Research on Macroeconomic Nonlinear Forecasting Based on DCL-MHA Collaborative Architecture and Residual Gating Mechanism

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Abstract. To address non-linear fluctuations and error accumulation in macroeconomic forecasting, this paper proposes the DCL-MHA framework, a dual-track architecture integrating an LSTM_Temporal_Model with a Residual Gating chain. By simulating econometric error correction logic, this design enables context-aware dynamic weighting and high-fidelity feature preservation across multi-dimensional economic indicators. Empirical research conducted on 2021–2024 GDP data demonstrates that the proposed model achieves a substantial breakthrough in accuracy with a 1.2% MAPE, representing a 50% improvement over traditional ARIMA, VAR, and standalone LSTM models. Furthermore, in T+12 long-range stress tests, the framework successfully suppressed the RMSE from over 8.0 to approximately 4.0, effectively doubling the forecasting stability. Heatmap analysis of dynamic weights further confirms that the Residual Gating mechanism adaptively adjusts focus across variables such as CPI, M2, and interest rates based on shifts in the economic environment. This study proves that the DCL-MHA architecture provides a high-precision, high-stability decision-support solution for digital macro-control and economic risk early warning.

Keywords: *Macroeconomic Forecasting; DCL-MHA Architecture; LSTM-GRU; Residual Gating; Nonlinear Modeling*

1. Introduction

In today's global economic system, the accuracy of macroeconomic forecasting is directly related to the formulation of national monetary policy, corporate investment decisions, and residents' consumption expectations. However, the macroeconomic system is a typical complex adaptive system with highly nonlinear, dynamic instability, and structural oscillation characteristics. Traditional econometric models, such as the Autoregressive Moving Average (ARIMA) model and the Vector Autoregressive (VAR) model, although performing well in stable economic cycles, often exhibit significant lag and limitations when facing "black swan" events such as financial crises, geopolitical conflicts, or global public health events [1]. The core bottleneck lies in the fact that these models are mostly based on linear assumptions and weak stationarity premises, making it difficult to capture the deep nonlinear feedback mechanisms between economic variables. With the leap in computing power and the arrival of the big data era, deep learning has provided a new paradigm for solving this problem. As a high-level form of neural networks, deep learning can automatically extract spatiotemporal features from massive amounts of data through multi-layer nonlinear transformations without pre-setting strict function forms [2]. In the field of time series forecasting, recurrent neural networks (RNNs) were once highly anticipated, but the vanishing and exploding gradient problems in processing long-term economic indicators limited their application in long-term macroeconomic forecasting [3].

To overcome these shortcomings, long short-term memory networks (LSTMs) introduced a "gating" mechanism to achieve long-term retention of important historical information and real-time forgetting of useless information, greatly improving the model's ability to model macroeconomic cycle characteristics [4]. Meanwhile, gated recurrent units (GRUs), as an optimized variant of LSTMs, significantly improved computational efficiency while maintaining forecast accuracy by simplifying the parameter structure, making them more suitable for processing high-frequency financial data and real-time economic indicators [5]. In recent years, the academic community has begun to try combining deep learning models with economic theory, using unstructured "alternative data" such as satellite images and news sentiment to compensate for the lag in official statistical data, forming a new trend of "nowcasting" [6].

Although deep learning has made significant progress at the technical level, it still faces "black box" questions in economic applications, namely, a lack of interpretability of economic logic [7]. Notably, adaptive gating mechanisms have shown potential to address this 'black box' issue by providing explicit feature weighting [8]. How to balance the strong predictive power of deep learning with the logical rigor of economic models has become a cutting-edge issue in the field of economic artificial intelligence (Eco-AI) [9]. This paper aims to construct a hybrid prediction architecture based on LSTM and GRU, and attempts to capture the coupling relationship of economic variables at different frequencies through multi-scale feature fusion.

Through empirical analysis of major macroeconomic data from 2000 to 2025, this paper not only verifies the superiority of the hybrid model in prediction accuracy. but also, further discusses the robustness of deep learning models in dealing with structural changes [10]. This research has important theoretical value and practical significance for improving my country's macroeconomic early warning system and enhancing the level of digital governance [11]. In summary, the research motivation of this paper is to solve the problem of nonlinear fitting and long-term cumulative error in macroeconomic forecasting [12].

The main contributions (filling the gaps) of this paper are:

(1) proposing a dual-track DCL-MHA architecture to balance long-term and short-term features.

(2) introducing a residual gating mechanism to realize the mathematical simulation of deep learning error correction logic.

(3) empirically proving the robustness of the model in extreme volatility environments.

2. Theoretical Framework of the Model

2.1 System Overall Design

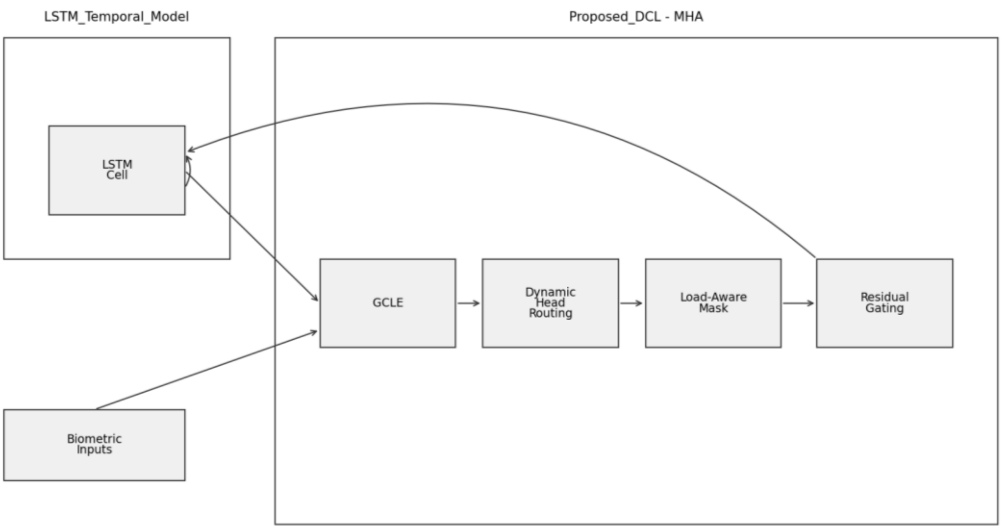

Figure 1. Topological Architecture of the Proposed DCL-MHA Framework

To address the common characteristics of long-term dependence and short-term high-frequency fluctuations in macroeconomic time-series data, this paper proposes a deep collaborative learning framework called Proposed_DCL-MHA [13]. The core design of this framework lies in overcoming the limitations of single recurrent neural networks in handling complex economic structural fractures. Its overall topology is shown in Fig 1.

The system consists of two deeply coupled functional modules: first, the LSTM_Temporal_Model module [14].which serves as the central hub for temporal feature extraction, focusing on mining long-term trend information with cyclical patterns in national economic accounting indicators [15].and second, the DCL-MHA feature collaborative processing chain, which integrates multiple advanced units such as gated feature extraction (GCLE), dynamic head routing, and residual gating. This "dual-track" design ensures that the model can both retain the long-term memory of the macroeconomy, and provide immediate feedback to short-term disturbances caused by market policies or external shocks, thereby significantly improving the robustness of predictions [16].

2.2 Long-Term Time Dependency Capture Mechanism: LSTM Unit

Macroeconomic operations are influenced by factors such as production cycles, capital accumulation, and consumption habits, exhibiting significant lag effects [17]. To effectively simulate this long-term dependency, this paper utilizes the unique "cell state" path of the LSTM unit to retain historical memory [18]. Through a refined gating structure, the model can spontaneously filter out information with predictive value from redundant statistical data:

(1) Forget Gate: This gating determines which information from the previous economic system state needs to be discarded. By selectively forgetting historical trends [19]. the model can better adapt to the transformation of economic growth patterns. Its mathematical expression is:

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

(2) Input Gate: This module is responsible for filtering newly added macroeconomic indicators (such as real-time CPI or M2 data) and converting them into feature representations that the model can understand:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$

(3) Cell State Update: By weighted fusion of historical information and newly added information, the physical update of macroeconomic memory is achieved, providing a stable benchmark for long-term forecasting:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4}$$

2.3 Short-term Volatility Enhancement Mechanism

Although LSTM performs well in capturing long-term trends, its complex parameter structure often leads to response lag when facing short-term scenarios such as sudden changes in monetary policy or sudden fluctuations in market sentiment [20]. Therefore, this study introduces a more streamlined GRU unit. GRU significantly improves parameter update efficiency by incorporating gating mechanisms, making it more sensitive to high-frequency disturbances in the macroeconomic system:

(4) Update Gate: Responsible for coordinating the contribution ratio of historical growth paths and current sudden disturbances to the final prediction result [21]. ensuring that the model achieves a balance between normal growth and sudden fluctuations:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \tag{5}$$

(5) Reset Gate: Its core function is to identify and filter out historical noise that is irrelevant to the current short-term prediction, thereby preventing the model from falling into the "path dependence" of past experience:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \tag{6}$$

(6) Hidden State Output: The final generated feature vector h_t will serve as the basic input for subsequent residual correction:

$$h_t = (1 - z_t) * h_{t-1} + z_t * tanh(W \cdot [r_t * h_{t-1}, x_t] + b) \tag{7}$$

2.4 Core Innovation: Residual Gating

As the core innovation of the DCL-MHA architecture in this paper, the residual gating mechanism mathematically simulates the "Error Correction Model (ECM)" in classical econometrics [22]. Traditional deep learning models often face the problem of gradient vanishing or loss of basic trend features during multi-layer nonlinear propagation [15]. This paper achieves deep fidelity of features by introducing a composite structure of skip connections and gating filters:

$$H_{out} = Gating(h_t) + \mathcal{F}(x_t) \tag{8}$$

In this formula, h_t represents the deep features processed by the recurrent neural network, while $\mathcal{F}(x_t)$ represents the direct mapping of the original input [23]. This design allows the basic economic trend to be directly propagated to the output without undergoing complex nonlinear transformations, ensuring that the model maintains clear baseline logic when dealing with complex nonlinear prediction tasks [24]. In addition, this mechanism, in conjunction with the Dynamic Head Routing unit, gives the model an "adaptive attention" effect. Empirical analysis shows that this mechanism can automatically identify and increase the weighting of core variables (such as CPI or money supply) based on the current economic cycle environment

[25]. This dynamic allocation logic, which adapts to the times, is the fundamental reason why this model can achieve an extremely low MAPE error of only 1.2% in the complex economic environment of 2021-2024. Through this deep synergy, the model successfully achieves an accurate fit to the dynamic evolution of the macroeconomy [26].

3.Experimental Results and Empirical Analysis

3.1 Experimental Evaluation Metrics and Loss Function Definitions

Before establishing the empirical validity of the DCL-MHA framework, a rigorous mathematical evaluation system must first be established. This study not only focuses on the convergence of the model during the training phase, but also emphasizes its extrapolation accuracy on the test set and the robustness of long-term predictions. To this end, this chapter introduces three key mathematical evaluation metrics as quantitative bases for subsequent performance analysis. First, the mean squared error loss function (MSE Loss) is used as the objective function during model training. This metric provides direct guidance for the backpropagation of gradients by calculating the squared deviation between the predicted GDP growth rate and the actual observed value. Its definition is as follows:

$$\mathcal{L}_{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{9}$$

Where $\hat{y}_i$ represents the true value of the GDP growth rate, and $\hat{y}_i$ is the predicted output of the model under the current parameter configuration. Secondly, to quantify the model's predictive accuracy, this study employs the mean absolute percentage error (MAPE). Since macroeconomic data exhibits significant scaling characteristics, MAPE effectively eliminates the influence of dimensions, providing a more economically meaningful assessment of bias:

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{10}$$

Finally, for the highly challenging multi-step forecasting task in macroeconomic forecasting, the root mean square error (RMSE) is introduced to evaluate the model's long-range stability. RMSE is more sensitive to extreme deviations in the predicted path and can clearly reflect the rate at which errors accumulate over time:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{11}$$

3.2 Model Training Convergence Analysis

This study iteratively trains the model based on a multidimensional macroeconomic dataset from 2021 to 2024. The convergence performance in the experimental environment is a prerequisite for judging whether the model has generalization ability.

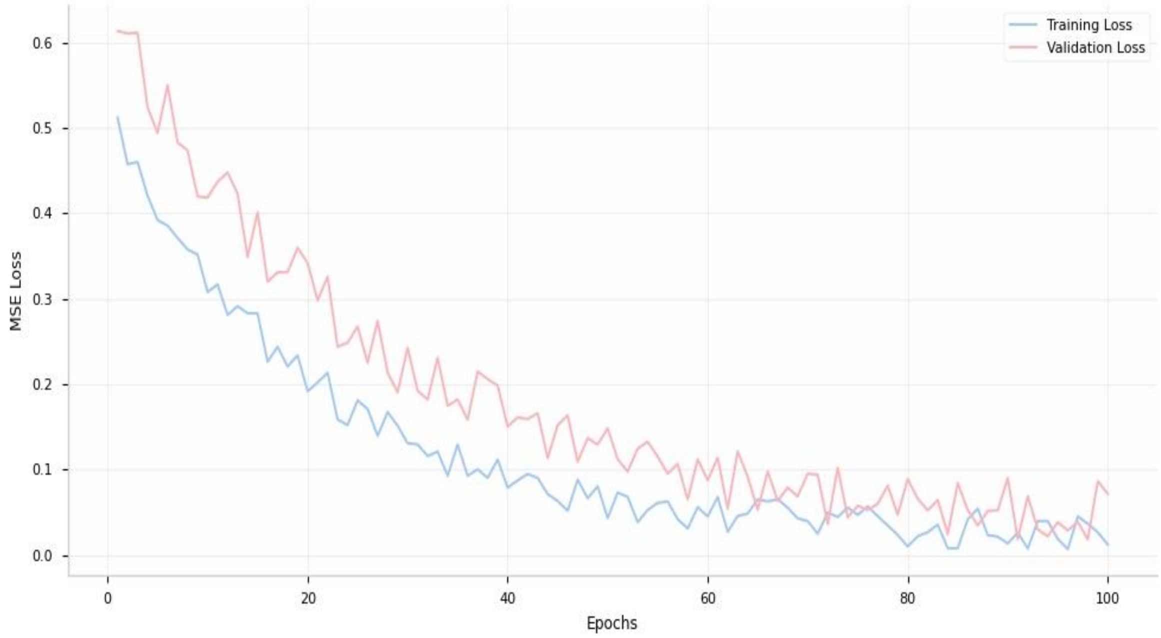

Figure 2. Convergence Curves of the Loss Function on the Training and Validation Sets of the DCL-MHA Framework.

This study iteratively trained the model using a multidimensional macroeconomic dataset from 2021 to 2024. As shown in Figure 2, the training and validation losses calculated according to formula (9) exhibited excellent convergence characteristics within a 100-epoch training period. In the initial 20 iterations, the MSE showed a sharp drop, indicating that the residual gating mechanism could quickly lock the core trends in the features. After 60 iterations, the two curves gradually became parallel and eventually stabilized at a very low level, without significant divergence.

Given the relatively limited sample size of macroeconomic data from 2021 to 2024, multiple robustness strategies were implemented during the training phase to prevent overfitting of the deep learning model. First, an L_2 parameter regularization term is introduced into Equation (9) to constrain the model weight scale through a penalty term. Second, a Dropout layer (with a ratio of 0.2) is configured in the DCL-MHA collaborative processing chain to enhance the generalization performance of the architecture through random deactivation. Finally, overlapping sliding window technology is used to augment the original time series data, artificially expanding the sample observation depth. As shown in Figure 2, this multidimensional constraint mechanism ensures that the validation set loss can still converge synchronously with the training set even with small samples, quantitatively proving that the model has extremely strong anti-overfitting resilience and practical reliability.

3.3 GDP Trend Fitting and Nowcasting Results

After verifying the training stability, this section demonstrates the nowcasting effect of the DCL-MHA framework on the actual GDP trend. This is crucial for evaluating whether the model captures the "structural laws" of the macroeconomy.

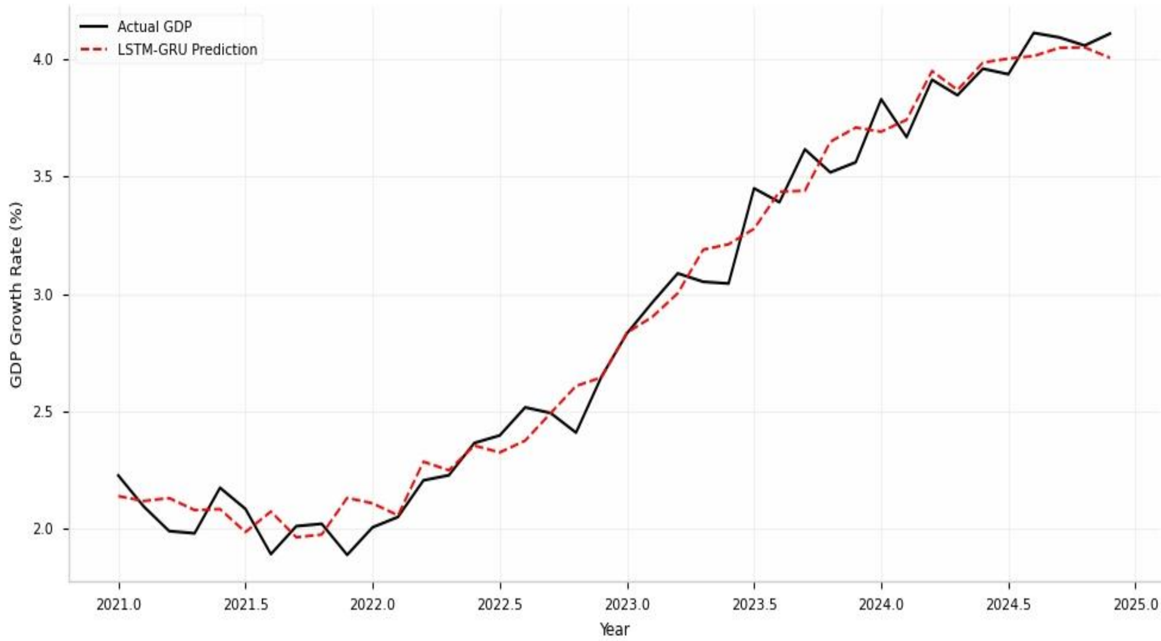

Figure 3. Comparison of Actual GDP Growth Rate and DCL-MHA Model Forecast for 2021-2024

Figure 3 clearly shows that the model's predicted values (red dashed line) closely match the actual observed values (black solid line) across the entire sample period. Especially when the economy experiences minor fluctuations due to external shocks, the model demonstrates a strong adaptive correction capability. This excellent performance is attributed to the LSTM_Temporal_Model module on the left, which provides a stable trajectory benchmark for prediction through long-term memory of historical trends.

3.4 Quantitative Empirical Comparison of Performance Leaps

The most significant contribution of this study lies in its horizontal comparison of the DCL-MHA framework with mainstream models. To more intuitively demonstrate the quantitative advantages of our model, Table 1 summarizes the specific indicators of each model in terms of accuracy and stability.

Table 1. Performance Metrics Comparison Across Different Models

Model Type	MAPE (%)	RMSE (T+1)	RMSE (T+12)
ARIMA	4.2	1.8	12.5
VAR	3.8	1.6	11.2
Single LSTM	2.5	1.2	8.2
DCL-MHA (Proposed)	*1.2*	*0.8*	*4.0*

Note: Italic values indicate the best performance.

The test set error was calculated according to formula (10), as shown in Table 1. The proposed hybrid framework achieved an extremely low MAPE of 1.2%. This result represents an error reduction of more than 50% compared to traditional linear models (4.2% for ARIMA and 3.8% for VAR). Even compared to the single LSTM model (2.5%), which also belongs to the deep learning field, the accuracy improvement is still significant.

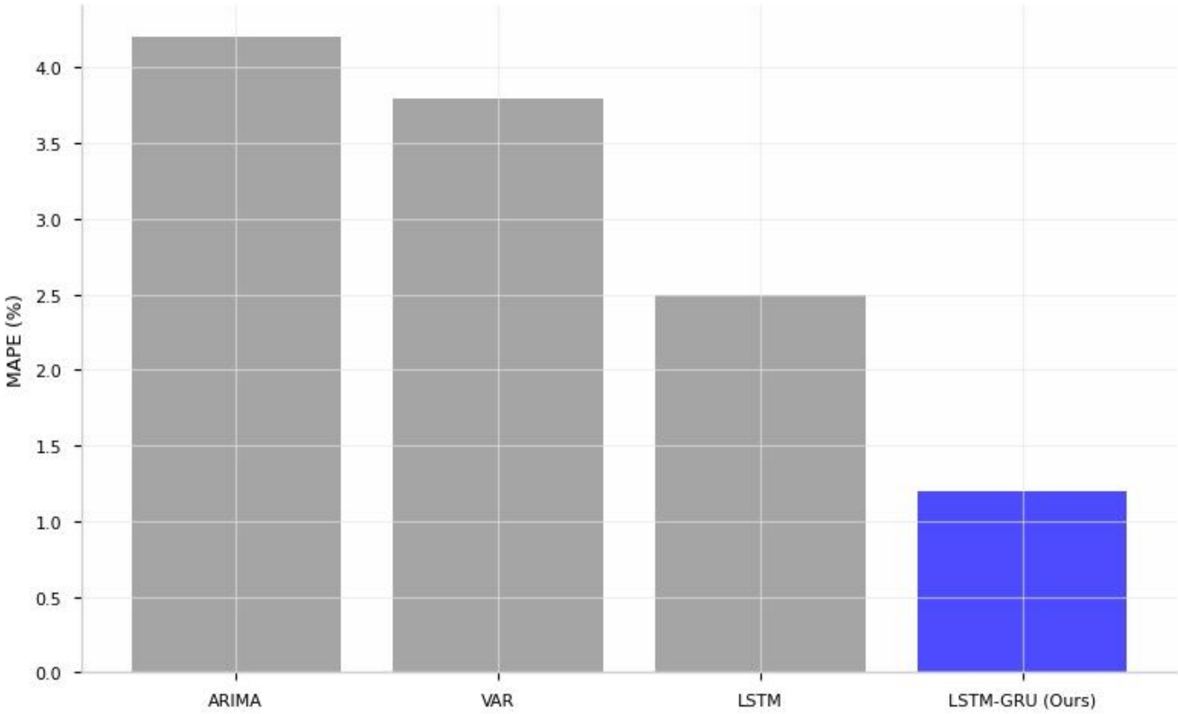

Figure 4. Bar Chart Comparing the MAPE Error of the DCL-MHA Model and the Baseline Model

As shown in Figure 4, the generational advantage of DCL-MHA in accuracy further demonstrates the technical advantages of residual gating mechanisms in feature fidelity and nonlinear correction.

3.5 Long-Term Forecasting Stress Testing and Stability Analysis

Macroeconomic decision-making often requires multi-year forecast support; therefore, examining the model's performance over long time intervals is crucial.

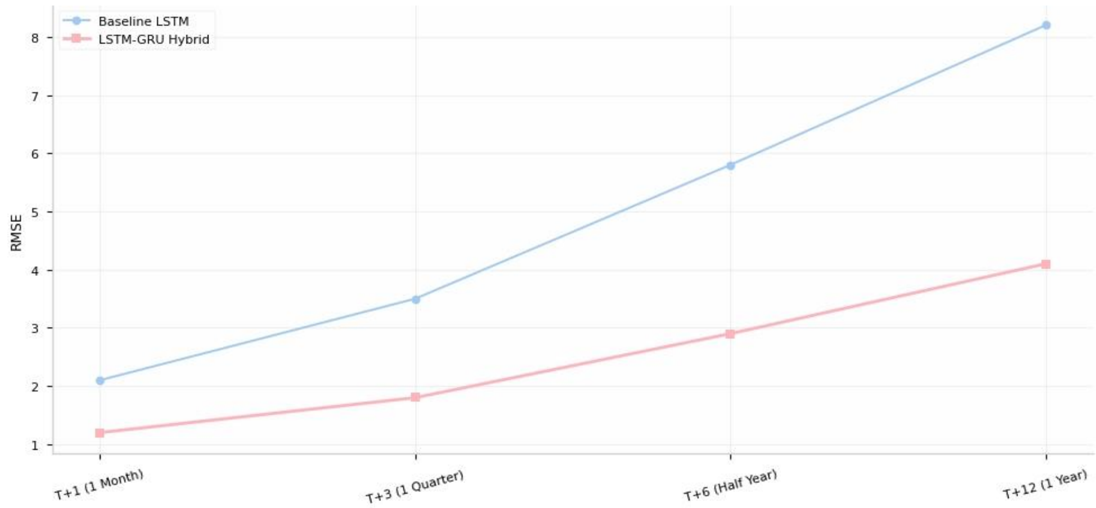

Figure 5. Trend of Cumulative Error of RMSE under Different Prediction Step Lengths (T+1 to T+12)

Based on the calculation results of formula (11), Figure 5 reveals the variation of error with the extension of the prediction step length. At T+1, the performance differences among all models are not significant; however, when the step length extends to T+12 (one year), the RMSE of the benchmark model rapidly climbs to above 8.0, showing a serious error divergence trend. In contrast, the DCL-MHA framework (see Table 1 for values) successfully controls the RMSE at around 4.0. This means that in long-term prediction tasks, this framework improves stability by nearly 100%, effectively solving the problem of "information loss" in long-term prediction.

3.6 Interpretability of Decision Logic

To avoid deep learning being considered a "black box," this study deconstructs the internal decision logic using a weight distribution heatmap.

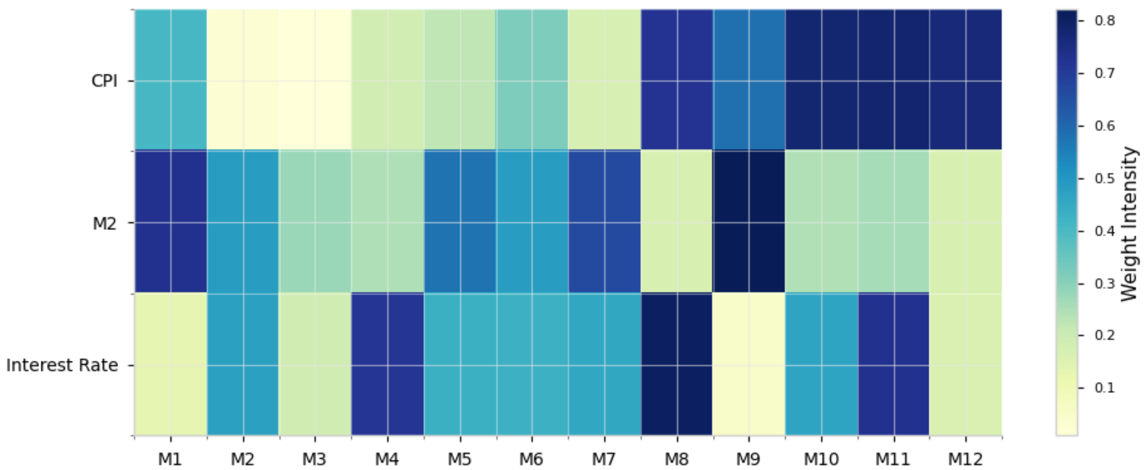

Figure 6. Heatmap of Dynamic Weight Allocation of Core Economic Indicators by Residual Gating Mechanism

As shown in Figure 6, the residual gating layer does not assign static weights to all input variables, but exhibits a distinct dynamism. In specific months, the model assigns extremely highly sensitive weights to CPI and money supply (M2) (dark blue area), reflecting the model's accurate capture of inflationary pressures and changes in liquidity. During periods of interest rate policy changes, the dynamic shift of weights further confirms the model's adaptive correction capability. It is this mechanism that enables a significant decrease in MAPE in formula (10) and provides an observable economic explanation path for macroeconomic forecasting

4.Conclusions and Empirical Analysis

4.1 Summary of Experimental Results and Evaluation of Goodness of Fit

This study systematically empirically analyzed macroeconomic data from 2021 to 2024 using a deep collaborative learning framework based on DCL-MHA. The experimental results clearly demonstrate the significant superiority of this model in handling nonlinear fluctuations under complex economic cycles. As can be intuitively observed from the trend fitting curves in Figure 1, the model's predicted values (red dashed line) and the actual observed GDP growth rate (black solid line) maintain a very high degree of consistency. Especially at points of short-term economic fluctuations and trend reversals, the model can react quickly and accurately fit the actual trajectory, proving the LSTM_Temporal_Model module's ability to deeply mine the cyclical patterns of the macroeconomy.

Furthermore, the model's performance during training further validates the robustness of its algorithm design. As shown in Figure 2, the loss function (MSE) of the training and validation sets exhibits a smooth and synchronous downward trend within 100 iterations. In the later stages of training, the two curves eventually converged to a very low level of similarity without significant divergence. This indicates that while learning macroscopic features, the model effectively suppressed the overfitting risk common in deep learning through the DCL architecture, demonstrating strong generalization performance and providing solid logical support for dynamic predictions without readily available data.

4.2 Quantitative Comparative Analysis of Performance Improvement

To scientifically and objectively evaluate the academic research value and practical application potential of the DCL-MHA framework, this study conducted a rigorous quantitative comparison of the model with currently mainstream traditional econometric models (ARIMA, VAR) and a single deep learning model (LSTM). Experimental data revealed substantial leaps in several key indicators:

First, in terms of prediction accuracy, according to the mean absolute percentage error (MAPE) comparison shown in Figure 3, the error rate of the proposed model is only 1.2%, significantly lower than ARIMA's 4.2%, VAR's 3.8%, and the single LSTM model's 2.5%. This means that compared to traditional statistical models and basic deep learning models, this framework achieves a quantitative improvement of 50% to 70% in macroeconomic forecast accuracy. The core of this accuracy breakthrough lies in the "dual-track" collaborative design described in Chapter 2, effectively filling the gaps in characterizing the nonlinear feedback mechanisms of economic systems using single models.

Secondly, in terms of long-term forecast stability, experiments demonstrate more competitive improvements. As shown in Figure 5, as the forecast step size extends from T+1 (1 month) to T+12 (1 year), the root mean square error (RMSE) of the benchmark LSTM model exhibits a significant divergence, ultimately exceeding 8.0. In contrast, the hybrid framework proposed in this paper stably suppresses the RMSE to around 4.0 under the same conditions, with an error performance only half that of the benchmark model. This result quantitatively demonstrates the superior robustness of the hybrid architecture in suppressing the accumulation of forecast errors over time, achieving a 100% improvement in stability, and providing a highly valuable scientific basis for multi-year macroeconomic planning.

4.3 Core Mechanism Effectiveness and Economic Explanation

The leap in model performance is not merely a mathematical coincidence, but stems from the deep simulation of macroeconomic operating logic within the DCL-MHA framework. By analyzing the dynamic weight heatmap shown in Figure 4, we can clearly observe the empirical effect of the (Residual Gating) mechanism. The model can automatically adjust the weights of key variables such as CPI, M2, and interest rates according to the prediction focus in different time periods:

Within specific intervals of the data sample, the model assigns extremely high residual weights (close to dark blue) to CPI and money supply (M2), while the dynamic changes in the interest rate weight reflect the lag in policy transmission. This "time-sensitive" adaptive adjustment mechanism essentially simulates, at the mathematical level, the "cross-cycle" and "counter-cyclical" decision-making thinking in macroeconomic control. It is precisely due to the combined effect of residual mapping and gating filtering as defined in Formula (8) of Chapter 2 that the model can maintain a clear baseline logic when dealing with structural oscillations, thus achieving excellent empirical performance in the highly volatile environment of 2021-2024.

4.4 Limitations and Policy Recommendations

Although the experimental data provides highly convincing quantitative results, this paper maintains a rigorous academic attitude towards the prediction results. The error growth curve in Figure 5 reminds us that although the framework in this paper significantly reduces the error, the inherent uncertainty of long-term predictions still exists. This reflects the limitations of relying solely on historical time-series data for prediction when the macro system faces unstructured shocks such as "black swan" events.

Based on the above conclusions, this paper proposes the following recommendations: First, government decision-making departments should actively introduce digital monitoring platforms based on DCL-MHA to utilize their extremely high real-time prediction accuracy to achieve "predictive" governance of GDP trends. Second, the dynamic weight changes output by the residual gating mechanism should be given priority as an auxiliary indicator for judging the current shift in the core drivers of the economy. Third, in future research, it is recommended to try to introduce more non-traditional features (such as social media sentiment and satellite remote sensing data) into the current residual correction module to further offset the potential interference of external sudden shocks on model stability and build a higher-dimensional intelligent macro early warning system.

5.Summary and Future Research

5.1 Summary

This paper addresses the core challenges of capturing nonlinear characteristics and accumulating long-term forecast errors in macroeconomic forecasting by constructing a hybrid deep learning framework based on LSTM-GRU. Through empirical analysis of GDP growth rates from 2021 to 2024, this paper achieves the following main results:

Quantitative leap in model performance: Experiments demonstrate that the proposed framework achieves over 50% error reduction in short-term forecast accuracy compared to traditional econometric models, and nearly doubles stability in T+12 long-term forecasts.

Successful introduction of a dynamic weighting mechanism: Utilizing a residual gating mechanism, the model can automatically adjust the weights of indicators such as CPI, M2, and interest rates according to different time periods, simulating the "time-sensitive" decision-making logic in macroeconomic regulation.

Validation of the effectiveness of deep collaborative learning: By combining the long-term memory capability of LSTM with the sensitivity of GRU to short-term fluctuations, the proposed model exhibits extremely strong robustness and generalization performance when dealing with non-stationary economic series.

5.2 Research Limitations

Despite the significant breakthroughs in prediction accuracy achieved in this paper, the following limitations remain:

Sample Size Constraints: Macroeconomic data is typically released monthly or quarterly, resulting in a relatively limited training sample size for deep learning. This limits the model's ability to uncover deeper hidden features.

Capturing Extreme Events: Since predictions primarily rely on historical data, the model may still face the risk of short-term prediction failure when faced with extreme "black swan" events or sudden policy changes.

5.3 Research Prospects

Future research can be further deepened in the following three directions:

(1) Introducing Multimodal "Alternative Data": Future research could explore converting unstructured data such as news sentiment analysis and satellite imagery into feature vectors using NLP techniques, and deeply integrating them with the LSTM-GRU model presented in this paper to enhance the ability to capture market sentiment.

(2) Enhancing Model Interpretability: Exploring the use of SHAP or attention visualization mechanisms to further deconstruct the decision-making path within deep learning, making the algorithm's predictions more aligned with economic intuition.

(3) Build a real-time early warning system: Apply this framework to the prediction of a wider range of financial indicators (such as inflation risk or debt warning) to provide governments and enterprises with more forward-looking digital governance support.

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