponential smoothing, to model monthly CPI series [1-4]. Although these models are interpretable, their performance is often limited when the data-generating process is nonlinear or when high-frequency information is needed. To overcome the low-frequency nature of official monthly data, some scholars have introduced mixed-frequency models and high-frequency observable indicators. Studies using MIDAS, mixed-frequency vector autoregressions, online price data, and search intensity data report meaningful improvements in short-term CPI forecasting [5-9].

The second strand uses machine learning methods that are less dependent on strong parametric assumptions and are better suited to nonlinear and high-dimensional data. Prior research shows that machine learning algorithms, including clustering methods and long short-term memory (LSTM) networks, can outperform traditional regression-based approaches in macroeconomic forecasting tasks [10-15]. With further advances in deep learning, researchers have improved LSTM models either by combining them with other algorithms such as CNN and SVR [16,17], or by first decomposing time series into multiple components before prediction [18,19]. Yet relatively little work has focused on improving the internal structure of the neural network itself for CPI forecasting, especially by modeling feature importance and temporal importance simultaneously within a single framework [20,21].

This study addresses that gap by introducing a double-layer attention mechanism into an LSTM network. Specifically, Multi-Representational Attention is used to identify and reweight important input features, while Soft Attention is used to highlight critical temporal states in the historical sequence. Based on this architecture, we construct the ATT-LSTM-ATT model and apply it to CPI forecasting in China [22-24].

The main contributions of this study are threefold. First, from the perspective of improving the internal structure of the neural network, we integrate feature-level and temporal-level attention into a single LSTM forecasting framework. This design allows the model to capture the dynamic effects of both important predictors and important time points on CPI movements. Second, by comparing seven machine learning models across long-, medium-, and short-horizon forecasting tasks, we show that ATT-LSTM-ATT achieves superior accuracy and stronger stability, while alternative models display horizon-dependent heterogeneity. Third, by combining text-mined online search indicators with the attention-enhanced deep learning model, the proposed framework can produce CPI forecasts roughly three weeks earlier than the official publication schedule.

The remainder of the paper is organized as follows. Section 2 presents the model design and data construction strategy. Section 3 reports the empirical results and comparative forecasting performance. Section 4 concludes and discusses policy implications.

II. MODEL DESIGN AND RESEARCH FRAMEWORK

A. MOTIVATION FOR THE ATT-LSTM-ATT MODEL

The LSTM model proposed by Hochreiter and Schmidhuber is well suited to multivariate time-series forecasting because it can learn long-term dependencies and handle nonlinear dynamics [22]. However, a standard LSTM implicitly treats input information more uniformly and does not explicitly distinguish between more informative and less informative signals. This limitation is important in CPI forecasting. China's CPI series is released in raw form without seasonal adjustment, and prior studies have shown that holiday effects, especially those associated with the Spring Festival, can materially affect short-term inflation dynamics [23]. If a model weights all time steps and features equally, it may fail to capture these asymmetric effects.

Attention mechanisms offer a practical way to address this issue. In deep learning, attention modules can suppress redundant information, amplify task-relevant signals, and allocate greater weights to observations that are more informative for the prediction target. In this study, two complementary attention mechanisms are introduced into the LSTM structure.

First, Multi-Representational Attention is applied at the feature level. This module assigns differentiated weights to input variables at the same time point so that the model can identify which predictors are most relevant for current CPI movements. Second, Soft Attention is applied at the temporal level. Based on the sequence of hidden states, the model computes attention weights across time steps and emphasizes historical moments that are particularly informative, such as major holidays or demand shocks.

By combining these two mechanisms, the ATT-LSTM-ATT architecture improves the model's ability to recognize important predictors and important time points simultaneously. This dual enhancement is intended to improve the interpretability, stability, and forecasting accuracy of the baseline LSTM.

B. DATA SOURCES

The target variable is China's consumer price index. Monthly CPI data are obtained from the CEInet Statistics Database for the period from January 2011 to August 2021. The predictor variables are keyword-based search indicators extracted through text mining and collected from the Baidu Search Index. The search series are weekly observations covering January 1, 2011 to August 28, 2021.

Because the monthly CPI sample is relatively small for machine learning training, and because price movements are gradual and continuous, the monthly CPI series is expanded to weekly frequency by cubic spline interpolation. The interpolated CPI series is denoted by y_t. This mixed data construction allows the model to exploit higher-frequency search information while preserving the structure of the official CPI series.

Online search data are a useful source of information because they are timely, highly responsive to user behavior, and relatively easy to collect. Search intensity can reflect consumer concern about prices, supply conditions, and specific categories of goods and services. Although raw online search data can contain noise, appropriate statistical screening can isolate the informative components for forecasting.

C. CONSTRUCTION AND SCREENING OF PREDICTOR VARIABLES

The text-mining procedure consists of three steps.

First, candidate keywords are generated by extending seed terms related to CPI forecasting. Following prior work, BERT-based semantic expansion and an interactive TF-IDF-based text-mining procedure are used to construct a broad candidate set of search terms associated with inflation, consumption, and price fluctuations [24].

Second, the candidate variables are screened using Pearson cross-correlation analysis with different lags. This procedure identifies predictors with strong lead-lag relationships with CPI and is therefore suitable for macroeconomic nowcasting. Using an absolute correlation threshold of 0.35, the initial set is reduced to nine potential predictors.

Third, the shortlisted variables are further filtered using stepwise regression with a significance level of 0.01. The final model retains five predictors with the strongest forecasting performance.

Table 1 reports the correlation analysis and lag structure of the screened predictors.

Table 1. Correlation analysis between candidate predictors and CPI

Predictor	Symbol	Lag	Data type	Absolute correlation	Period	p-value
Lagged CPI observation	y_{t-1}	1	-	0.9958	2011.03.12-2021.08.28	<0.01
Natural gas	$X_{1,t-1}$	1	Seed term	0.5176	2011.03.12-2021.08.28	<0.01
Gold and U.S. dollar	$X_{2,t-9}$	9	BERT-expanded term	0.5142	2011.03.12-2021.08.28	<0.01
Daily necessities	$X_{3,t-1}$	1	TF-IDF-expanded term	0.5092	2011.03.12-2021.08.28	<0.01
Real estate policy	$X_{4,t-10}$	10	BERT-expanded term	0.4375	2011.03.12-2021.08.28	<0.01
Sesame oil	$X_{5,t-6}$	6	BERT-expanded term	0.4313	2011.03.12-2021.08.28	<0.01
Tobacco	$X_{6,t-1}$	1	Seed term	0.4290	2011.03.12-2021.08.28	<0.01
Leverage	$X_{7,t-1}$	1	Seed term	0.4277	2011.03.12-2021.08.28	<0.01
Macro regulation	$X_{8,t-6}$	6	TF-IDF-expanded term	0.3737	2011.03.12-2021.08.28	<0.01
Benchmark interest rate	$X_{9,t-5}$	5	BERT-expanded term	0.3599	2011.03.12-2021.08.28	<0.01

Note: Predictors marked in the original study as final inputs are retained in the forecasting model. Because online search data are available from 2011 onward, the sample starts in 2011.

D. INPUT SET CONSTRUCTION AND DATA PREPROCESSING

The correlation results show that current CPI is strongly positively associated with its first lag, with a correlation coefficient of 0.9958. It is therefore necessary to include lagged CPI in the model input. The other retained predictors also have clear economic relevance. The "gold and U.S. dollar" index reflects shifts in safe-haven demand, investment sentiment, and exchange-rate conditions that may influence consumption and pricing behavior. Natural gas and daily necessities are closely related to household expenditures and can directly affect the allocation of consumption budgets. Real estate policy can influence asset allocation and consumption structure through price controls and purchase restrictions, thereby helping to capture future CPI movements.

Based on these considerations, the final supervised learning dataset is defined as:

$$\{y_{t-1}, X_{1,t-1}, X_{2,t-9}, X_{3,t-1}, X_{4,t-10} : y_t\}.$$

The model input is therefore the set $\{y_{t-1}, X_{1,t-1}, X_{2,t-9}, X_{3,t-1}, X_{4,t-10}\}$, and the output variable is y_t, the current-period CPI. Because the explanatory variables lead the target, the model can generate a current-month CPI estimate in the middle or latter part of the month.

To improve convergence and reduce the influence of scale differences and outliers, all variables are normalized using min-max scaling:

$$N(x_i) = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}.$$

After prediction, the model outputs are transformed back to the original scale through inverse normalization.

E. EVALUATION METRICS

Following the forecasting literature, four evaluation metrics are used: mean absolute error (MAE), mean squared error (MSE), the correlation coefficient R, and relative error σ. MAE and MSE measure forecast precision, with smaller values indicating better performance. The correlation coefficient R reflects predictive fit, with values closer to one indicating stronger alignment between predicted and actual series. Relative error is used to examine the deviation of forecasts from the true values over time, especially around key events.

III. EMPIRICAL ANALYSIS

A. EXPERIMENTAL DESIGN

To evaluate both forecasting performance and model stability, the sample is divided into long-, medium-, and short-horizon forecasting tasks. Following the original study design and related forecasting practice, a sliding window of 12 periods is selected through repeated experiments [14,23]. In other words, the previous 12 weekly observations are used to forecast the next CPI value.

Based on out-of-sample forecasting steps, the test sets are defined as follows: 72 periods for long-horizon forecasting, 36 periods for medium-horizon forecasting, and 12 periods for short-horizon forecasting. For comparability, the same data partitioning strategy is used for all benchmark models.

The forecasting experiments are implemented in Python under the TensorFlow framework for LSTM-based models. The three neural architectures considered are ATT-LSTM-ATT, ATT-LSTM, and standard LSTM. In addition, four benchmark machine learning models are included: SVR, RF, XGBoost, and LGBM. The best model configurations are selected via grid search [23,24,26].

B. EFFECT OF THE DOUBLE-LAYER ATTENTION MECHANISM ON LSTM FORECASTING

The first set of experiments examines how the introduction of attention affects the forecasting performance of the baseline LSTM model. Visual inspection of the fitted curves in the long-horizon experiment shows that the standard LSTM generally follows the overall CPI trend but produces sharp local oscillations, suggesting instability. After the introduction of Soft Attention, the fitted curve becomes smoother and the large local fluctuations are reduced, although deviations from the actual CPI path remain. When Multi-Representational Attention is further introduced, the fitted curve becomes both smoother and closer to the observed series.

Relative-error analysis leads to the same conclusion. Around key dates such as National Day, the Double Eleven shopping festival, and the Spring Festival, the ATT-LSTM model exhibits substantially smaller relative forecast errors than the baseline LSTM. This finding suggests that Soft Attention effectively reallocates temporal attention toward critical historical moments and thereby improves predictive performance. Once Multi-Representational Attention is added, the dispersion between predictions and actual values declines further, indicating that feature-level attention provides additional gains beyond temporal weighting alone.

The original study also extracts feature-attention weights before and after introducing Multi-Representational Attention. Without attention, the standard LSTM assigns the same weight (0.2) to each of the five input variables. After attention is added, the model allocates greater weight to lagged CPI and real estate policy, both of which receive attention values above the average. This result indicates that the feature-level attention module improves the network' s ability to distinguish more informative predictors from less informative ones.

Taken together, these results show that the double-layer attention design strengthens the LSTM model's focus on important features and critical time points, reduces forecast error, and improves stability in CPI prediction.

C. COMPARATIVE FORECASTING PERFORMANCE ACROSS MACHINE LEARNING MODELS

The next set of experiments compares ATT-LSTM-ATT with six benchmark models. In the long-horizon prediction task, the tree-based models LGBM, XGBoost, and RF track CPI reasonably well when the observed series changes smoothly, but they deviate more substantially when the CPI exhibits persistent fluctuations. By contrast, ATT-LSTM-ATT and SVR remain closer to the actual series throughout the forecasting period.

Table 2 reports the long-horizon forecasting results. ATT-LSTM-ATT achieves the smallest MAE and MSE and the largest correlation coefficient among all seven models.

Table 2. Forecasting performance for long-horizon CPI prediction

Model	MAE	MSE	R
ATT-LSTM-ATT	0.0350	0.0019	0.9849
ATT-LSTM	0.0446	0.0052	0.9670
LSTM	0.2346	0.0885	0.9456
XGBoost	0.3329	0.2429	0.9264
LGBM	0.4649	0.4549	0.7694
RF	0.3875	0.3287	0.9126
SVR	0.1229	0.0286	0.9808

Relative to ATT-LSTM and standard LSTM, ATT-LSTM-ATT improves MAE by 40.13% and 88.62%, respectively. Using the correlation coefficient as the performance criterion, the gains are 1.85% over ATT-LSTM and 4.16% over LSTM. Compared with XGBoost, LGBM, RF, and SVR, the proposed model improves forecasting precision by 91.98%, 94.25%, 93.11%, and 78.27%, respectively. These results indicate that combining feature-level and temporal-level attention materially enhances the learning capacity of the baseline LSTM.

To examine robustness across forecasting horizons, the same comparison is conducted for medium- and short-horizon tasks. The results are shown in Table 3.

Table 3. Forecasting performance for medium- and short-horizon CPI prediction

Model	Medium MAE	Medium MSE	Medium R	Short MAE	Short MSE	Short R
ATT-LSTM-ATT	0.0156	0.0037	0.9853	0.0088	0.0013	0.9930
ATT-LSTM	0.0171	0.0042	0.9812	0.0116	0.0024	0.9790
LSTM	0.1686	0.0402	0.8999	0.0498	0.0060	0.9930
XGBoost	0.1226	0.0264	0.9654	0.0970	0.0147	0.8791
LGBM	0.3026	0.1535	0.8121	0.1281	0.0232	0.7731
RF	0.1321	0.0307	0.9771	0.0722	0.0072	1.0000
SVR	0.0904	0.0116	0.9761	0.1018	0.0176	1.0000

The results confirm two important patterns. First, the double-layer attention mechanism consistently improves the LSTM model in both medium- and short-horizon settings, and ATT-LSTM-ATT remains the best overall model. Second, the benchmark models exhibit clear horizon heterogeneity. Tree-based models such as XGBoost, LGBM, and RF perform relatively better in short-horizon prediction than in medium- or long-horizon prediction, whereas SVR performs better in medium- and long-horizon tasks. Standard LSTM performs relatively well in long- and short-horizon prediction but is less competitive in the medium horizon. This heterogeneity likely reflects differences in the internal structures and inductive biases of the competing models.

D. CROSS-VALIDATION ANALYSIS

To avoid conclusions that depend too heavily on one fixed sample split, the study further evaluates model accuracy and robustness through cross-validation. Because LSTM-type models require temporally ordered inputs, using conventional random k-fold validation would break the sequential structure of the data and violate the operating principle of the network. Therefore, the original study uses the `TimeSeriesSplit` variant in scikit-learn for LSTM and attention-enhanced LSTM models, while standard k-fold validation is used for the non-sequential benchmark models. In all cases, the number of folds is set to six.

Table 4 reports the cross-validation results under the metrics available from the original experiment. For the sequential LSTM-based models, the reported metric is MSE, so lower values indicate better generalization. For the non-sequential benchmark models, the original cross-validation output was `neg_mean_absolute_error`; in Table 4 this score has been converted back to positive MAE for readability. Because the two panels use different error metrics, Table 4 should be interpreted for within-panel comparison rather than direct cross-panel magnitude comparison.

Table 4. Cross-validation results for different machine learning models

Model	Metric	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Mean
ATT-LSTM-ATT	MSE	0.0024	0.0161	0.0042	0.0182	0.0198	0.0052	0.0109
ATT-LSTM	MSE	0.0034	0.0281	0.0062	0.0342	0.0268	0.0072	0.0176
LSTM	MSE	0.0040	0.0072	0.0006	0.0885	0.0013	0.0088	0.0193
SVR	MAE	0.0573	0.0093	0.0062	0.0171	0.0090	0.0089	0.0179
RF	MAE	0.0307	0.0041	0.0018	0.0260	0.0034	0.0557	0.0203
XGBoost	MAE	0.0617	0.0043	0.0023	0.0053	0.0043	0.0604	0.0231
LGBM	MAE	0.0931	0.0046	0.0019	0.0054	0.0041	0.0762	0.0308

Note: For the non-LSTM models, the original score was reported in scikit-learn as `neg_mean_absolute_error`; the values shown here are the sign-reversed MAE values. Accordingly, ATT-LSTM-ATT, ATT-LSTM, and LSTM are compared within the MSE panel, while SVR, RF, XGBoost, and LGBM are compared within the MAE panel.

The cross-validation evidence is directionally consistent with the fixed-split experiments. Within the LSTM-based group, the mean MSE declines as attention mechanisms are introduced sequentially, indicating that the double-layer attention structure improves both accuracy and generalization. Within the benchmark group, SVR yields the smallest mean MAE among the non-sequential machine learning models. These results support the broader conclusion from the fixed-split experiments that ATT-LSTM-ATT strengthens the performance of the baseline LSTM, while the benchmark models continue to display differentiated behavior across evaluation settings.

E. MAIN FINDINGS AND INTERPRETATION

Three conclusions emerge from the empirical analysis.

First, integrating Multi-Representational Attention and Soft Attention significantly improves LSTM-based CPI forecasting. The model becomes better at recognizing both salient features and important temporal states, which reduces forecast error and enhances stability.

Second, ATT-LSTM-ATT outperforms six benchmark machine learning models and remains stable across long-, medium-, and short-horizon forecasting tasks. At the same time, the benchmark models display horizon-specific heterogeneity. Tree-based models are relatively better suited to short-horizon CPI prediction, SVR is better suited to medium- and long-horizon tasks, and standard LSTM performs relatively well in long- and short-horizon settings.

Third, the text-mining-based predictor set allows the model to nowcast the current month's CPI approximately three weeks earlier than the official publication date. This lead time is economically meaningful because it provides decision-makers with a more timely signal of consumption and inflation dynamics.

IV. CONCLUSION

This paper develops a double-layer attention-enhanced LSTM model for forecasting China's CPI under conditions of complex macroeconomic change, lagged official data release, and increasingly rich online information flows. By combining text-mined search indicators with feature-level and temporal-level attention modules, the proposed ATT-LSTM-ATT model improves on standard LSTM and performs better than a set of benchmark machine learning models.

The empirical results show that the proposed model has three main advantages. It improves the identification of important features and critical time points, delivers higher forecasting accuracy and stronger stability across different horizons, and produces current-month CPI estimates about three weeks ahead of the official release schedule. These results suggest that big-data indicators and attention-enhanced deep learning can provide a useful methodological foundation for macroeconomic nowcasting.

The findings also have practical implications. For policymakers, more timely CPI forecasts can support resource allocation, consumption policy design, and macroeconomic regulation. For official statistics, the integration of big data and natural language processing may complement traditional survey-based systems and improve the timeliness of economic monitoring. More broadly, the proposed double-layer attention framework may be extended to the prediction of other macroeconomic indicators.

At the same time, the study has limitations. The predictor set is based on text-mined search indicators and may still omit other relevant real-time signals. The sample period ends in August 2021, which leaves room for validation with more recent data. Future research can expand the feature space, test additional deep learning architectures, and further refine the model under updated macroeconomic conditions.

REFERENCES

1. Protopapadakis F. Macroeconomic factors do influence aggregate stock returns. *Review of Financial Studies*, 2002, 15(3): 751-782.
2. Du Y D, Cai Y, Chen M X, et al. A novel divide-and-conquer model for CPI prediction using ARIMA, gray model and BPNN. *Procedia Computer Science*, 2014, 31: 842-851.
3. Sultana K, Rahim A, Moin N, et al. Forecasting inflation and economic growth of Pakistan by using two time series methods. *International Journal of Business and Economics Research*, 2013, 2(6): 174-178.
4. Zhou S B, Wang X B, Guo J F. The dynamic relevance of inflation expectations and actual inflation: An analysis based on the macro-finance model. *Chinese Journal of Management Science*, 2014, 22(11): 27-35.
5. Gong Y T, Chen Q, Zheng X. Short-term forecasting of CPI based on MIDAS models. *Statistical Research*, 2014, 31(12): 25-31.
6. Li X, Shang W, Wang S Y, et al. A MIDAS modelling framework for Chinese inflation index prediction incorporating Google search data. *Electronic Commerce Research and Applications*, 2015, 14(16): 112-125.
7. Zhang J F, Gang J H, Qian Z X, et al. Macroeconomic forecasts based on the MF-BVAR. *Journal of Financial Research*, 2018(7): 34-48.
8. Zhang H, Shen H L, Xia L. Research on CPI prediction based on multi-source asynchronous mixed sampling data. *Journal of Quantitative and Technological Economics*, 2020, 37(10): 149-168.
9. Lin K Y, Xun C, Wang F, et al. Research on the influence of volatility of international energy commodity futures market on CPI in China. *Complexity*, 2021, 2021(1): 7069193.
10. Zahara S, Ilmiddafiq M B. Prediksi indeks harga konsumen menggunakan metode long short term memory (LSTM) berbasis cloud computing. *Journal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, 2019, 3(3): 357-363.
11. Acosta M A. Machine learning core inflation. *Economics Letters*, 2018, 169: 47-50.
12. Chen M G, Ren T P. CPI predictive model for new normal economy: Construction and empirical comparison. *The World of Survey and Research*, 2020(2): 3-8.

13. Chen Y B, Liu L J, Chen X L. Prediction of China's inflation rate: A comparative analysis based on the LSTM model and the BVAR model. *Research on Financial and Economic Issues*, 2021(6): 18-29.
14. Yang Q, Wang C W. A study on forecast of global stock indices based on deep LSTM neural network. *Statistical Research*, 2019, 36(3): 65-77.
15. Tang X B, Dong M R, Zhang R. Research on the prediction of consumer confidence index based on machine learning LSTM&US model. *Statistical Research*, 2020, 37(7): 104-115.
16. He X W, Xu J J, Wang B, et al. Research on cloud computing resource load forecasting based on GRU-LSTM combination model. *Computer Engineering*, 2022, 48(5): 11-17, 34.
17. Li B R, Pi D C, Hou M R. Destination prediction of moving objects based on convolutional neural networks and long-short term memory. *Computer Science*, 2021, 48(4): 70-77.
18. He Y Y, Li P, Han J B. Research on predictive modeling on stock market index based on CEEMDAN-LSTM. *Journal of Statistics and Information*, 2020, 35(6): 34-45.
19. Shi X L, Li L, Zhao Q H. Air quality index prediction based on improved LSTM network. *Statistics and Decision*, 2021, 37(16): 57-60.
20. Tao Z Y, Li X B, Liu Y, et al. Classifying short texts with improved-attention based bidirectional long memory network. *Data Analysis and Knowledge Discovery*, 2019, 3(12): 21-29.
21. Zhou Y, Liu Y, Cai J. Sentiment analysis of microblogs based on attention mechanism. *Information Studies: Theory and Application*, 2018, 41(3): 89-94.
22. Hochreiter S, Schmidhuber J. Long short-term memory. *Neural Computation*, 1997, 9(8): 1735-1780.
23. Wang Z Z, Chen S J, Tu Y D. Analyzing Chinese consumer price index comparatively with that of the United States. *Journal of Applied Statistics and Management*, 2023, 42(1): 109-126.
24. Tang X B, Dong M R, Xu R. Design and application of text mining techniques for CPI prediction based on big data. *Statistical Research*, 2021, 38(8): 146-160.
25. Liang F, Shen S H, Huang Z. Forecasts of macroeconomic variables in China: Combination forecasts of surveys and models. *Journal of Financial Research*, 2021(7): 58-76.
26. Shahid F, Zameer A, Muneeb M. Predictions for COVID-19 with deep learning models of LSTM, GRU and Bi-LSTM. *Chaos, Solitons and Fractals*, 2020, 140: 110212.