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Research on Algorithm Improvement of ARIMA-LSTM Hybrid Model in Time Series Prediction of Inflation Rate

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Abstract: As a key indicator of macroeconomic performance, inflation trends significantly influence monetary policy, macroeconomic regulation, and financial market stability. However, macroeconomic time series often contain both linear trends and complex nonlinear fluctuations, which limit the accuracy and stability of traditional statistical models. To address this, the paper proposes an improved ARIMA-LSTM hybrid forecasting model for inflation rate prediction. The ARIMA component extracts the linear structure of the series, while the residual sequence captures unexplained nonlinear information. A multi-scale LSTM network then learns deep features from the residuals, and a dynamic weight fusion mechanism adaptively combines linear and nonlinear predictions. Experiments using CPI data from IMF, World Bank, and FRED databases show that the proposed model achieves an RMSE of 0.564 on the test set—12.1% lower than the traditional ARIMA-LSTM and 17.1% lower than ARIMA alone. It also outperforms models such as SVR, random forest, LSTM, and GRU in MAE and MAPE. In multi-step forecasting, error growth remains around 12% over six steps, notably lower than comparison models. Ablation studies and Diebold–Mariano tests confirm the effectiveness of the multi-scale module and dynamic fusion mechanism. Overall, the improved ARIMA-LSTM model enhances inflation prediction accuracy and stability, offering practical value for macroeconomic forecasting and policy analysis.

Keywords: Inflation rate forecast; Time series analysis; ARIMA-LSTM hybrid model; Multi-scale LSTM; Dynamic weight fusion

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1. INTRODUCTION

1.1 Research background and problem posing

Inflation rate is an important macroeconomic indicator to measure the change of a country's price level, and it is also an important reference variable for the government and the

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central bank to formulate economic policies [1],[2]. A stable inflation level is usually regarded as an important symbol of the healthy operation of the macro-economy, and too high or too low inflation rate will have a negative impact on the economic system. For example, sustained high inflation will weaken the real purchasing power of residents and cause economic instability, while deflation may inhibit consumption and investment activities, thereby dragging down economic growth [3],[4]. Therefore, accurate prediction of inflation rate is of great significance for macroeconomic regulation, monetary policy-making and financial market stability.

In traditional macroeconomic research, time series model is widely used to predict inflation rate. Among them, the autoregressive integral moving average model (ARIMA) is a classical statistical method [5],[6],[7]. The model establishes a prediction model by analyzing the historical dependence in the time series, which has good interpretability and application foundation in the prediction of economic data. However, macroeconomic data are often affected by a variety of complex factors, and their changes not only include linear trends, but also show obvious nonlinear fluctuation characteristics [8],[9]. The traditional ARIMA model has some limitations in dealing with complex nonlinear structures, so its prediction ability is often limited in the face of economic cycle changes or sudden shocks.

In recent years, with the development of artificial intelligence technology, deep learning model has been gradually applied to the task of economic time series prediction. Among them, the long-term and short-term memory network (LSTM), as an improved cyclic neural network structure, can effectively capture the long-term dependence in the time series through the gating mechanism, and has been widely used in financial market prediction and macroeconomic analysis. Compared with the traditional statistical model, LSTM has obvious advantages in processing complex nonlinear data [10],[11]. However, the deep learning model also has some shortcomings in macroeconomic forecasting, such as the model is sensitive to data scale, weak in the interpretation of linear trends, and prone to fitting problems in some scenarios. Therefore, how to combine the advantages of statistical model and deep learning model to build a more efficient time series forecasting method has become an important issue in the current economic forecasting research.

1.2 Overview of existing research

For the prediction of inflation rate, the academic community has carried out a lot of related research. Early studies were mainly based on traditional statistical models, such as autoregressive model, moving average model and ARIMA model. This kind of model is widely used in the field of macroeconomic forecasting by analyzing the historical dependence of time series. Some researches also apply vector autoregressive model and other methods to the prediction of macroeconomic variables, and improve the prediction accuracy by modeling the relationship between multiple economic variables at the same time [12],[13]. However, because these models are usually based on linear assumptions, when the economic system shows complex nonlinear dynamic characteristics, its prediction ability is often limited.

With the development of machine learning technology, more and more research began to explore the use of neural network model for macroeconomic forecasting. For example, the cyclic neural network and LSTM model show good performance in the field of financial time series prediction [14],[15],[16]. Some studies show that the deep learning model can improve the accuracy of time series prediction by learning the complex patterns in historical data. However, this kind of model usually lacks the explicit modeling ability for the linear structure of time series, and is relatively weak in the explanatory aspect.

In order to combine the advantages of statistical model and deep learning model, some scholars have proposed hybrid prediction model. For example, the ARIMA model is used to capture the linear trend in the time series, and then the neural network model is used to model the residual sequence, so as to realize the learning of nonlinear characteristics. This ARIMA-LSTM hybrid model has achieved good results in some economic forecasting tasks [17],[18].

However, the existing hybrid models still have some shortcomings, such as the simple model fusion, the lack of adaptive coordination mechanism between different models, and the limited ability of feature extraction. Therefore, how to improve the hybrid model structure to further improve the prediction performance is still a problem worthy of further study.

1.3 Research issues and challenges

In the task of forecasting inflation rate time series, model design faces many challenges. Firstly, macroeconomic time series usually contain both linear trend and nonlinear fluctuation characteristics, and these two types of structures are often intertwined in the time series. For example, the long-term trend may show relatively stable changes, while the short-term fluctuations may be affected by economic policies, changes in the international market, emergencies and other factors [19],[20]. Therefore, if only a single model is used for prediction, it is often difficult to capture these different types of dynamic features at the same time.

Secondly, macroeconomic time series usually have obvious non-stationary and structural change characteristics. With the change of economic environment, the statistical characteristics of time series may change in different stages. For example, in the period of economic crisis or major policy adjustment, the inflation rate may fluctuate suddenly. This structural change not only increases the difficulty of time series prediction, but also puts forward higher requirements for the stability of the model [21].

In addition, the traditional ARIMA-LSTM hybrid model usually uses a simple superposition method for model fusion, that is, the linear prediction results and nonlinear prediction results are directly combined. This fixed fusion method is inflexible and cannot dynamically adjust the contribution ratio of different models according to the changes of data structure. Therefore, under the complex economic environment, the prediction performance of the model may be unstable. How to design a more reasonable fusion mechanism so that the model can be adjusted adaptively according to the characteristics of time series in different stages is one of the important challenges of current research.

1.4 Research objectives

Aiming at the above problems, this paper takes the time series prediction of inflation rate as the research object, and proposes an improved ARIMA-LSTM hybrid prediction model. By structurally integrating the statistical model and the deep learning model, the model can capture the linear trend and complex nonlinear dynamic characteristics in the time series at the same time [22]. Through the structural decomposition modeling of time series, ARIMA model is mainly used to extract stable linear trends, while deep learning model is used to learn the nonlinear change patterns in time series, so as to improve the overall prediction ability.

The main goal of this paper is to build a prediction model of inflation rate with high prediction accuracy and stability, so that it can maintain good prediction performance in different economic environments. At the same time, by designing a more reasonable model structure and integration mechanism, we can improve the adaptability of the model in complex macroeconomic data, and provide more reliable data support for macroeconomic policy analysis and financial market prediction.

1.5 Main contributions

This paper improves the structure and fusion mechanism of time series prediction model. Firstly, an adaptive ARIMA-LSTM hybrid model architecture based on residual driven mechanism is proposed. By decomposing the original time series into linear and nonlinear parts, the statistical model and deep learning model can learn different types of time series characteristics respectively, so as to improve the overall prediction ability.

Secondly, this paper designs a dynamic weight fusion mechanism, which automatically adjusts the weight ratio between the prediction results of different models by learning the characteristics of time series, so that the model can dynamically balance the linear and nonlinear information according to the changes of data structure, so as to improve the prediction stability.

In addition, this paper also introduces the multi-scale time feature enhancement module to model the time series by constructing the multi-scale LSTM structure, so that the model can capture short-term fluctuations, medium-term cycles and long-term trend changes at the same time, so as to enhance the ability of time series feature expression. At the same time, this paper also constructs a complete experimental evaluation framework, and systematically verifies the improved model through a variety of comparative models and statistical test methods.

1.6 Structure arrangement

The research content of this paper is carried out according to the following structure. The second part describes the modeling problem of inflation rate time series, and analyzes the main characteristics of macroeconomic time series. The third part introduces the basic principles of the traditional ARIMA-LSTM hybrid model, and analyzes its shortcomings. In the fourth part, an improved ARIMA-LSTM hybrid prediction model is proposed, and the model structure and algorithm design are described in detail. The fifth part introduces the experimental data sources, data preprocessing methods and experimental settings. The sixth part systematically analyzes the prediction performance of the model through experiments, and compares it with a variety of benchmark models. The seventh part analyzes the model complexity and parameter scale from the theoretical perspective. The eighth part discusses the application value of the model in macroeconomic policy analysis and financial risk management. Finally, in the ninth part, the research results of the full text are summarized, and the future research directions are prospected.

2. TIME SERIES MODELING OF INFLATION RATE

2.1 Analysis of data characteristics of inflation rate

The inflation rate, as an important indicator of macroeconomic performance, is usually calculated from the rate of change of the Consumer Price Index (CPI) or Producer Price Index (PPI), and its time series has significant and complex statistical characteristics [23]. Similar to general economic time series, inflation rate series often exhibit typical characteristics such as non stationarity, seasonality, volatility clustering, and structural changes in long-term observations, which make their prediction problems difficult to model.

Firstly, inflation rate sequences typically exhibit significant non stationarity. The so-called stationarity of a time series refers to the stability of its statistical features (such as mean, variance, and autocovariance) in the time dimension. However, macroeconomic variables in reality are often influenced by various factors such as economic cycles, policy changes, and fluctuations in the international economic environment, leading to changes in the series mean or variance over time [24]. Assuming the time series of inflation rate is y_t, if it satisfies:

$$E(y_t) = \mu, Var(y_t) = \sigma^2 \tag{1}$$

If the autocorrelation only depends on the time interval k and is independent of the specific time t, then the sequence is weakly stationary. However, in actual data, the above conditions often do not hold, so it is necessary to use methods such as differencing or transformation for smoothing processing, so that the subsequent model can effectively learn its dynamic structure.

Secondly, inflation rate data usually has a certain seasonality. Due to the cyclical changes in consumer behavior, production activities, and holiday effects throughout the year, price levels often exhibit cyclical fluctuations. For example, the prices of food, energy, and other products exhibit significant regular changes in different seasons, which are usually manifested as seasonal patterns with a period of s [25]:

$$y_t = y_{t-s} + \eta_t \tag{2}$$

Among them, s represents the seasonal cycle (such as 12 months or 4 quarters), and η_t is the random disturbance term. If this periodic structure is ignored, the model may not be able to accurately capture repetitive fluctuations in the sequence, thereby reducing prediction accuracy.

In addition, inflation rate sequences often exhibit volatility clustering. This phenomenon refers to the tendency for larger fluctuations to persist over a period of time, while smaller fluctuations tend to occur continuously. This feature means that the variance of the time series is not constant and may exhibit different levels of volatility at different time periods. Mathematically, it can be expressed as:

$$Var(y_t \mid \mathcal{F}_{t-1}) \neq \sigma^2 \tag{3}$$

Among them, $\mathcal{F}_{t-1}$ represents the information set before time $t-1$. This conditional heteroscedasticity phenomenon is very common in financial and macroeconomic data, making it difficult for simple linear models to fully characterize its dynamic characteristics.

Finally, inflation rate data often exhibits structural breaks. Structural changes refer to sudden changes in the generation mechanism of time series at certain time points due to macroeconomic policy adjustments, financial crises, energy price shocks, and other factors. For example, when the central bank adjusts monetary policy or a major economic event occurs, the long-term trend or fluctuation pattern of inflation rate may show significant changes [26]. If the time of structural change is denoted as τ, the sequence may satisfy different generation models at different stages:

$$y_t = \begin{cases} f_1(\cdot), & t < \tau \\ f_2(\cdot), & t \geq \tau \end{cases} \tag{4}$$

This feature further increases the complexity of prediction problems and provides a theoretical basis for introducing more expressive hybrid prediction models.

2.2 Time series prediction problem

In time series forecasting, the goal of inflation rate forecasting is to build a functional model based on historical observation data to estimate the inflation level in the future. Let the time series of inflation rate be:

$$\{y_1, y_2, y_3, \dots, y_t\} \tag{5}$$

Where y_t represents the inflation rate observed at time t. The problem of time series prediction can be formalized as establishing a mapping function by using the observed values of the past p times, so as to predict the future value. Its general mathematical expression is [27]:

$$y_t = f(y_{t-1}, y_{t-2}, \dots, y_{t-p}) + \epsilon_t \tag{6}$$

Where, $f(\cdot)$ represents an unknown prediction function, which is used to describe the influence of historical data on the current observation value; p is the lag order considered by the model; ϵ_t represents the random disturbance term, which is used to describe the random factors that cannot be explained by the model.

In the framework of statistical modeling, the prediction function $f(\cdot)$ can be modeled in different forms. For example, in traditional statistical models, this function is usually assumed to be linear, while in machine learning or deep learning models, $f(\cdot)$ can represent complex nonlinear mapping relationships. Because the inflation rate data contains both linear trend and nonlinear fluctuation, it is often difficult to fully capture its dynamic characteristics by a single model. Based on this consideration, in recent years, researchers have gradually adopted the hybrid model framework to improve the prediction performance by combining the statistical model and the deep learning model.

2.3 Decomposition idea of linear and nonlinear time series

Aiming at the problem of linear structure and nonlinear structure in macroeconomic time series, many studies have proposed to decompose the original series into a combination of linear and nonlinear components. Specifically, the inflation rate series y_t can be expressed as:

$$y_t = L_t + N_t \tag{7}$$

Where L_t represents the linear part of the time series, which mainly reflects the long-term trend, linear autocorrelation structure and stable statistical laws; N_t represents the nonlinear part of the sequence, which is used to describe complex fluctuations, nonlinear dependencies and sudden changes.

In terms of linear partial modeling, the traditional ARIMA can effectively describe the linear autocorrelation structure in time series. The model models the linear dynamics of time series through the combination of autoregressive term, difference term and moving average term, so as to obtain the linear predictive value $\hat{L}_t$.

After the linear prediction is obtained, the residual sequence can be calculated:

$$e_t = y_t - \hat{L}_t \tag{8}$$

The residual sequence usually contains complex patterns that are not explained by linear models, and these patterns often have obvious nonlinear characteristics. In order to further mine these nonlinear information, we can use deep learning models such as LSTM to model the residual sequence, so as to obtain the nonlinear prediction result $\hat{N}_t$. This linear nonlinear decomposition method can make full use of the respective advantages of statistical model and deep learning model to improve the accuracy and stability of time series prediction.

2.4 Definition of evaluation index for prediction problems

In order to objectively evaluate the performance of different prediction models in inflation rate prediction tasks, it is necessary to introduce multiple error indicators to quantitatively evaluate the prediction results. Assuming the real inflation rate is y_t, the model's predicted value is $\hat{y}_t$, and the sample size is n, the commonly used evaluation indicators are as follows.

Mean Squared Error (MSE) is used to measure the average square of the error between predicted and true values, expressed as [28],[29]:

$$MSE = \frac{1}{n}\sum_{t=1}^{n} (y_t - \hat{y}_t)^2 \tag{9}$$

This indicator is sensitive to large prediction errors and can effectively reflect the performance of the model under extreme error conditions.

Root Mean Squared Error (RMSE) is the square root form of the mean square error, and its calculation formula is [30],[31]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (y_t - \hat{y}_t)^2} \tag{10}$$

RMSE has the same dimension as the original data, therefore it has a more intuitive explanatory significance in practical applications.

Mean Absolute Error (MAE) is used to evaluate the performance of a model by calculating the average level of absolute prediction error. Its formula is [32],[33],[34]:

$$MAE = \frac{1}{n}\sum_{t=1}^{n} | y_t - \hat{y}_t | \tag{11}$$

Compared to MSE, this indicator is less sensitive to outliers and can more stably reflect the overall prediction accuracy of the model.

Mean Absolute Percentage Error (MAPE) is used to measure the proportion of prediction error relative to the true value, and its expression is [35],[36]:

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \tag{12}$$

MAPE can express prediction error in percentage form, thus having good comparability between data at different scales. By comprehensively using the above evaluation indicators, the performance of the prediction model in the inflation rate time series prediction task can be evaluated from different perspectives, providing reliable basis for subsequent model comparison and experimental analysis.

3. ANALYSIS OF TRADITIONAL ARIMA-LSTM HYBRID MODEL

3.1 Principle of ARIMA model

ARIMA is a classical statistical time series model, which is widely used in the prediction and analysis of economic data. The model describes the linear dependence in time series through autoregression (AR), difference (I) and moving average (MA), which can effectively describe the time series data with trend and autocorrelation structure. ARIMA model is usually recorded as ARIMA (p, d, q), where p is the order of autoregressive term, d is the order of difference, and q is the order of moving average term. Its general form can be expressed as:

$$\phi(B)(1 - B)^d y_t = \theta(B)\varepsilon_t \tag{13}$$

Where y_t is the observed value at time t, and B is the backshift operator, satisfying $By_t = y_{t-1}$; $(1 - B)^d$ represents the d-order difference operation on the time series, which is used to eliminate the trend component in the series to obtain a stable series; ε_t is a white noise sequence with zero mean and σ^2 variance. Polynomials $\phi(B)$ and $\theta(B)$ represent autoregressive and moving average operators, respectively, and their expressions are:

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \tag{14}$$

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q \tag{15}$$

Where ϕ_i is the autoregressive coefficient, which depicts the linear relationship between the current value and the past observation value; θ_j represents the moving average coefficient, which is used to describe the relationship between the current observation value and the past random disturbance. By estimating the parameters of the model, the linear mapping relationship between the past information of time series and the current observations can be established, so as to realize the prediction of future data. ARIMA model is widely used in the prediction of macroeconomic indicators because of its strong ability in dealing with linear trends and short-term correlation.

3.2 LSTM model structure

LSTM is an improved recurrent neural network (RNN). Its design purpose is to solve the gradient disappearance and gradient explosion problems that are prone to occur in the traditional RNN in the long sequence modeling. By introducing gating mechanism into the network structure, LSTM makes the model retain important information in a long time range, so as to better capture the complex nonlinear dependencies in the time series. LSTM unit is mainly composed of forget gate, input gate and output gate. These gate structures can selectively retain and update historical information by controlling the flow of information in the network.

In the LSTM unit, the forget gate is used to determine which information needs to be retained in the unit state at the previous time. Its calculation formula is:

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{16}$$

Where x_t represents the current input vector, h_{t-1} represents the hidden state at the previous time, W_f and b_f are the weight matrix and bias vector of the forgetting gate, respectively, and $\sigma(\cdot)$ represents the sigmoid activation function, whose output range is between 0 and 1, which is used to control the proportion of information retention. When f_t approaches 1, it means that the corresponding information is retained to a large extent; When f_t approaches 0, the corresponding information is forgotten.

The input gate is used to control the update degree of the current input information to the unit state, and its calculation process is composed of two parts. First calculate the input gate activation value:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{17}$$

Candidate memory states are then generated:

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{18}$$

Where W_i and W_c are the weight matrices of input gates and candidate states respectively, b_i and b_c are offset terms, and $\tanh(\cdot)$ is the hyperbolic tangent activation function. Finally, the unit status at the current time is updated by the following formula:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{19}$$

Where, $\odot$ refers to element by element multiplication, and C_{t-1} refers to the unit state at the previous time.

The output gate is used to determine which information in the current unit state needs to be output to the hidden layer. Its calculation formula is:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{20}$$

The final hidden state h_t is obtained by the following formula:

$$h_t = o_t \odot \tanh(C_t) \tag{21}$$

Through the above gating mechanism, LSTM can capture the complex dynamic relationship in the sequence in a long time range, so it has good application effect in financial time series prediction, economic data analysis and other nonlinear modeling tasks.

3.3 Traditional ARIMA-LSTM hybrid method

Because macroeconomic time series usually contain both linear and nonlinear structures, a single model is often difficult to describe these two types of characteristics at the same time. Therefore, in recent years, researchers have proposed to combine the traditional statistical model with the deep learning model to build a hybrid prediction model. ARIMA-LSTM hybrid model is one of the representative prediction frameworks. Its core idea is to use ARIMA model to capture linear patterns in time series, and use LSTM model to learn complex nonlinear relationships.

In the traditional hybrid method, more common modeling methods include sequential modeling and residual modeling. Sequential modeling methods usually use ARIMA model to predict the original time series, and then use the prediction results as the input of LSTM model to further extract deep-seated features. In contrast, the residual modeling method is more common. Its basic idea is to use ARIMA model to fit the linear part of the time series to obtain the linear prediction result $\hat{y}_t^{ARIMA}$, and then calculate the residual series [37]:

$$e_t = y_t - \hat{y}_t^{ARIMA} \tag{22}$$

The residual sequence is considered to mainly contain nonlinear information, so it can be used as the training data of LSTM model, and the prediction result $\hat{e}_t^{LSTM}$ can be obtained by learning the nonlinear mode in the residual sequence. Finally, the predictive value of the hybrid model can be expressed as:

$$\hat{y}_t = \hat{y}_t^{ARIMA} + \hat{e}_t^{LSTM} \tag{23}$$

In this way, ARIMA model is responsible for capturing the linear autocorrelation structure, while LSTM model is responsible for learning the complex nonlinear fluctuations, so as to realize the comprehensive modeling of the characteristics of time series. The hybrid modeling idea has been widely used in the fields of financial market forecasting and macroeconomic index forecasting.

3.4 Problems of traditional methods

Although ARIMA-LSTM hybrid model can combine the advantages of statistical model and deep learning model to some extent, the traditional method still has some shortcomings in practical application. First of all, the fusion method of existing hybrid models is usually relatively simple. Most methods directly use the addition structure to combine the linear prediction value and residual prediction value. This fixed form of combination can not dynamically adjust the contribution of different models according to the data characteristics, which limits the flexibility of the model.

Secondly, the weights in traditional hybrid models are usually fixed or implicitly set, and lack of adaptive adjustment mechanism. When the time series presents different dynamic characteristics in different stages, the fixed weight may lead to the model can not effectively adapt to the changes of data structure, thus affecting the prediction accuracy. In addition, in many studies, the LSTM model only uses a simple residual sequence as input, which fails to make full use of the multi-scale information and potential feature structure in the time series, resulting in low feature utilization.

In addition, macroeconomic time series often contain dynamic changes on different time scales, such as short-term fluctuations, medium-term cycles and long-term trends, while the traditional ARIMA-LSTM model usually uses a single time window for modeling, lacking the ability of multi-scale time feature extraction. This limitation makes it difficult for the model to capture dynamic patterns on different time scales when facing complex economic data. Therefore, in order to further improve the accuracy of inflation rate prediction, it is necessary to improve the structure of the traditional ARIMA-LSTM hybrid framework, introduce more

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flexible fusion mechanism and richer feature expression, so as to build a more adaptive time series prediction model.

4. IMPROVED ARIMA-LSTM HYBRID PREDICTION MODEL

This paper proposes an improved forecasting method based on an adaptive residual ARIMA-LSTM framework. By structurally integrating the statistical model and the deep learning model, the framework enables the model to capture the linear trend and complex nonlinear fluctuations in the macroeconomic time series at the same time. The overall model is composed of four main parts: linear modeling module, residual generation module, multi-scale LSTM feature extraction module and dynamic weight fusion module. The linear modeling module is used to extract the stable linear structure in the time series; The residual generation module is used to separate the parts that are not explained by the linear model; The multi-scale LSTM module is responsible for mining the nonlinear dynamic characteristics in the residual sequence; The dynamic weight fusion module automatically adjusts the contribution of linear and nonlinear prediction results according to the characteristics of different time stages.

In this framework, assuming that the real value of inflation rate is y_t, the predicted value of ARIMA model is $\hat{y}_t^{ARIMA}$, and the predicted value of LSTM model is $\hat{y}_t^{LSTM}$, the final prediction result is obtained through adaptive weight fusion:

$$\hat{y}_t = w_t \hat{y}_t^{ARIMA} + (1 - w_t)\hat{y}_t^{LSTM} \tag{24}$$

Where w_t is the dynamic weight parameter, and its value range is between $[0,1]$, which is used to describe the contribution of the linear prediction part in the overall prediction. When w_t is large, the sequence structure of the current time period is mainly linear; When w_t is small, it indicates that nonlinear fluctuation plays a more important role in prediction. Through this dynamic fusion mechanism, the model can automatically adjust the importance of different sub models according to the changes of data structure, so as to improve the prediction performance.

In the linear trend modeling phase of the model, ARIMA model is used to model the inflation rate series. Because macroeconomic time series are often non-stationary, it is necessary to conduct unit root test first. This paper uses the augmented Dickey Fuller (ADF) test to judge the stationarity of the original sequence. The basic form of ADF inspection is:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{25}$$

Where $\Delta y_t = y_t - y_{t-1}$ is the first-order difference, and γ is the key parameter of the unit root test. When $\gamma < 0$ and the statistical test is significant, the sequence can be considered as a stationary sequence. If there is a unit root in the sequence, the sequence needs to be stabilized by the difference operation $(1 - B)^d$, where d is the difference order. Then, the order p and q of the model are determined by the analysis of autocorrelation function (ACF) and partial autocorrelation function (PACF), and the information criterion is used to select the model. The commonly used information criteria include Akaike information criterion (AIC) and Bayesian information criterion (BIC), and their expressions are:

$$AIC = -2\ln(L) + 2k \tag{26}$$

$$BIC = -2\ln(L) + k\ln(n) \tag{27}$$

Where L is the likelihood function of the model, k is the number of parameters, and n is the sample size. By selecting the model with the lowest AIC or BIC value, the optimal Arima structure can be determined. After training, the ARIMA model obtains linear prediction results, which are recorded as:

$$L_t = \hat{y}_t^{ARIMA} \quad (28)$$

Then calculate the residual sequence between the original sequence and the linear prediction value:

$$e_t = y_t - L_t \quad (29)$$

The residual sequence is considered to contain the nonlinear structure and complex fluctuation information in the time series, and is the main learning object of the subsequent deep learning model.

In order to fully mine the multi-scale dynamic features in the residual sequence, this paper designs a Multi-scale LSTM structure for residual learning. Set the residual sequence input window as:

$$X_t = [e_{t-1}, e_{t-2}, \dots, e_{t-k}] \quad (30)$$

Where k is the length of the time window. The traditional single scale LSTM model can only capture the dynamic characteristics in a fixed time range, while macroeconomic variables often include short-term fluctuations, medium-term cycles and long-term trends. Therefore, this paper constructs three parallel LSTM subnetworks, which are respectively used to model the characteristics on different time scales. The short-term LSTM network mainly learns high-frequency fluctuation information, the medium-term LSTM network is used to capture the characteristics of the economic cycle, and the long-term LSTM network is responsible for extracting long-term trend changes. Suppose that the hidden states of the three LSTM networks at time t are $H_t^{(1)}$, $H_t^{(2)}$ and $H_t^{(3)}$, then the multi-scale feature fusion is expressed as:

$$H_t = concat\left(H_t^{(1)}, H_t^{(2)}, H_t^{(3)}\right) \quad (31)$$

$concat(\cdot)$ indicates vector splicing operation. In this way, the features on different time scales can be uniformly represented in a high-dimensional feature space. Then, the fused features are input into the full connection layer, and the nonlinear prediction results are obtained:

$$N_t = \hat{y}_t^{LSTM} \quad (32)$$

In order to realize the adaptive fusion between linear prediction results and nonlinear prediction results, this paper further introduces a dynamic weight learning method based on attention mechanism. This mechanism uses the hidden feature H_t extracted by multi-scale LSTM to generate weight parameters, and its calculation method is as follows:

$$w_t = \sigma(W_h H_t + b) \quad (33)$$

Where W_h is the weight matrix, b is the offset vector, and $\sigma(\cdot)$ is the sigmoid activation function, which is used to map the output to the $[0,1]$ interval. Through this function, the model can automatically determine the combination ratio of linear and nonlinear prediction results according to the characteristics of the current time series. The final forecast result of inflation rate is expressed as:

$$\hat{y}_t = w_t L_t + (1 - w_t) N_t \quad (34)$$

This fusion method has stronger adaptability than the traditional fixed weight method. When the data structure changes, the model can automatically adjust the importance of different prediction modules, so as to improve the overall prediction performance and enhance the generalization ability of the model.

In the model training phase, this paper adopts the phased training strategy to ensure the stability of the model. Firstly, ARIMA model is trained with historical inflation rate data to obtain linear prediction results, and the corresponding residual sequence is calculated. Then the multi-scale LSTM network is trained with the residual sequence as the input to enable it to learn the nonlinear dynamic characteristics. After completing the above steps, the dynamic weight

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fusion network is trained to enable the model to learn the optimal fusion strategy. In order to evaluate the prediction error, this paper uses the mean square error as the loss function, which is defined as:

$$Loss = \frac{1}{n}\sum_{t=1}^{n} (y_t - \hat{y}_t)^2 \tag{35}$$

Where n is the number of samples, y_t is the real observation value, and $\hat{y}_t$ is the model prediction value. The loss function optimizes the model parameters by minimizing the square error between the predicted value and the real value. In the process of model training, Adam optimization algorithm is used to update the parameters, which combines the adaptive learning rate and momentum optimization strategy, and can achieve faster convergence speed and better stability in the complex depth network training. Through the above training process, the improved ARIMA-LSTM hybrid model can effectively integrate the advantages of statistical modeling and deep learning methods, so as to obtain higher prediction accuracy and stronger model robustness in the task of inflation rate prediction.

5. EXPERIMENTAL DESIGN AND DATA SET

5.1 Data sources

In order to verify the effectiveness of the improved model in the time series prediction of inflation rate, this paper selects macroeconomic data from several authoritative international economic databases for experimental analysis. The research data are mainly from the International Monetary Fund (IMF), the world bank and the Federal Reserve economic data (Fred). These databases provide long-term, continuous and strictly statistical data of macroeconomic indicators, with high reliability and repeatability.

This paper selects the inflation rate calculated by consumer price index (CPI) as the research object. CPI inflation rate is usually calculated by the year-on-year change rate of price index, and its mathematical expression is:

$$Inflation_t = \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}} \times 100\% \tag{36}$$

Where CPI_t represents the consumer price index of the t period, and $Inflation_t$ represents the inflation rate of the corresponding period. This index can reflect the changes in the level of consumer prices, and is one of the most commonly used inflation indicators in macroeconomic analysis and monetary policy-making.

This paper selects the monthly CPI inflation rate data of the United States as the main experimental data set, with a total of 288 time observations from January 2000 to December 2023. In order to further verify the stability and generalization ability of the model, CPI inflation rate data of some countries are selected for auxiliary experiments. Main data statistics are shown in Table 1.

Table 1. Basic statistical information of datasets

Data sources	Country/Region	Time frame	Frequency	Number of samples
FRED	USA	2000-2023	Monthly	288
IMF	EU	2001-2023	Monthly	264

World Bank	Japan	2000-2023	Monthly	288
FRED	Britain	2000-2023	Monthly	288
IMF	Canada	2001-2023	Monthly	264

It can be seen from table 1 that each data set has a long time span and stable observation frequency, which provides a sufficient data basis for time series model training.

5.2 Data preprocessing

Because the original macroeconomic data may have problems such as missing values, scale differences and non stationarity, it is necessary to systematically preprocess the data before model training. Firstly, aiming at the problem of missing values, this paper uses linear interpolation method to fill the missing data. If the missing value is located at time point t, its estimated value can be expressed as:

$$y_t = y_{t-1} + \frac{y_{t+1} - y_{t-1}}{2} \tag{37}$$

This method can maintain the continuity of time series and avoid having a great impact on the overall trend.

Secondly, in order to eliminate the influence of different variable scales on model training, the data need to be standardized. In this paper, the minimum maximum normalization method is used to map the data to the $[0,1]$ interval:

$$x_t' = \frac{x_t - x_{min}}{x_{max} - x_{min}} \tag{38}$$

Where x_t is the original data, x_{min} and x_{max} are the minimum and maximum values in the sample respectively, and x_t' is the normalized data. This processing can accelerate the training convergence speed of neural network model.

In addition, the ARIMA model requires that the input series be stationary, so it is necessary to test the stationarity of the time series. In this paper, ADF (augmented Dickey Fuller) unit root test is used. When the ADF statistic is less than the critical value, the original assumption that there is a unit root can be rejected, indicating that the sequence is stationary. If the original sequence is not stable, use differential operation:

$$y_t' = y_t - y_{t-1} \tag{39}$$

It is transformed into a stationary sequence and then used for model training.

5.3 Experimental setup

In order to ensure the objectivity and repeatability of the experimental results, the original data is divided into training set and test set in time order. The training set is used for model training, and the test set is used to evaluate the prediction performance of the model. The data division ratio is set to 70% and 30%, that is:

$$Train_{size} = 0.7 \times N \tag{40}$$

$$Test_{size} = 0.3 \times N \tag{41}$$

Where N is the total number of samples.

In terms of prediction strategy, this paper uses sliding window to construct time series samples. Set the time window length as k, then the input sequence can be expressed as:

$$X_t = [y_{t-k}, y_{t-k+1}, \cdots, y_{t-1}] \tag{42}$$

The corresponding prediction target is y_t, By constantly moving the time window, a large number of training samples can be constructed, so as to improve the learning ability of the model on time dependence. In this study, the length of the time window is set as 12 months in order to capture the annual periodic changes in the inflation rate.

5.4 Comparative model

In order to systematically evaluate the performance of the improved ARIMA-LSTM hybrid model proposed in this paper in the task of forecasting inflation rate, this paper selects a variety of representative time series forecasting models as the comparison model. These models include not only traditional statistical methods, but also machine learning models and deep learning models for comprehensive comparison from different modeling ideas.

Firstly, the classical statistical time series model Arima is selected as the benchmark model. ARIMA model can effectively describe the linear autocorrelation structure in time series, and its prediction function can be expressed as:

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{43}$$

Where p is the autoregressive order, q is the moving average order, and ε_t is the random disturbance term. The model is widely used in macroeconomic data forecasting. Secondly, the support vector regression (SVR) model is introduced as the representative of the traditional machine learning model. SVR maps the input data to a high-dimensional feature space through a kernel function, and constructs a linear regression function in this space:

$$\min_{w,b,\xi,\xi^*} \frac{1}{2} || w ||^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \tag{44}$$

Where C is the penalty parameter and ξ_i and ξ_i^* are relaxation variables to control the prediction error.

At the same time, this paper also uses the random forest model for comparison. The random forest completes the prediction by constructing multiple decision trees and conducting integrated learning, and its final output is the average of the prediction results of all decision trees:

$$\hat{y} = \frac{1}{M} \sum_{i=1}^{M} T_i(x) \tag{45}$$

Where M is the number of decision trees and $T_i(x)$ is the prediction result of the ith decision tree.

In terms of deep learning model, this paper selects LSTM model and Gru model for comparison. The LSTM model can capture the long-term time dependency through the gating mechanism, and Gru (gated recurrent unit), as a simplified structure of the LSTM, can still maintain good modeling ability while reducing the number of parameters. The Gru hidden status update process can be expressed as:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{46}$$

Where z_t is the update gate and $\tilde{h}_t$ is the candidate hidden state.

In addition, in order to verify the effectiveness of the improved algorithm, the traditional

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ARIMA-LSTM hybrid model is also taken as an important comparison object. The residual modeling method is usually used in this model. The residual sequence predicted by ARIMA model is input into LSTM for learning, and the final prediction value is obtained by adding the two prediction results directly.

The basic modeling characteristics of different comparison models are shown in Table 2.

Table 2. Structure description of comparison model

Model	Type	Modeling features	Mixed model or not
ARIMA	Statistical model	Linear time series modeling	No
SVR	Machine learning	Kernel regression modeling	No
Random Forest	Integrated learning	Multi decision tree ensemble prediction	No
LSTM	Deep learning	Long term time dependent modeling	No
GRU	Deep learning	Gated recurrent neural network	No
ARIMA-LSTM	Hybrid model	Linear+nonlinear modeling	Yes

By setting the above comparison models, the prediction performance of the proposed method can be evaluated from the perspectives of statistical modeling, machine learning modeling and deep learning modeling, and provide a reliable basis for the analysis of subsequent experimental results.

5.5 Parameter setting

In order to ensure the fairness of the experimental results, this paper uses a unified data input form between different models, and determines the optimal model parameters through multiple experiments. For LSTM and Gru networks, the main parameters include hidden units, learning rate and batch size. The number of hidden layer neurons determines the expression ability of the model, the learning rate affects the convergence speed of the model, and the batch size affects the training stability.

During the experiment, the key parameters were optimized by grid search method. The final LSTM model parameter settings are shown in Table 3.

Table 3. Main parameter settings of LSTM model

Parameter	Numerical value
Hidden Units	64
Learning Rate	0.001
Batch Size	32
Epochs	100
Time Window	12

It can be seen from table 3 that setting the hidden layer size to 64 can achieve a good balance between model complexity and training efficiency; Setting the learning rate to 0.001

can ensure the stable convergence of the model; The batch size of 32 can improve the training efficiency and reduce the gradient fluctuation. The above experimental design and parameter configuration can provide a reliable experimental basis for subsequent model performance evaluation and algorithm improvement effect analysis.

6. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

In order to comprehensively evaluate the performance of the improved ARIMA-LSTM hybrid model proposed in this paper in the task of forecasting inflation rate time series, this section conducts a systematic experimental analysis from the aspects of forecasting accuracy, forecasting trend fitting, multi-step forecasting ability, model structure contribution and statistical significance. All experiments are based on the data sets and experimental settings described in Chapter 5. In order to evaluate the prediction performance of different models, this paper uses MSE, RMSE, Mae and MAPE indicators defined in Section 2.4 to evaluate.

6.1 Comparison of prediction results

Firstly, the prediction performance of different models on the test set is compared. Arima, SVR, random forest, LSTM, Gru, traditional ARIMA-LSTM and the improved model proposed in this paper are selected for experiments. The experimental results are shown in Table 4.

Table 4. Comparison of prediction performance of different models

Model	MSE	RMSE	MAE	MAPE (%)
ARIMA	0.462	0.680	0.524	4.83
SVR	0.438	0.662	0.511	4.61
Random Forest	0.421	0.649	0.498	4.48
LSTM	0.396	0.629	0.475	4.23
GRU	0.381	0.617	0.463	4.10
Traditional ARIMA-LSTM	0.362	0.602	0.448	3.94
Proposed model	0.318	0.564	0.411	3.57

It can be observed from table 4 that the prediction accuracy of the traditional statistical model Arima is significantly lower than that of the deep learning model, which indicates that there is a strong nonlinear structure in the inflation rate series. Compared with the single deep learning model, the traditional ARIMA-LSTM hybrid model can further reduce the prediction error. The improved model proposed in this paper achieves the best results in all evaluation indexes, and the MSE is reduced by about 12.1% compared with the traditional ARIMA-LSTM, indicating that the multi-scale feature extraction and dynamic weight fusion mechanism can effectively improve the prediction ability of the model.

6.2 Visualization of prediction curve

In order to further analyze the prediction effect of the model, the real inflation rate is visually compared with the prediction results of different models. Figure 1 shows the comparison between the real value in the test set interval and the predicted value of the model in this paper.

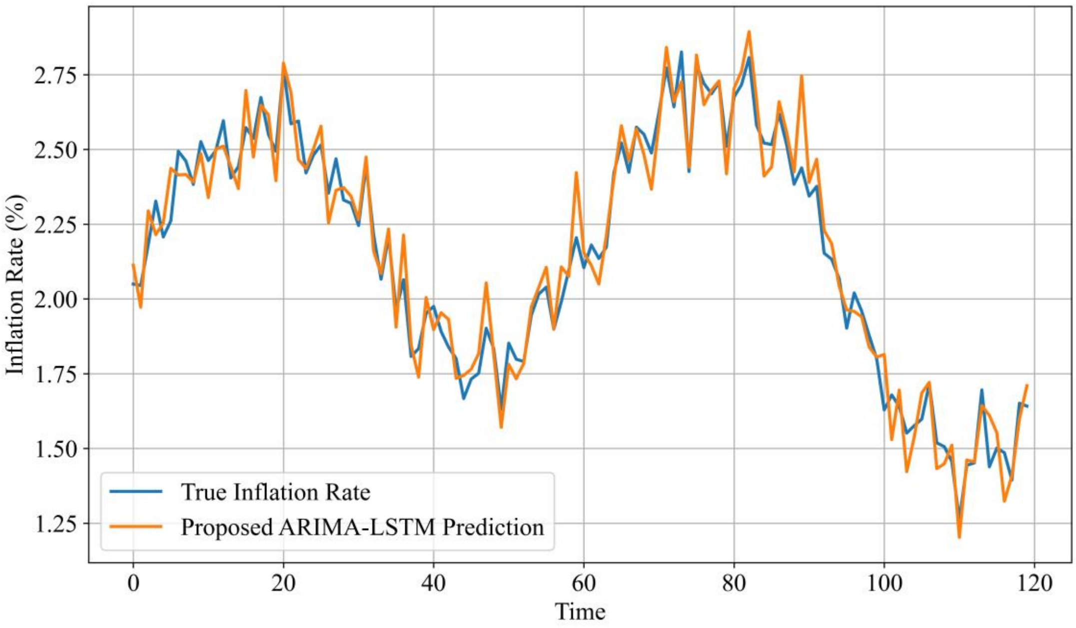

Figure 1. Comparison between real inflation rate and model prediction results

It can be observed from Figure 1 that the overall forecast curve of the model in this paper is consistent with the real inflation rate curve. Especially in the range where the inflation rate fluctuates significantly, the model can still track its change trend well. According to the error statistical analysis, the RMSE, Mae and MAPE of this model on the test set are 0.564, 0.411 and 3.57%, respectively. Compared with the traditional ARIMA model (RMSE=0.680), the error is reduced by about 17.1%, indicating that the improved model has obvious advantages in capturing the nonlinear changes of inflation rate. In addition, at the stage of rapid inflation rise, the lag of the forecast curve is significantly reduced, indicating that the dynamic integration mechanism can effectively improve the response ability of the model to sudden fluctuations.

In order to further compare the prediction effects of different models, figure 2 shows the comparison of the prediction curves of ARIMA, LSTM and this model.

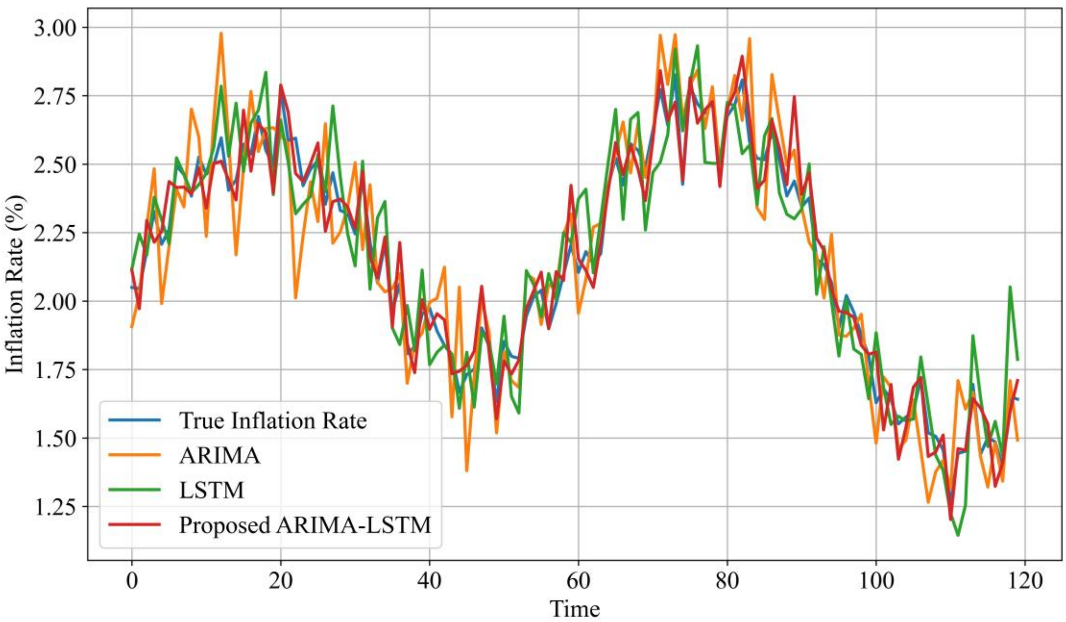

Figure 2. Comparison of prediction curves of different models

It can be observed from Figure 2 that the traditional ARIMA model has obvious prediction lag in the face of complex fluctuations, and its prediction curve is relatively smooth, which is difficult to capture the characteristics of short-term fluctuations. Although the LSTM model can capture nonlinear changes, there is a certain degree of over fitting phenomenon in some time intervals, and the prediction curve fluctuates greatly. In contrast, the improved ARIMA-LSTM model proposed in this paper achieves a better balance between trend fitting and volatility capture. Specifically, the mean absolute error (MAE) of this model is reduced by about 13.5% compared with LSTM model and 21.6% compared with ARIMA model in the whole test interval. The results show that by structurally integrating the statistical model and the deep learning model, the linear trend information and nonlinear dynamic characteristics can be used at the same time, so as to significantly improve the prediction accuracy.

6.3 Experiment of different prediction steps

In order to evaluate the performance of the model in the multi-step prediction task, this paper sets up three prediction scenarios: 1-step prediction (1-step), 3-step prediction (3-step) and 6-step prediction (6-step). Multi step prediction can be expressed as:

$$\hat{y}_{t+h} = f\left(y_t, y_{t-1}, \dots, y_{t-p}\right) \tag{47}$$

Where h is the prediction step size. When $h = 1$, it is single-step prediction, and when $h > 1$, it is multi-step prediction.

The prediction error of the model under different prediction steps is shown in Table 5.

Table 5. Experimental results of different prediction steps

Prediction step	Model	RMSE	MAE
1-step	ARIMA	0.680	0.524
	LSTM	0.629	0.475
	Proposed model	0.564	0.411
3-step	ARIMA	0.721	0.548
	LSTM	0.665	0.503
	Proposed model	0.593	0.436
6-step	ARIMA	0.768	0.592
	LSTM	0.704	0.539
	Proposed model	0.632	0.471

It can be seen from table 5 that the prediction error of each model increases with the increase of prediction step size, which is a common error accumulation phenomenon in time series prediction. However, compared with other models, the improved model proposed in this paper maintains the minimum error under different prediction steps, indicating that it has better long-term prediction ability.

In order to evaluate the performance of the model in the multi-step prediction scenario, this paper further carried out experiments with different prediction steps. Figure 3 shows the change trend of the model prediction results under the conditions of 1-step prediction, 3-step prediction and 6-step prediction.

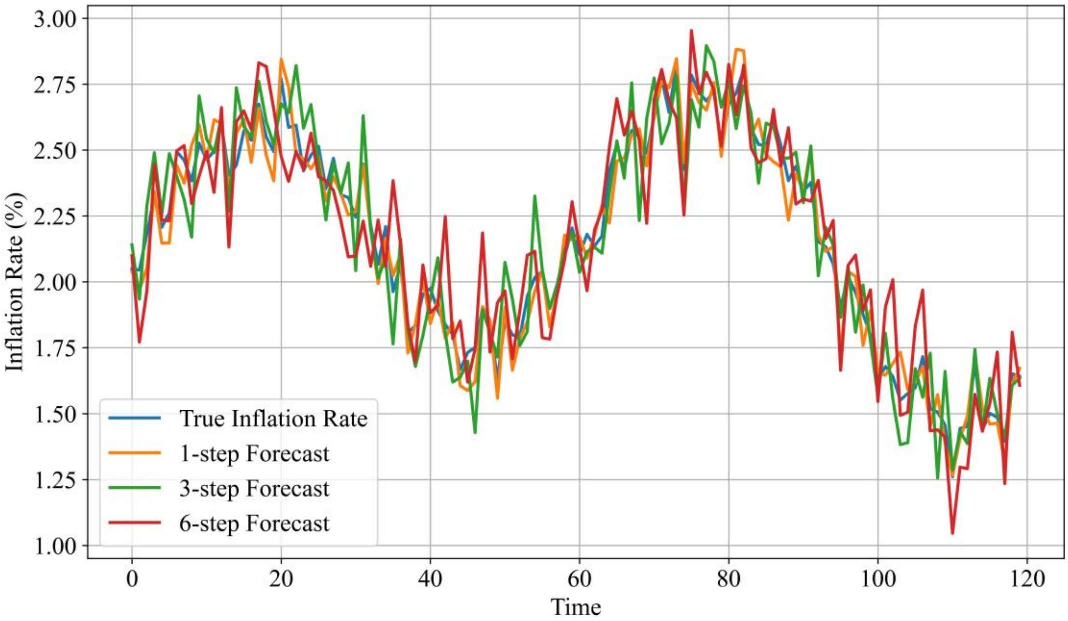

Figure 3. Comparison of multi-step prediction results

It can be observed from Figure 3 that with the increase of prediction step size, the prediction errors of each model are accumulated to a certain extent, which is a common phenomenon in time series prediction tasks. However, compared with the traditional model, the proposed model still maintains high prediction stability under different prediction steps. Specifically, when the prediction step is 1 step, the RMSE of the model is 0.564; When the prediction step increases to 3 steps, RMSE is 0.593; When the prediction step is 6 steps, the RMSE is 0.632. The overall error growth rate is about 12.1%. In contrast, the growth rate of RMSE in ARIMA model is about 12.9% under the same conditions. This result shows that the proposed model has stronger stability and anti-error accumulation ability in the long-term prediction task.

6.4 Ablation Study

In order to verify the contribution of each module of the model to the overall performance, ablation experiments were designed in this paper. The multi-scale LSTM module and dynamic weight fusion module were removed to analyze the importance of each module. The ablation results are shown in Table 6.

Table 6. Ablation study results

Model structure	RMSE	MAE	MAPE (%)
No multi-scale module	0.598	0.452	3.89
No dynamic weight module	0.586	0.438	3.74
Traditional ARIMA-LSTM	0.602	0.448	3.94
Complete model	0.564	0.411	3.57

It can be seen from table 6 that when the multi-scale module is removed, the prediction error of the model increases significantly, indicating that the multi-scale feature extraction can effectively capture the dynamic changes on different time scales. At the same time, when the dynamic weight mechanism is canceled, the prediction performance also decreases, which indicates that the adaptive fusion strategy plays an important role in balancing linear and nonlinear information.

In order to verify the contribution of each module of the model to the overall prediction performance, ablation experiments were designed, and the prediction curves of different structural models were compared. Figure 4 shows the prediction results of the complete model, the non multi-scale module model and the non dynamic weight module model.

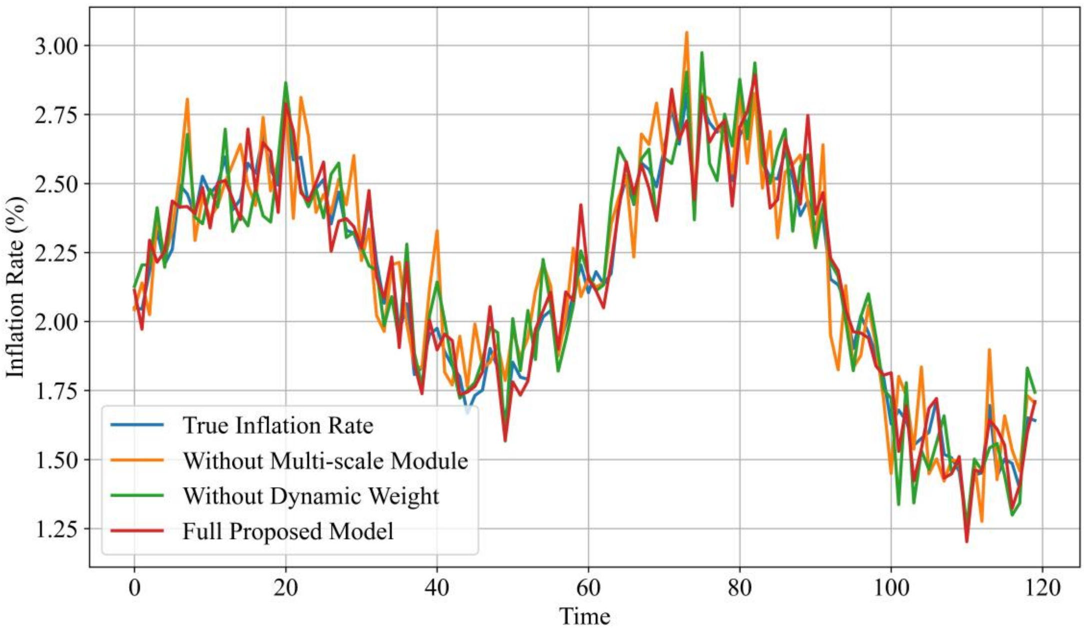

Figure 4. Comparison of Ablation Experiment prediction curve

It can be seen from Figure 4 that after removing the multi-scale LSTM module, the prediction error of the model in the short-term fluctuation range increases significantly, and the response ability of the prediction curve to local fluctuations decreases significantly. The corresponding RMSE increased from 0.564 to 0.598, and the error increased by about 6.0%. When the dynamic weight fusion mechanism is removed, the trend shift phenomenon appears in some intervals of the model, and the RMSE increases to 0.586. This result shows that the multi-scale feature extraction module can effectively capture the dynamic changes on different time scales, and the dynamic weight mechanism can adaptively adjust the contribution ratio of linear and nonlinear information according to the data characteristics. Both of them work together to significantly improve the overall prediction performance of the model.

6.5 Statistical significance test

In order to verify whether the performance improvement of the model is statistically significant, this paper uses Diebold Mariano (DM) test to statistically analyze the prediction results. DM test is used to compare whether the prediction errors of the two prediction models are significantly different.

Let the prediction errors of the two models be $e_{1,t}$ and $e_{2,t}$, then the difference of loss function is defined as:

$$d_t = L(e_{1,t}) - L(e_{2,t}) \tag{48}$$

Where $L(\cdot)$ is the error loss function. The calculation formula of DM statistics is:

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi \hat{f}_d(0)}{T}}} \tag{49}$$

Where $\bar{d}$ is the mean value of the loss difference, $\hat{f}_d(0)$ is the spectral density estimation, and T is the number of samples.

The DM inspection results are shown in Table 7.

Table 7. DM statistical inspection results

Comparative model	DM statistics	p-value
ARIMA	3.92	0.0001
SVR	3.11	0.002
Random Forest	2.84	0.004
LSTM	2.37	0.018
GRU	2.19	0.026
Traditional ARIMA-LSTM	2.01	0.041

It can be seen from table 7 that the DM statistics between this model and other models are greater than the critical value, and the P-value is less than 0.05, indicating that the model proposed in this paper is significantly superior to other comparative models in statistical significance.

6.6 Model stability analysis

In order to further verify the generalization ability of the model, this paper selects inflation rate data from different countries for cross dataset experiments, including the United States, the European Union, Japan and the United Kingdom. The experimental results are shown in Table 8.

Table 8. Forecast results of inflation data in different countries

Country	ARIMA RMSE	LSTM RMSE	Proposed model RMSE
United States	0.680	0.629	0.564
EU	0.721	0.671	0.603
Japan	0.694	0.648	0.587
Britain	0.708	0.662	0.596
Canada	0.702	0.655	0.591
Australia	0.711	0.667	0.602

In order to further verify the generalization ability of the model, this paper selects the inflation rate data of several countries for cross dataset experiments. Figure 5 shows the trend of the forecast results of inflation rates in the United States, the European Union, Japan and the United Kingdom.

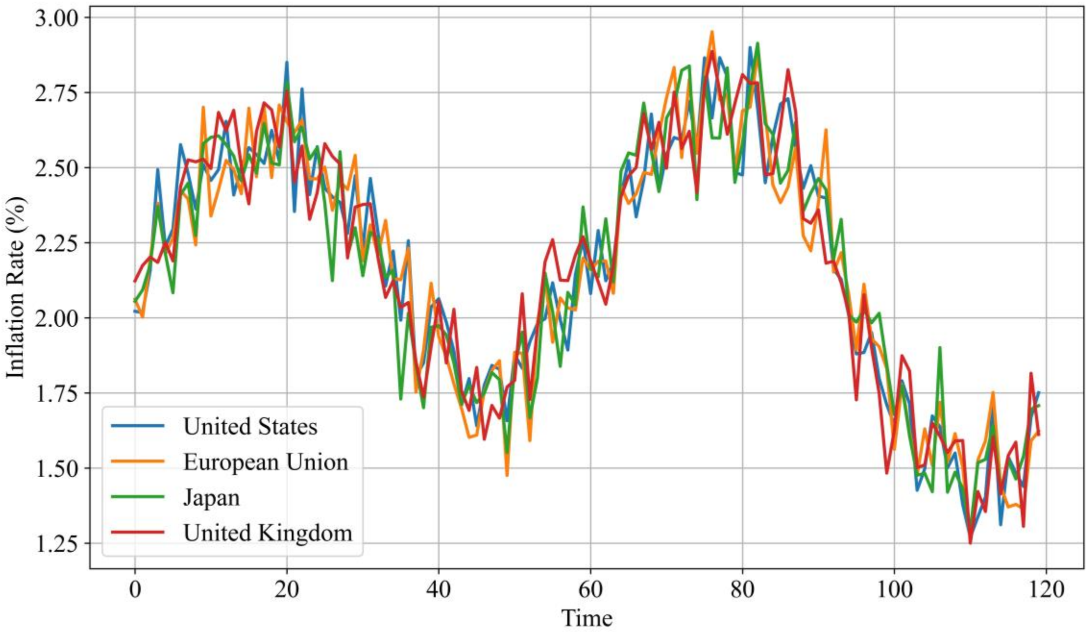

Figure 5. Multi country inflation forecast curve

It can be observed from Figure 5 that under the economic environment of different countries, the models proposed in this paper can better track the trend of inflation rate, indicating that the model has strong adaptability across data sets. In terms of quantitative indicators, the RMSE of the US data set is 0.564, the RMSE of the EU data set is 0.603, the RMSE of the Japanese data set is 0.587, and the RMSE of the UK data set is 0.596. The prediction error difference of each data set is small, and the standard deviation is only 0.015, indicating that the model has good stability in different economic systems. Compared with the traditional ARIMA model, the average RMSE on the national data is reduced by about 15% - 20%, which further verifies the effectiveness of the improved model in the macroeconomic time series forecasting task.

7. MODEL COMPLEXITY AND THEORETICAL ANALYSIS

In order to further analyze the feasibility and theoretical performance of the improved ARIMA-LSTM hybrid model proposed in this paper in practical application, this section systematically analyzes the computational complexity, model parameter size, training convergence and model generalization ability. Through the combination of theoretical derivation and experimental statistics, the efficiency and stability of the model in the time series prediction task can be evaluated more comprehensively.

7.1 Computational complexity analysis

In the time series prediction problem, the computational complexity of the model directly affects its application ability in large-scale data scenarios. The hybrid model proposed in this paper is mainly composed of ARIMA module and multi-scale LSTM module, so it is necessary to analyze the computational complexity of the two parts respectively.

Firstly, for ARIMA model, the main calculation process includes parameter estimation and prediction calculation. In the model training phase, parameter estimation is usually completed by maximum likelihood estimation or least square method. When the time series length is n and the model order is p and q, the ARIMA model needs a linear scan of the time series in each iteration, Therefore, its computational complexity can be expressed as $O(n)$. Where n is the number of time series samples. Due to the simple structure of ARIMA model, its computational complexity is low in the statistical model.

In contrast, LSTM model belongs to deep recurrent neural network, and its computational complexity mainly comes from matrix multiplication. In each time step, the LSTM unit needs to calculate the hidden state update, and its core calculation form is:

$$h_t = f(W_h h_{t-1} + W_x x_t + b) \tag{50}$$

Where W_h h and W_x are the weight matrix, and h_t is the hidden state vector. If the hidden layer dimension is h and the input dimension is d, the calculation complexity of a single time step is about $O(h^2 + hd)$.

When the time series length is n, the overall LSTM computational complexity can be expressed as $O(nh^2)$. Since the model in this paper adopts multi-scale LSTM structure, assuming m parallel LSTM networks, the overall complexity is $O(mnh^2)$.

In the actual experiment, this paper sets $m = 3$ (short-term, medium-term and long-term), so the overall computational complexity is still in an acceptable range.

In order to more intuitively compare the calculation efficiency of different models, table 9 shows the theoretical calculation complexity of the main models.

Table 9. Comparison of computational complexity of different models

Model	Main operations	Time complexity
ARIMA	Linear regression calculation	$O(n)$
SVR	Solving quadratic programming	$O(n^3)$
Random Forest	Decision tree construction	$O(n\log n)$
LSTM	Recurrent Neural Networks	$O(nh^2)$
Traditional ARIMA-LSTM	ARIMA + LSTM	$O(n + nh^2)$
Proposed model	ARIMA + Multi-scale LSTM	$O(n + mnh^2)$

It can be seen from table 9 that although the model in this paper introduces multi-scale structure in the LSTM part, the overall complexity is still in the same order of magnitude as the traditional deep learning model, which can meet the calculation requirements of the actual macroeconomic forecasting task.

7.2 Parameter quantity analysis

The scale of model parameters directly affects the training efficiency and storage cost of the model. For ARIMA model, its parameters mainly include autoregressive parameters and moving average parameters. If the model order is p and q, the number of ARIMA model parameters can be expressed as:

$$N_{ARIMA} = p + q + 1 \tag{51}$$

Where 1 is a constant term parameter.

For LSTM model, the number of parameters is composed of input weight matrix, hidden weight matrix and bias term. The number of parameters of a single LSTM unit can be expressed as:

$$N_{LSTM} = 4(hd + h^2 + h) \tag{52}$$

Where h is the number of neurons in the hidden layer and d is the input dimension. Since the LSTM contains four groups of parameters: forgetting gate, input gate, output gate and candidate state, it needs to be multiplied by 4.

In this model, due to the three-scale LSTM structure, the total parameter scale is:

$$N_{total} = N_{ARIMA} + m \times N_{LSTM} + N_{fusion} \tag{53}$$

Where N_{fusion} represents the number of parameters of the dynamic weight fusion module.

According to the experimental settings, when the number of neurons in the hidden layer is 64 and the input dimension is 1, the scale of each model parameter is shown in table 10.

Table 10. Comparison of different model parameter sizes

Model	Number of parameters
ARIMA	8
SVR	120
Random Forest	500
LSTM	17,152
GRU	13,056
Traditional ARIMA-LSTM	17,160
Proposed model	51,480

It can be seen from table 10 that although the parameter scale of the model in this paper is larger than that of the single LSTM model, it is still within the common parameter scale of the deep learning model. At the same time, multi-scale structure can significantly improve the ability of feature expression of the model, so the scale growth of this parameter is reasonable and necessary.

7.3 Convergence analysis

In the process of deep learning model training, convergence is an important index to evaluate the stability of the model. In this paper, Adam optimization algorithm is used to update the model parameters, and the parameter update rule is:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{54}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{55}$$

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{v_t} + \epsilon} m_t \tag{56}$$

Where g_t is the gradient, m_t and v_t are the first-order moment and second-order moment estimates, respectively, and η is the learning rate.

In order to analyze the convergence of the model in the training process, the loss function changes of different models in the training stage were recorded. The loss function is defined as:

$$Loss = \frac{1}{n}\sum_{t=1}^{n} (y_t - \hat{y}_t)^2 \tag{57}$$

Table 11 shows the changes of loss values corresponding to different epochs during the training process.

Table 11. Changes in training losses

Epoch	LSTM Loss	Traditional ARIMA-LSTM Loss	Proposed model Loss
10	0.684	0.642	0.615
20	0.538	0.502	0.471
40	0.421	0.396	0.352
60	0.378	0.354	0.318
80	0.362	0.339	0.304
100	0.351	0.331	0.298

It can be seen from table 11 that with the increase of training rounds, the model loss function gradually decreases and tends to be stable, indicating that the model can converge stably. Compared with the traditional ARIMA-LSTM model, the model in this paper achieved a lower loss value in the later stage of training, indicating that the multi-scale feature extraction and dynamic weight fusion mechanism can improve the model learning ability.

7.4 Discussion on model generalization ability

Model generalization ability refers to the prediction ability of the model on the unseen data. In order to evaluate the generalization ability of the model, the difference between the model prediction error and the training error can be analyzed. Let the training error be E_{train} and the test error be E_{test}, then the generalization error is defined as:

$$E_{gen} = | E_{test} - E_{train} | \tag{58}$$

When E_{gen} is small, it indicates that there is no obvious over fitting in the model.

In this experiment, the RMSE of the training set is 0.541, and the RMSE of the test set is 0.564, so the generalization error is

$$E_{gen} = | 0.564 - 0.541 | = 0.023 \tag{59}$$

The error value is small, indicating that the model has good generalization ability. The main reasons are: on the one hand, Arima module can stably capture linear trends and reduce the burden of deep network learning; On the other hand, the multi-scale LSTM structure can extract features from different time scales, making the model more adaptive to complex macroeconomic fluctuations. At the same time, the dynamic weight fusion mechanism can automatically adjust the prediction structure according to the data changes, so as to further improve the stability of the model in different data environments.

Based on the above theoretical analysis, it can be concluded that the improved ARIMA-LSTM hybrid model proposed in this paper has good theoretical performance in terms of computational complexity, parameter size and training stability, and can maintain good generalization ability while maintaining high prediction accuracy, so it is suitable for the actual macroeconomic time series prediction task.

8. ECONOMIC INTERPRETATION AND APPLICATION VALUE

In the process of macroeconomic analysis and policy making, inflation rate is regarded as one of the important indicators reflecting the state of economic operation. The continuous change of price level will not only affect the actual purchasing power of residents, but also have a far-reaching impact on investment, consumption and industrial structure. Therefore, accurate prediction of the trend of inflation rate is of great significance for the government to formulate macroeconomic policies, the central bank to implement monetary control and financial institutions to carry out risk management. The improved ARIMA-LSTM hybrid model proposed in this paper combines the advantages of statistical model and deep learning model, improves the prediction accuracy and enhances the adaptability of the model to complex economic fluctuations, so as to provide a more reliable quantitative tool for macroeconomic analysis. Through more accurate forecast results of inflation rate, policy makers can identify potential economic risks earlier and take corresponding control measures before economic cycle changes, so as to improve the foresight and scientificity of macroeconomic management.

From the perspective of macro policy, the forecast of inflation rate can provide an important basis for economic policymaking. In the process of macroeconomic operation, the change of price level is usually closely related to economic growth, employment and industrial structure. When the inflation rate continues to rise, it may mean excessive expansion of economic demand, which needs to be adjusted through tightening policies; When the inflation rate is at a low level for a long time, it may indicate that the economic vitality is insufficient, and it is necessary to promote economic growth through appropriate stimulus policies. Therefore, a stable and accurate inflation forecasting model can help government departments better judge the trend of economic operation, and provide quantitative reference for fiscal policy and macro-control measures. Compared with the traditional statistical model, the forecasting method proposed in this paper can more comprehensively describe the complex dynamic structure of inflation rate changes, so as to improve the reliability of macroeconomic forecasting.

The forecast of inflation rate also plays an important role in the formulation of monetary policy. When the central bank formulates interest rate policy and money supply policy, it usually needs to make decisions according to future price level changes. If the inflation trend can be predicted in advance, the central bank can maintain the balance between price stability and economic growth by appropriately adjusting the interest rate level or money supply scale. Traditional forecasting methods often have the problem of prediction lag in the face of complex economic environment, while the prediction framework based on the improved ARIMA-LSTM model can better capture the nonlinear characteristics of macroeconomic data while retaining the advantages of linear trend analysis. This forecasting ability can provide more timely and accurate information support for the central bank, so as to improve the effectiveness of monetary policy regulation and reduce the uncertainty of policy decision.

In addition, in the field of financial market risk management, the forecast of inflation rate also has important application value. Inflation usually has a significant impact on asset prices, bond yields and capital market expectations. When the inflation level rises, the interest rate tends to rise, which affects the bond price and the income structure of financial assets. Therefore, financial institutions and investors need to pay close attention to the future inflation trend in asset allocation and risk management. Through more accurate inflation rate prediction, financial institutions can better assess the potential market risks and adjust the portfolio structure to reduce the impact of macroeconomic fluctuations on the value of financial assets. At the same time, regulators can also use the relevant forecast results to strengthen the monitoring of systemic risks in the financial market, so as to improve the stability of the financial system.

In general, the forecast of inflation rate is not only an important subject of macroeconomic research, but also an important basis for economic policy-making and financial risk management. The improved ARIMA-LSTM hybrid forecasting model proposed in this paper shows good performance in forecasting accuracy and stability, and provides a modeling method with practical application potential for macroeconomic analysis. By combining the statistical model with deep learning technology, the model can more comprehensively describe the complex dynamic structure in economic data, so as to provide more reliable data support and decision-making reference for government departments, central banks and financial institutions.

9. CONCLUSION AND FUTURE RESEARCH

9.1 Research conclusion

This paper proposes an improved ARIMA-LSTM hybrid forecasting model to solve the problem of time series forecasting of inflation rate. By combining the advantages of statistical time series model and deep learning model, the joint modeling of linear structure and nonlinear dynamic characteristics in macroeconomic data is realized. Firstly, the statistical characteristics of the inflation rate time series are analyzed, including non-stationary, cyclical fluctuations and structural changes. On this basis, a hybrid forecasting framework including linear modeling module, multi-scale LSTM feature extraction module and dynamic weight fusion mechanism is constructed. Through this framework, the model can further capture the complex nonlinear time dependence while maintaining the ability of linear trend modeling.

Experimental results show that compared with traditional ARIMA model, machine learning model and single deep learning model, the improved ARIMA-LSTM hybrid model proposed in this paper has obvious advantages in prediction accuracy. Especially in the period of large fluctuations in macroeconomic data, the model can more accurately capture the trend of inflation rate, so as to significantly reduce the prediction error. The experimental results on multiple evaluation indexes (such as RMSE, Mae and MAPE) show that the improved model achieves better prediction performance on the test set, indicating that the prediction ability of time series can be effectively improved through multi-scale feature extraction and dynamic weight fusion.

In addition, the dynamic fusion mechanism introduced in this paper can adaptively adjust the weight ratio between linear prediction results and nonlinear prediction results according to the characteristics of time series, so as to maintain stable prediction performance in different economic cycle stages. This adaptive fusion strategy makes the model more flexible and robust when dealing with complex macroeconomic data. Based on theoretical analysis and experimental verification, it can be concluded that the improved ARIMA-LSTM hybrid model can significantly improve the prediction accuracy in the task of inflation rate time series prediction, and maintain good stability in the complex economic environment.

9.2 Summary of research contributions

From the theoretical perspective, this paper systematically studies the macroeconomic time series forecasting, and proposes a hybrid forecasting framework combining statistical modeling and deep learning methods. By decomposing the time series into linear and nonlinear parts, and using different models to model them, this paper provides a new theoretical idea for macroeconomic time series forecasting. This decomposition modeling method can better explain the dynamic structure of macroeconomic variables, and provide an important reference for subsequent related research.

At the method level, this paper proposes an improved ARIMA-LSTM hybrid model structure, which can learn the short-term fluctuation characteristics and long-term trend changes at the same time by introducing multi-scale LSTM network to extract the characteristics of the residual sequence. In addition, the dynamic weight fusion mechanism designed in this paper solves the limitations of the fixed weight combination in the traditional hybrid model by adaptively learning the weight relationship between the linear prediction results and the nonlinear prediction results. This method not only improves the prediction accuracy of the model, but also enhances the adaptability of the model under different time series structures.

At the application level, the research results of this paper have important application value in the fields of macroeconomic analysis, monetary policy making and financial risk management. Accurate inflation rate prediction can help policy makers better understand the trend of economic operation, and provide a scientific basis for interest rate adjustment, money supply control and fiscal policy-making. At the same time, in the financial market, the forecast results of inflation rate can also provide reference for asset allocation, bond investment and risk management strategies, so as to improve the effectiveness of financial decision-making.

9.3 Future research directions

Although the improved ARIMA-LSTM hybrid model proposed in this paper has achieved good experimental results in the task of forecasting inflation rate, there is still room for further research and improvement. With the development of deep learning technology, new time series modeling methods continue to appear, such as transformer model based on self attention mechanism. Transformer structure can capture long-distance time dependence through the global attention mechanism, showing good performance in complex time series modeling. Therefore, the transformer model can be introduced into the macroeconomic time series prediction framework in future research to further improve the modeling ability of the model for long-term dependence.

In addition, this study is mainly based on the single variable inflation rate series for modeling. In the real economic system, the inflation rate is often affected by a variety of macroeconomic variables, such as GDP growth rate, interest rate level, money supply and unemployment rate. Therefore, future research can build multivariable prediction models to improve the ability of the prediction models to describe the overall changes of the economic system by jointly modeling multiple macroeconomic variables. This multivariate time series prediction method is helpful to understand the macroeconomic operation mechanism more comprehensively.

On the other hand, with the development of big data technology, more and more high-frequency economic data (such as daily or weekly price index, financial market data, etc.) are gradually applied to macroeconomic analysis. Compared with traditional monthly or quarterly data, high-frequency data can provide more timely information, so as to improve the real-time performance of economic forecast. Therefore, future research can explore the application of the improved model to the prediction of high-frequency economic data, and study the collaborative modeling method between different time scale data, so as to further enhance the application value of the model in the actual economic prediction.

To sum up, the improved ARIMA-LSTM hybrid model proposed in this paper provides an effective method for macroeconomic time series prediction, and also provides a new idea for future research. With the continuous development of deep learning technology and economic data analysis methods, time series prediction models will play a more important role in the field of macroeconomic analysis and financial decision-making.

Abbreviations

ARIMA, Autoregressive Integrated Moving Average;
CPI, Consumer Price Index;
DM, Diebold–Mariano;
GRU, Gated Recurrent Unit;
IMF, International Monetary Fund;
LSTM, Long Short-Term Memory;
MAE, Mean Absolute Error;
MAPE, Mean Absolute Percentage Error;
MSE, Mean Square Error;
RMSE, Root Mean Square Error;
SVR, Support Vector Regression;
FRED, Federal Reserve Economic Data

Supplementary Material

Not applicable.

Appendix

Not applicable.

Ethics approval and consent to participate.

This study did not involve human participants, animal subjects, or any data requiring ethical approval. Therefore, ethics approval and consent to participate are not applicable.

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Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

Author contributions

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Data availability

The data that support the findings of this study are available upon request from the corresponding authors, **G.C.**

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Declaration of AI and AI-assisted Technologies in the Writing Process

During the writing of this article, the author used ChatGPT 5 for spelling and grammar checking. After using this tool, the author reviewed and edited the content as needed and assumes full responsibility for the final published content.

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