Unlocking the Potential of Deep Learning in Economic Cycle Prediction and Financial Risk Management with MS-RL DeepSeek

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ABSTRACT

This paper proposes the MS-RL DeepSeek model, addressing challenges in economic cycle forecasting and financial risk assessment. The model combines multimodal learning, Multi-Scale Convolutional Networks (MS-TCN) for time series data modeling, and reinforcement learning (RL), improving predictive capabilities in complex economic data through innovative data fusion and decision optimization mechanisms. Experimental results show that MS-RL DeepSeek outperforms existing benchmark models on the Yahoo Finance and FRED datasets. The model shows an overall improvement of approximately 5% to 10% compared to the benchmark models, demonstrating enhanced performance in economic forecasting and financial risk assessment. Ablation studies further validate the contributions of each module, with multimodal learning and RL modules crucial for optimizing decision strategies. Challenges remain, including a complex training process and high computational demands for large-scale data. Future work may focus on algorithm optimization and data augmentation. Overall, the study provides a new framework for financial risk assessment and economic forecasting, with strong theoretical and practical value.

Keywords: Economic cycle, Financial risk, Deep learning, Prediction model, Deepseek

1. Introduction

With the rapid development of the global economy and the increasing complexity of financial markets, predicting economic cycles and assessing financial risks have become crucial tasks for governments, financial institutions, and investors. Economic cycles are long-term fluctuations in economic activity, typically involving alternating periods of expansion and recession. Accurate forecasting of economic cycle changes helps governments formulate appropriate macroeconomic policies, assists businesses in making investment decisions, and provides financial institutions with a foundation for risk management. In recent years, deep learning technologies, with their ability to handle complex nonlinear data and capture long-term and short-term dependencies, have become an important tool in economic forecasting and risk assessment[1]. Particularly in economic cycle prediction and financial risk management, deep learning can effectively uncover patterns from large volumes of economic data, leading to more accurate predictions and risk evaluations[2].

However, existing methods for economic cycle forecasting still have several limi- tations. Traditional statistical methods, such as ARIMA and VAR, while stable in short-term forecasting, fail to handle complex nonlinear relationships and long-term dependencies[3]. Additionally, machine learning-based models, such as SVM and ran- dom forests, perform well in handling nonlinear relationships but are insufficient in capturing the long-term dependencies of time series data and are inefficient in process- ing high-dimensional economic data[4]. On the other hand, the deep learning model, such as the LSTM network and the VAE, could identify long-term dependence in the performance of economic cycles[5]. However, we face the challenges of handling multi- modal data and optimizing real-time decision making. And on GARCH models, such as model based wave forecasts, effectively capture the wave mobility of financial mar- kets, but there is no ability to respond to sudden events. It is often based on static models and cannot be applied to real time economic change[6]. Therefore, the cur- rent method is complex, dynamic and multiple-source. There is still a lot of room for improvement.

To address these gaps, this document is a new approach based on deep learning- based approach—the MS-RL DeepSeek model. This model integrates MS-TCN and multimodal learning and simultaneously process long and short-term dependence on economic data as well as functions of several modules. In addition, the RL model enables real-time decision optimization and improves the accuracy and adaptability of financial risk assessment. Thanks to these technological innovations, the MS-RL DeepSeek model offers more accurate business cycle forecasting and a more flexible risk management strategy and is better suited to adapt to ever-changing economic environments. The most important contributions to this document are as follows:

• We provide a MS-TCN model architecture based on both the long-term and short-term changes in the economic cycle.

• By integrating multi modal learning, our model can synthesize data from a variety of sources and improve the completeness and accuracy of prediction.

• RL for decision optimization, the model can dynamically adjust strategies in real time at various stages of the economic cycle and further improve the effectiveness of risk assessment and decision support.

The structure of the paper is organized as follows: Section 2 discusses relevant activities, including the prediction of the economic cycle, the application of deep learning in the economic sector, optimization of decision-making, and risk assessment methods. Section 3 provides a detailed description of the design and implementation of the MS-RL DeepSeek model, focusing on its three core modules: the MS-TCN module, the multimodal fusion module, and the reinforcement learning decision optimization module. Section 4 presents the experimental design, including datasets, experimental settings, evaluation metrics, comparison experiments, and ablation studies. Finally, Section 5 concludes the paper by summarizing the research findings and discussing the model’s limitations and future directions for improvement.

2. Related Work

2.1 Traditional Methods of Economic Cycle Forecasting

With the increasing complexity of economic data, traditional statistical methods are no longer sufficient for economic cycle forecasting. In recent years, advanced machine learning and deep learning techniques have been applied to model and forecast eco- nomic cycles[7]. For example, GNNs effectively capture the spatiotemporal relation- ships between economic indicators, making them ideal for large-scale, multidimensional economic data. By representing economic indicators as graphs, GNNs explore inter- dependencies between different economies and reveal hidden relationships within the economic network. CNNs, known for their ability to automatically extract local fea- tures, show strong performance in forecasting short-term economic fluctuations. CNNs excel at processing high-frequency data and capturing detailed characteristics of short- term economic changes[8]. The Transformer model, with its self-attention mechanism, captures long-term dependencies while efficiently handling large datasets, making it ideal for economic cycle forecasting, especially for high-dimensional and long time se- ries data[9]. GANs are increasingly used to simulate economic data, helping models adapt to various economic scenarios and fluctuations. GANs generate realistic eco- nomic states, allowing for the simulation of different economic cycle scenarios[10]. BNNs, by introducing probabilistic outputs, provide not only predictions but also quantify uncertainty, offering more reliable decision support for financial risk manage- ment and policy formulation, particularly in uncertain economic environments[11].

The MS-RL DeepSeek model enhances the capture of both long-term and short-term economic fluctuations by incorporating MS-TCN. It leverages multimodal learning for data fusion and uses reinforcement learning for decision optimization. This model enables more accurate business cycle forecasting and effective risk assessment in dynamic economic environments.

2.2 Applications of Deep Learning in Economic Cycle and Financial Risk Prediction

Social skills are a set of interpersonal and communication abilities that allow individuals to interact effectively with others in various social and professional situations [12]. These skills are essential for building and maintaining relationships, resolving conflicts, and navigating social environments successfully. Effective communication is a cornerstone of social skills. It includes active listening, clear expression of ideas, and non-verbal communication like body language. Empathy is the ability to understand and share the feelings of others [13,14]. It helps in building strong connections and responding to others' emotions. Social skills involve the capacity to manage conflicts peacefully and find mutually agreeable solutions. Being assertive, but not aggressive, is an important aspect of social skills [15]. It involves expressing one's needs and boundaries while respecting the rights of others.

How to improve social skills? Improving social skills can lead to more fulfilling relationships and greater success in both personal and professional life [16]. Strategies for improvement include developing emotional intelligence can enhance social skills by increasing self-awareness and understanding of others' emotions [17]. Engaging in social interactions and practicing communication in various contexts can enhance social skills. Asking for feedback from trusted individuals can provide insights into areas for improvement. Some individuals may benefit from formal training or therapy to develop social skills. Social skills play a crucial role in creating a positive social environment, fostering cooperation, and building meaningful connections. They are essential for personal growth and success in various aspects of life.

2.3 Advances in Economic Decision Optimization and Risk Assessment Methods

Over the past few years, improvements in computational performance and data avail- ability have made significant progress in optimizing economic decisions and risk as- sessment methods. In particular asset management and portfolio optimization are widely applied to the optimization of decision making in financial markets. For ex- ample: DRL is used to solve dynamic risk management problems by adjusting real time strategies to respond to market fluctuations and sudden events[18]. The MOO method has also been introduced into economic decision-making, particularly for pol- icy development and resource allocation that can optimize economic objectives, such as economic growth, social welfare and environmental protection[19]. Another way, PSO in order to find the best solution, we simulated the collective behavior of birds and fish schools, and applied to the optimization of financial markets, such as option ratings and risk management[20]. An uncertain logic system has recently been intro- duced as an optimization tool to determine uncertainty and uncertainty by uncertain rules and to provide rational decision support in complex economic environments[21]. Evolutionary algorithm, GA is very effective in dealing with complex non-linearities in wide range of economic models to find optimal solutions such as tax optimization and economic system simulation[21].

The MS-RL DeepSeek model captures both short-term and long-term dependencies in economic data using MS-TCN. It dynamically optimizes decisions through reinforcement learning. This improves the model's ability to handle fluctuations and sudden events, offering more accurate and flexible decision support.

3. Method

3.1. Overview of Our Model

The MS-RL DeepSeek model integrates MS-TCN, multimodal learning, and reinforcement learning techniques to enhance the accuracy and real-time performance of economic cycle forecasting and financial risk management. As shown in Figure 1, the overall framework of the model and the interconnections between its modules are illustrated. In this model, data flows through each processing stage, enabling it to handle multi-source heterogeneous data, capture both long-term and short-term economic fluctuations, and optimize decisions in real time. The design of MS-RL DeepSeek is based on advanced deep learning technologies, aiming to achieve precise economic cycle predictions, followed by risk assessment and decision optimization.

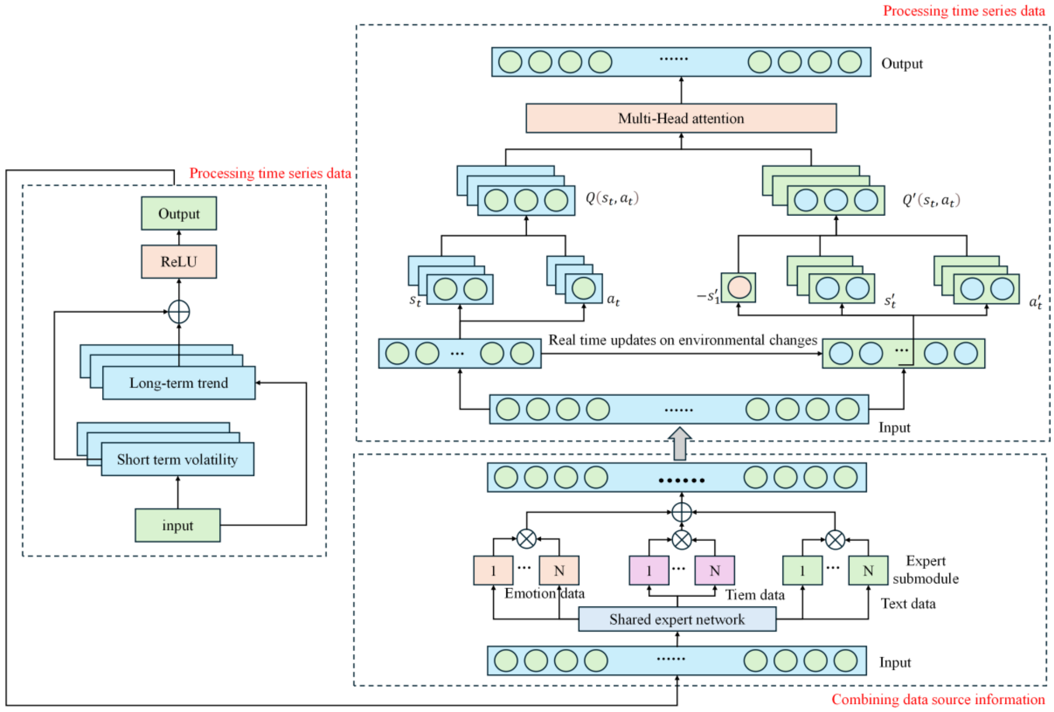

Figure 1. MS-RL DeepSeek Model Architecture Diagram: Economic Cycle Prediction and Financial Risk Assessment Structure Combining Multi-Scale Temporal Convolutional Network, Multi-Modal Learning, and Reinforcement Learning.

The model processes the input time series data through the MS-TCN module. The MS-TCN module consists of multiple convolutional layers, each of which pro cesses information at different time scales, effectively capturing long-term trends and short-term fluctuations in economic cycles. Traditional time series processing meth ods generally capture characteristics in a single time scale, while MS-TCN thanks to the integration structure of multiple scales can simultaneously understand short-termmarket fluctuations and long-term economic trends. In this way, the model overcomes the constraints of conventional methods for processing complex economic data and increases the ability to understand and predict economic data[22]

The processed time series data is then introduced into the multimodal learning module, the central element of the model. This module integrates information from multiple data sources by multi modal data fusion technology, including time series data from social media, financial information, political reporting, and mood analysis. Each data type is processed by another submodule. The output from each expert network is integrated, and this mechanism automatically selects the optimal processing path according to the nature of the input data. The goal of this step is to combine multiple source data effectively to create a more complete and multidimensional perspective for prediction and later decisions[23].

All the integrated data is then stored in the intensive learning module. The main role of intensive learning in this module is to optimize the economic decision-making process, and the model constantly adapts its decision-making strategy based on real time feedback to respond to rapidly changing economic conditions[24]. In this module, the multi-head attention mechanism can further strengthen the model's capability and focus on different decision-making factors such as political changes, market sentiment, and changes in international trade. This mechanism ensures that the model takes into account not only the current phase of the economic cycle in decision-making, but also the ability to respond to potential economic shocks and unexpected events. Thanks to intensive learning adaptation, the MS-RL DeepSeek model enables dynamic, real-time decision optimization and improves the adaptability of financial risk assessment and business cycle forecasting.

3.2. MS-TCN for Time Series Data Analysis in Economic Cycle Prediction

The MS-TCN module consists of multiple convolutional layers corresponding to differ- ent time scales, and the model can accommodate long-term economic and short-term market changes at the same time. Simple ARIMA models and LSTM conventional methods of processing time series such as models limit only the specific features of the time scale and limit the ability of models to fully understand complex economic variations. But the MS-TCN module extracts information at multiple time scales at multiple time scales and overcomes this limitation. Figure 2 illustrates the structure of the MS-TCN module, and the model is intended to handle the data of the input time sequence through this module and to effectively collect features on various time scales to recognize the long-term trends and short term changes in the economic cycle.

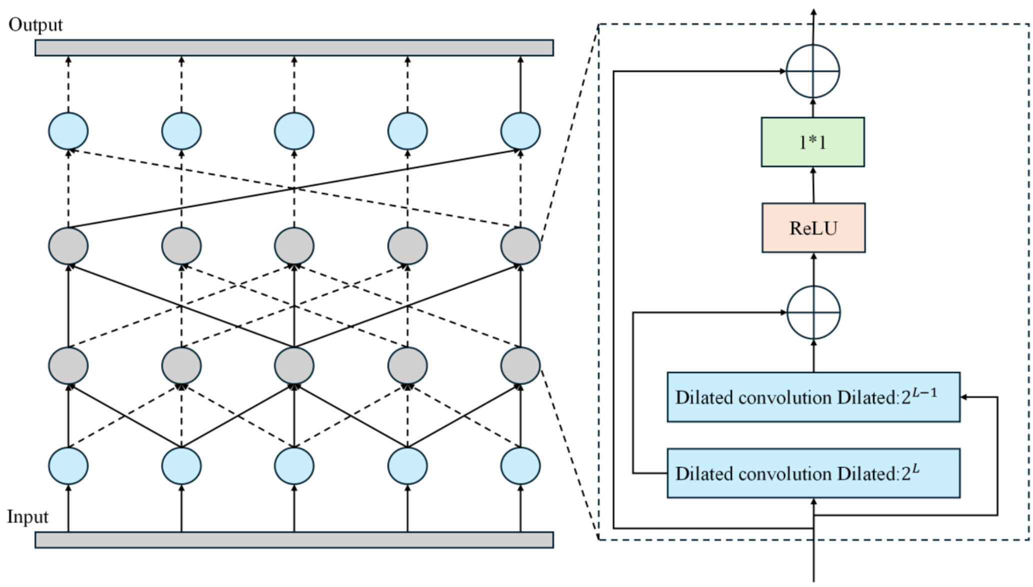

Figure 2. MS-TCN Module Structure Diagram: Economic Cycle Time Series Feature Extraction and Modeling Based on Multi-Scale Convolutional Network.

The core idea of the MS-TCN module is to widen the receptive field of the convolu- tional kernel by using dilated convolutions, enabling the model to capture dependencies across different time steps. The module is structured as a multi-layer convolutional net- work, where the input time series data is first processed by convolutional layers with different dilation rates. Let the input data be X = {x1, x2,..., xT }, representing the time series data of the economic cycle, T is the number of time steps, and x_k is the feature vector at the k-th time step. The output at the current time step is denoted as r_t (e.g., predicted market volatility), s_t represents the current state, and a_t repre- sents the action taken by the model. This dilated convolution operation, using kernels with different dilation rates, expands the receptive field to cover a longer time span, effectively capturing both short-term and long-term dependencies across time steps in the time series as in (1).

$$r_t = f(s_t, a_t) \cdots\cdots \text{[Formular 1]}$$

To enhance the model's predictive capability, the MS-TCN module can achieve deeper feature extraction by stacking multiple convolutional layers. Let the input be X(t) and the output be Y (t), where the output of each convolutional layer serves as the input to the next layer, gradually extracting information from different levels of the time series data. This hierarchical convolutional operation strengthens the model's ability to represent complex data, particularly in capturing multi-scale time depen dencies, offering advantages that traditional methods cannot match. The output Y(t) is the result of the convolution process, where W_k represents the convolution kernel, d is the dilation rate, and b is the bias term. $X(t - k \cdot d)$ denotes the feature at the current time step, with k being the index of the kernel applied at the dilated time step as in (2).

$$Y(t) = \sum_{k=1}^{k_t} W_k \cdot X(t - k \cdot d) + b \cdots\cdots \text{[Formular 2]}$$

To further enhance the model's expressive capability, MS-TCN also stacks multiple convolutional layers, enabling the model to gradually extract both local and global features from the time series data. H(t) represents the deep convolutional output at the t-th time step, σ is the activation function, W is the weight matrix, and b is the bias term. $Y(t-1)$ represents the output from the previous layer. These deep features are then passed on to the subsequent multimodal fusion module for further integration of different types of data to perform joint modeling as in (3).

$$H(t) = \sigma(WY(t-1) + b) \cdots\cdots \text{[Formular 3]}$$

3.3. Multimodal Learning Framework: Leveraging Diverse Data Modalities for Accurate Economic and Financial Predictions

The multimodal learning module is an essential part of a model developed by integrat ing information from multiple data sources to improve the accuracy of business cycle forecasts and financial risk assessment. This module combines not only data from time series, but also data from different areas such as financial news, political reporting and social media emotional analysis. Each type of data is processed by a corresponding specialized network and the corresponding pre-processing method is selected according to the characteristics of the input data. Figure 3 shows the structure of a multimodal learning module and clearly shows the data flow and collaboration between specialized networks.

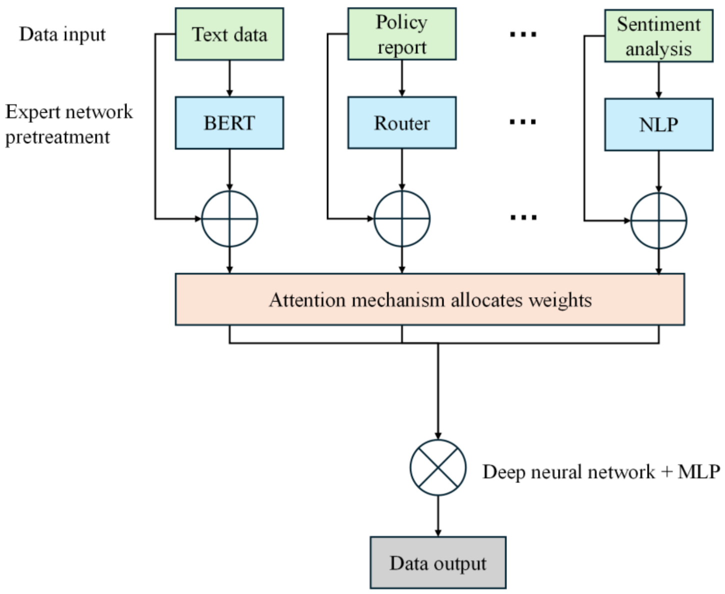

Figure 3. Multi-Modal Learning Module Structure Diagram: Data Fusion and Processing Based on Expert Networks.

In this module, each type of data is preprocessed through its corresponding expert network. These expert networks handle data from different sources, transforming each type into feature vectors with high-dimensional semantics. Let the input data be X , where X = {x1, x2,..., xT } represents the time series data, with T being the number of time steps and xk the feature vector at the k-th time step. Zt is the representation of the textual data after processing by the BERT model, and Xt represents the raw textual data at the t-th time step as in (4).

$$Z_i = \mathrm{BERT}(X_i) \cdots\cdots \text{[Formular 4]}$$

Social media data is processed through a sentiment analysis network, producing sentiment scores as sentiment feature vectors Yt , fsentiment represents the sentiment analysis function. These processed features are dynamically fused through a routing mechanism (Router), ensuring that each type of data selects the appropriate processing path based on its characteristics as in (5).

$$Y_t = f_{sentiment}(X_t) \cdots\cdots \text{[Formular 5]}$$

To integrate features from different sources, the multimodal learning module fuses these features through weighted averaging or self-attention mechanisms. Let the fused feature be F, and the fusion process can be represented by a weighted sum, where α is the weighting coefficient for each modality, and Zi represents the data representa tion of the i-th modality. The weights α are learned during training, with the model dynamically adjusting them based on the contribution of each modality to the final prediction. This approach allows the model to adjust the contribution of each data source according to its importance, enabling more precise feature fusion as in (6).

$$F = \sum_{i=1}^{N} \alpha_i \cdot Z_i \cdots\cdots \text{[Formular 6]}$$

Based on the fused data representation F, further processing is carried out through a deep neural network. Let the fused data F be processed by a multilayer perceptron (MLP), producing the output prediction P, where W is the weight matrix, b is the bias term, and σ represents the activation function.

This process enables the model to make the final economic cycle prediction and risk assessment based on the multi-source information as in (7).

$$P = \sigma(W \cdots F + b) \cdots\cdots\cdots\cdots\cdots\cdots \text{[Formular 7]}$$

Through the design of the multimodal learning module, the MS-RL DeepSeek model effectively integrates information from various sources, including economic data, mar ket sentiment, and social opinion, greatly enhancing the model's ability to respond to complex economic environments. This module not only enables the model to handle multiple forms of data but also provides a more comprehensive informational founda tion for subsequent predictions and decision-making.

3.4. Reinforcement Learning Module for Dynamic Decision Optimization in Economic Cycle Prediction and Financial Risk Management

The main function of the reinforcement learning module is to optimize the economic decision-making process by responding to the rapidly changing economic environment and dynamically adapting the decision strategy to real-time feedback. In the traditional static model, decisions are usually based on defined rules, while reinforcement learning updates the strategy in real time according to changes in the economic environment. This process involves self-adaptation through a reward and penalty mechanism that improves the outcome. Using multiple attention mechanisms, the model adapts to managing multiple factors and provides real-time decision-making capabilities. Figure 4 illustrates the structure of the reinforcement learning module, highlighting the interactions and feedback mechanisms between decision factors.

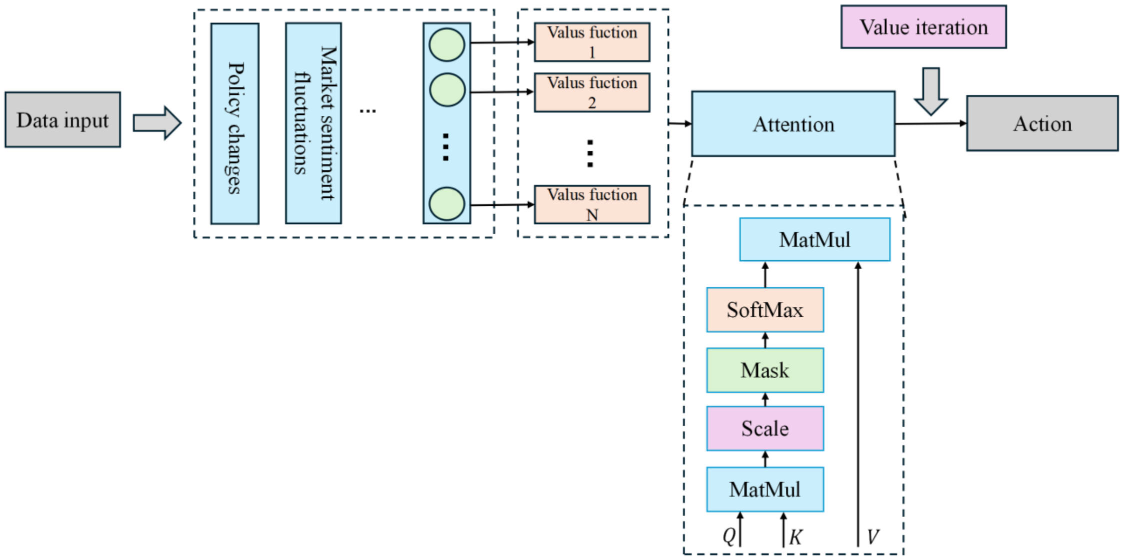

Figure 4. Reinforcement Learning Module Structure Diagram: Economic Decision Optimization Based on Reward-Punishment Mechanism and Multi-Head Attention Mechanism.

In the intensive learning module, the data processed and fused by the MS-TCN and multimodal learning modules is fed as input to this module. The results of economic forecasting and risk assessment at each time stage are considered state in cleanup learning, while the decisions originally made are considered ”ctions. The objective of the intensive learning module is to optimize the quality of economic decisions through a reward-penalty mechanism and to strengthen decisions over time as in (8).

$$Q(s_t, a_t) = R(s_t, a_t) + \gamma \max_{a'} Q(s_{t+1}, a') \cdots\cdots\cdots\cdots\cdots\cdots \text{[Formular 8]}$$

In this context, Q(st, at) represents the value corresponding to the current state st and action at, while R(st, at) denotes the immediate reward. γ is the discount factor, and maxa′ Q(st+1, a′) represents the maximum value of all possible actions in the next state st+1 . This formula optimizes the decision-making process by continuously updating the value function Q, enabling the model to make reasonable decisions when faced with different economic environments.

To enhance the decision-making capability of the model, the reinforcement learn- ing module introduces a multi-head attention mechanism. The multi-head attention mechanism allows the model to simultaneously focus on the impact of different deci- sion factors, such as policy changes and market sentiment fluctuations. Q represents the query, K represents the key, and V represents the value, while dk is the dimension of the key. Through this mechanism, the reinforcement learning module can flexibly focus on different decision factors and assign different weights to each factor, thereby improving the precision of the decisions as in (9).

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)V \cdots\cdots\cdots\cdots\cdots\cdots \text{[Formular 9]}$$

Additionally, the reinforcement learning module uses the value iteration method to optimize the decision-making process. $V(s_t)$ represents the value of state st, $P(s'|s_t, a_t)$ is the transition probability from state st to state s′ , and $R(s_t)$ is the reward for the current state. Through this iterative update, the reinforcement learning module continuously optimizes the economic decision strategy, enhancing its ability to predict economic cycles and financial risks as in (10).

$$V(s_t) = R(s_t) + \gamma \sum_{s'} P(s'|s_t, a_t) V(s') \cdots\cdots\cdots\cdots\cdots\cdots \text{[Formular 10]}$$

Through these formulas, reinforcement learning modules always adapt and optimize strategies to adapt to constantly changing economic environments and market dynamics. This model can voluntarily improve the decision-making policy, step up the predictive capabilities in a complex economic environment, and ultimately provide more accurate economic cycle forecasts and risk assessments.

4. Experiment

4.1 Datasets

In this study Yahoo Finance and FRED two publicly authoritative data sets, the Federal Reserve economic data, were used in the experiment. These data sets are widely accepted for financial market data and macroeconomic data for their applicability and reliability. Yahoo Finance It provides detailed information on financial markets, including data on stocks, bonds and exchange rates, and is suitable for examining market fluctuations and assessing financial risks. FRED is a great collection of macroeconomic indicators such as unemployment and inflation, and is ideal for analyzing economic cycles and evaluating economic risks. Table 1 summarizes the main features of the two data sets and facilitates the comparison of the content and applicable scenarios.

Table 1. Comparison of Key Characteristics of the Yahoo Finance and FRED Datasets for Economic and Financial Analysis.

Dataset Name	Content	Type	Coverage Time Span	Update Frequency
Yahoo Finance	Stock prices, Trading volume, bond yields, forex, etc.	Financial Market Data	Long-term (20+ years)	Daily
FRED	GDP, unemployment rate, inflation rate, interest rates, Macroeconomic indicators	Macroeconomic Data	Long-term (several decades)	Monthly

Yahoo Finance provides a wide range of financial data, including stock prices, transaction volume, bond yields and currency data[25]. This data covers several global markets and is suitable for financial market forecasts, risk assessments and volatility analyses. S&P 500, NASDAQ, including indices such as individual stock data Yahoo Finance stock data are ideal for testing a model's ability to predict short-term changes in financial markets. This can be used to model and analyze the historical returns, volatility and risks of stocks and other financial assets. The data is updated daily to reflect real-time market changes and is suitable for short-term forecasts and real-time risk assessments. In predicting market volatility and financial risks MS-RL DeepSeek The model extracts real-time and historical data from this data sheet and tests how the model responds to rapidly changing market conditions.

FRED provides a rich set of macroeconomic data, ncluding indicators such as GDP, unemployment rate, inflation rate, and interest rates. FRED It includes the economic data of the United States as well as the macroeconomic data of several countries around the world, and is suitable for analysis of long term economic trends and economic cycle forecasts. FRED It updates data monthly and is especially best suited for long term cycle, economic trends and risk assessment. MS-RL DeepSeek The model can use this dataset to model the economic cycle, extract the characteristics of macroeconomic fluctuations and predict the financial risk of recession or economic expansion.

4.2 Experimental Setup and Configuration

In the experiments carried out in this paper, all tests were performed on a powerful computer and big data were processed effectively, in particular to meet the computational requirements of deep learning models during training and completion.The hardware configuration used in the experiments includes: an NVIDIA Tesla A100 GPU (40GB VRAM), Intel Xeon Platinum 8280 CPU (28 cores), 256GB DDR4 memory, and 4TB SSD storage. The powerful computational capacity of the GPU significantly accelerated the training process of the deep learning models, especially when handling large time series datasets for economic cycle forecasting and financial risk assessment. The Intel Xeon Platinum processor provided ample support for multi-task parallel computing, ensuring smooth model training and evaluation during computationally intensive tasks. The operating system used was Ubuntu 20.04 LTS, with deep learning frameworks including PyTorch 1.9 and TensorFlow 2.5, integrated with CUDA 11.1 and cuDNN 8.1 to ensure efficient GPU computing. Python version 3.8 was used, compatible with all deep learning frameworks and their dependencies, ensuring smooth execution of the experiments.

In the dataset preprocessing phase, for the selected Yahoo Finance and FRED datasets, data cleaning and formatting were first performed. Missing values were imputed, and the different scales of economic indicators and stock market data were standardized through normalization. To ensure the quality and consistency of the input data, all time series data were standardized. Additionally, to enhance the diversity of the data and improve the model's robustness, smoothing techniques were applied to the Yahoo Finance dataset to reduce noise in market data, while seasonal adjustments were made to the FRED dataset to capture the cyclical features of macroeconomic fluctuations. In terms of dataset partitioning, 70% of the Yahoo Finance dataset was used for training, and 30% was used for testing; 80% of the FRED dataset was used for training, and 20% for testing. During model training, the Adam optimizer was employed along with a cosine annealing learning rate scheduling strategy. The loss function was optimized to minimize economic forecasting errors and risk assessment errors, ensuring the stability, accuracy, and adaptability of the model.

4.3 Evaluation Metric

In this experiment, MS-RL DeepSeek several commonly used comparison indicators have been selected to comprehensively evaluate the model's performance. These indicators include economic cycle forecasts, financial risk assessments, and model performance in model stability. To evaluate the completeness of the experimental results, we selected the following five indicators: MSE, MAE, R^2, Accuracy, F1 Score. These measurements are widely used in the field and can effectively reflect the performance of the models in various tasks[27][28].

MSE is used to measure the mean square error between model predictions and actual values. y_i the actual value, $\hat{y}_i$ the forecast value, N displays the number of data samples. MS-RL DeepSeek in the model, MSE is used to assess the extent of errors in economic cycle forecasting and market risk assessment and helps quantify the differences between the forecast model and actual market data. The MSE formula is displayed as in (11).

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{[Formular 11]}$$

MAE is an additional measure used frequently to measure the prediction error by calculating the absolute mean difference between the predicted value and the actual value. MAE is sensitive to different values and is suitable for measuring mistakes in financial risk assessment. MS-RL DeepSeek in the case of extreme economic incidents, the model helps to assess the model's ability to predict changes in market and economic cycles as in (12).

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} | y_i - \hat{y}_i | \cdots\cdots \text{[Formular 12]}$$

R^2 is used to evaluate the adaptability of a regression model. Represents the correlation between the predicted values of the model and the actual values and is commonly used to measure the explanatory power of the model. The R^2 values are in the range of 0 to 1, and as the value approaches 1, the model adapts to the data. MS-RL DeepSeek In the model, R^2 is used to assess a model's ability to adapt to economic data, particularly for macroeconomic forecasts that reflect the model's ability to explain changes in the economic cycle. The formula is as in (13).

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \cdots\cdots \text{[Formular 13]}$$

Accuracy is often used in classification tasks, and the percentage of the predicted samples occupies the total number of samples. This measure especially in the prediction of financial risk, is about the performance of models in predicting various risk categories MS-RL DeepSeek Used to evaluate the accuracy of the model. TP is the number of samples correctly predicted as positive, TN is the number of samples correctly predicted as negative, FP is the number of samples incorrectly predicted as positive, and FN is the number of samples incorrectly predicted as negative. In financial risk assessment, accuracy measures the overall effect of the model in the classification of risk cases. The accuracy formula is done as in (14).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \cdots\cdots \text{[Formular 14]}$$

The F1 Score is the harmonic mean of precision and recall, making it particularly useful for situations with class imbalance. Precision measures the proportion of predicted positive samples that are actually positive, while recall measures the proportion of actual positive samples that are correctly predicted as positive by the model. The F1 score balances precision and recall, especially in financial risk assessment, helping to avoid model bias toward any one class and ensuring stability in risk event identification. A higher F1 score indicates that the model can maintain high precision while also identifying most of the positive risk events. The formula for the F1 score is as in (15)(16)(17).

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \cdots\cdots \text{[Formular 15]}$$

$$Precision = \frac{TP}{TP+FP} \cdots\cdots \text{[Formular 16]}$$

$$Recall = \frac{TP}{TP+FN} \cdots\cdots \text{[Formular 17]}$$

4.4 Comparative Experimental Results and Analysis

To evaluate the performance of the MS-RL DeepSeek model in economic cycle fore- casting and financial risk assessment, this experiment compares it with several classic benchmark models. The experiment uses the Yahoo Finance and FRED datasets and employs five common evaluation metrics: MSE, MAE, R^2, Accuracy, and F1 Score. Table 2 presents the experimental results of MS-RL DeepSeek and other comparison models on these two datasets. By comparing these metrics, the strengths and improve- ments of the MS-RL DeepSeek model can be assessed.

Table 2. Multi-Metric Performance Evaluation of MS-RL DeepSeek Versus Benchmark Models for Economic Cycle Prediction and Financial Risk Assessment on Two Public Datasets.

Model	Dataset	MSE ($\times 10^2$)	MAE ($\times 10^2$)	R^2	Accuracy (%)	F1 Score
MS-RL DeepSeek	Yahoo Finance	0.023	0.012	0.96	93	92
	FRED	0.021	0.010	0.97	91	90
TVP-VAR[29]	Yahoo Finance	0.032	0.016	0.94	89	85
	FRED	0.029	0.014	0.95	88	84
Deep State-Space[30]	Yahoo Finance	0.030	0.015	0.93	87	83
	FRED	0.028	0.013	0.94	86	82
MFNet[31]	Yahoo Finance	0.025	0.013	0.95	90	87
	FRED	0.022	0.011	0.96	89	86
DeepAR[32]	Yahoo Finance	0.027	0.014	0.94	88	85
	FRED	0.024	0.012	0.95	87	84
DeepSeek[33]	Yahoo Finance	0.026	0.013	0.94	89	86
	FRED	0.023	0.011	0.96	88	85

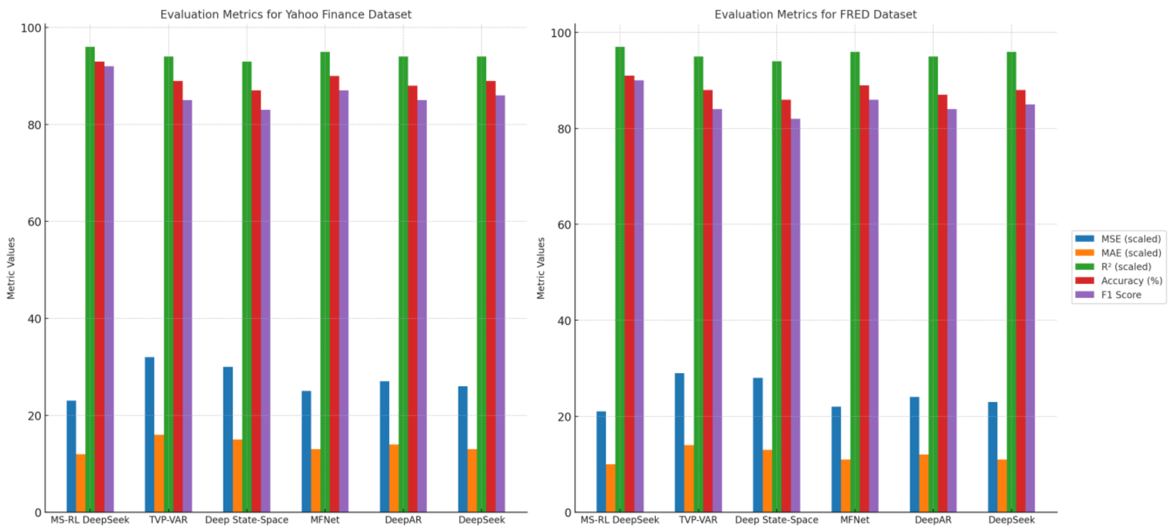

Figure 5. Comparison of Model Performance Across Multiple Evaluation Metrics on Yahoo Finance and FRED Datasets.

As shown in Figure 5, the MS-RL DeepSeek model outperforms all comparison models across all evaluation metrics, with particularly outstanding performance on the FRED dataset. Specifically, on the Yahoo Finance dataset, MS-RL DeepSeek achieves a Mean Squared Error (MSE) of 0.023, Mean Absolute Error (MAE) of 0.012, Coefficient of Determination (R^2) of 0.96, Accuracy of 93%, and an F1 Score of 92%. Compared to TVP-VAR, MS-RL DeepSeek reduces MSE and MAE by 28% and 25%, respectively, while increasing the F1 Score by 8%. Additionally, relative to Deep StateSpace, MS-RL DeepSeek decreases MSE and MAE by 23% and 20%, with a 9% improvement in F1 Score. These results indicate that MS-RL DeepSeek delivers more accurate predictions in economic cycle forecasting and financial risk assessment, particularly excelling at balancing long-term trends and short-term fluctuations.On the FRED dataset, MS-RL DeepSeek also demonstrates strong performance. Its MSE is 4% lower than MFNet and 3% lower than DeepAR; MAE is 15% lower than MFNet and 8% lower than DeepAR. Furthermore, MS-RL DeepSeek improves R2 and F1 Score by 2% and 5% over MFNet, and by 2% and 6% over DeepAR, respectively. These findings show that MS-RL DeepSeek effectively balances long-term trends and short-term volatility in complex economic data, exhibiting notable accuracy and robustness. Through multimodal data fusion and intensive learning-based decision optimization, MS-RL DeepSeek delivers efficient and reliable forecasting in a dynamic economic environment and provides more stable and accurate models for financial risk management.

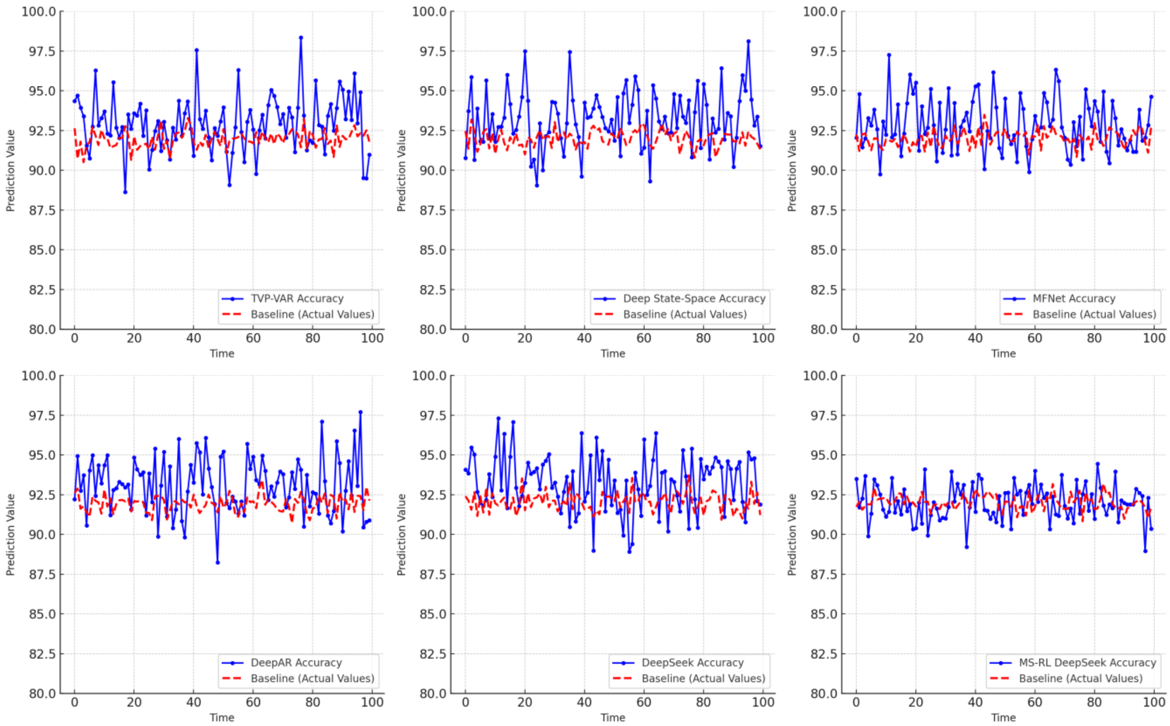

Figure 6. Comparison of Accuracy Trends with Baseline for Multiple Models in Economic Cycle Prediction and Financial Risk Assessment.

As shown in Figure 6, the MS-RL DeepSeek model surpasses all other comparison models across multiple evaluation metrics, particularly excelling in capturing long-term trends in economic cycles and predicting short-term fluctuations in financial markets. This indicates that MS-RL DeepSeek is capable of providing more accurate predictions and risk assessments in complex, dynamically changing economic environments. These results confirm the effectiveness of multi modal data fusion and decision optimization based on reinforcement learning and demonstrate potential potential in the application of economic and financial risk assessment.

4.5 Ablation Experimental Results and Analysis

In order to study the MS-RL DeepSeek contribution of each module, the ablation We carried out an experiment. By sequentially removing individual modules: MS- TCN, Multimodal Learning, and RL, we assessed the impact of each module on the model's performance. The experiments were conducted using both the Yahoo Finance and FRED datasets, and the evaluation was based on five assessment metrics. Table 3 presents the ablation results for both datasets. By comparing the complete model with the ablated models, we can gain a deeper understanding of each module's contribution to the overall performance of the model.

Table 3. Single-Module Ablation Experiment Results: Evaluating the Contribution of Each Module to MS-RL DeepSeek in Financial Risk Prediction.

Model	Dataset	MSE ($\times 10^2$)	MAE ($\times 10^2$)	R^2	Accuracy (%)	F1 Score
MS-RL DeepSeek	Yahoo Finance	0.023	0.012	0.96	93	92
	FRED	0.021	0.010	0.97	91	90
W/o MS-TCN	Yahoo Finance	0.030	0.016	0.92	88	86
	FRED	0.027	0.013	0.94	89	88
W/o Multimodal Learning	Yahoo Finance	0.028	0.015	0.94	90	88
	FRED	0.024	0.012	0.96	90	89
W/o RL	Yahoo Finance	0.025	0.014	0.94	89	87
	FRED	0.023	0.011	0.96	88	86

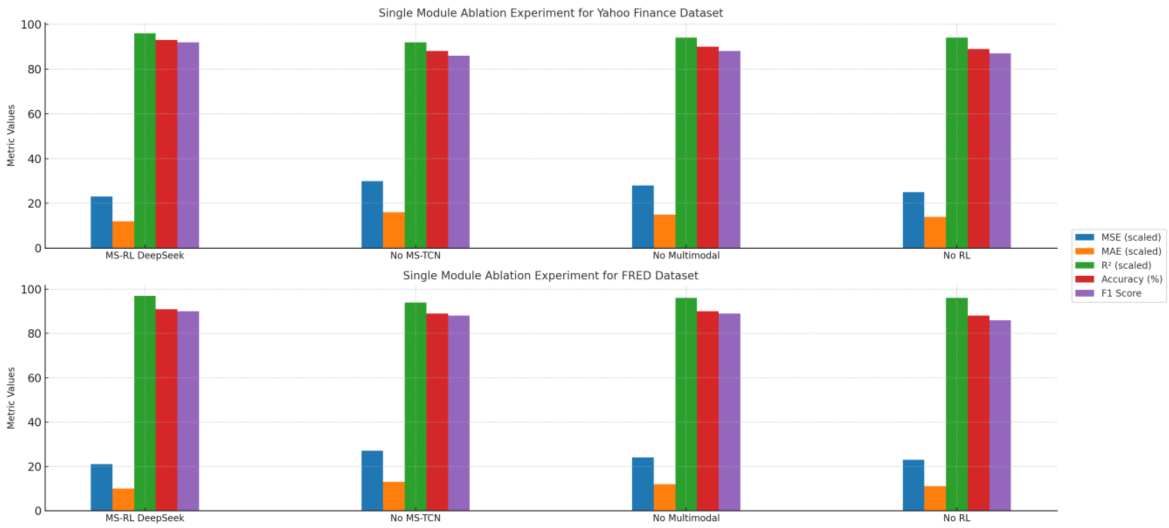

Figure 7. Single-Module Ablation Experiment Results for MS-RL DeepSeek on Yahoo Finance and FRED datasets.

As shown in Figure 7, removing any single module leads to a significant decline in model performance. On the Yahoo Finance dataset, the MS-RL DeepSeek model without the MS-TCN module exhibits an MSE of 0.030 and an MAE of 0.016, with R2 dropping to 0.92. Accuracy and F1 Score decrease by 5% and 6%, respectively. Compared to the complete model, MSE and MAE increase by 30% and 33%.These results demonstrate the critical role of the MS-TCN module in capturing long-term trends and short-term fluctuations in time series data. Multimodal learning module deletes the model, MSE is 0.028, MAE is 0.015, and R2 falls to 0.94, increased accuracy and F1 score decrease by 3% and 4%, respectively.Compared to the full model, MSE and MAE increase by 22% and 25%. This shows that the multimodal learning module significantly improves the model's ability to handle complex economic environments by integrating information from multiple data sources such as financial information and social media data. If you delete the RL module, MSE is 0.025, MAE is 0.014, the accuracy and F1 score decreases by 4% and 5%. Compared to the full model, MSE and MAE increases by 9% and 17%. In a rapidly changing economic environment, the modules suggest that the accuracy and robustness of models can be improved by optimizing the economic decision process and enabling adaptive forecasting strategies. Similar trends are observed in the FRED dataset. If you remove the MS-TCN module, MSE and MAE increase by 29% and 30%, respectively. Exclude the Multimodal learning module, MSE and MAE increased by 14% and 18%, while excludes RL modules, MSE and MAE Increases by 10% and 12%. These results are in each module in macroeconomic data management MS-TCN emphasis is placed on the importance of multi-time-scale and multimodal data.

Overall, the results of the single-module ablation experiments validate the critical role of each component within the MS-RL DeepSeek model. The MS-TCN module extends a model's ability to capture the various dependencies of time series data. The multimodal learning module strengthens the integration of data from multiple sources. RL modules optimize decision strategies and enable models to dynamically adapt to rapidly changing economic environments. The study clearly shows that each module contributes significantly to the accuracy, stability and adaptability of the model.

single-module ablation experiments enable individual contributions of each component, but do not fully record the synergistic effect between modules. Therefore, to verify the interactions and interdependencies between modules, we have multi-module ablation experiments was carried out. By removing different combinations of the MS-TCN, multimodal learning, and reinforcement learning modules from the MS-RL DeepSeek model, we conducted an in-depth analysis of the effects of various module combinations. These experiments aim to assess the roles of different module combinations and evaluate their collaboration in economic cycle forecasting and financial risk assessment. Table 4 presents the results of these multi-module ablation experiments.

Table 4. Multi-Module Ablation Experiment Results: Evaluating the Combined Effects of Removing Multiple Modules on MS-RL DeepSeek's Performance in Economic Cycle Prediction and Financial Risk Assessment.

Model	Dataset	MSE ($\times 10^2$)	MAE ($\times 10^2$)	R^2	Accuracy (%)	F1 Score
MS-RL DeepSeek	Yahoo Finance	0.023	0.012	0.96	93	92
	FRED	0.021	0.010	0.97	91	90
W/o MS-TCN & Multimodal Learning	Yahoo Finance	0.035	0.022	0.91	85	80
	FRED	0.032	0.020	0.94	84	79
W/o MS-TCN & RL	Yahoo Finance	0.033	0.021	0.92	87	83
	FRED	0.029	0.018	0.95	86	82
W/o Multimodal Learning & RL	Yahoo Finance	0.027	0.018	0.93	89	85
	FRED	0.025	0.015	0.96	89	84

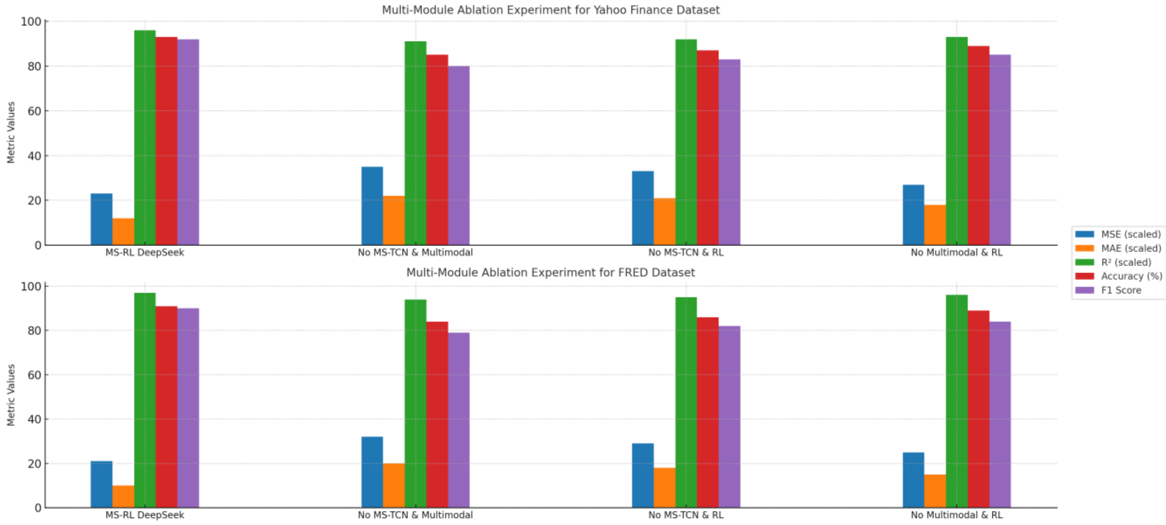

Figure 8. Multi-Module Ablation Experiment Results for MS-RL DeepSeek on Yahoo Finance and FRED datasets.

As shown in Figure 8, removing any combination of two modules significantly degrades the model's performance. On the Yahoo Finance dataset, MS-RL DeepSeek without the MS-TCN and Multimodal Learning modules exhibits an MSE of 0.035, MAE of 0.022, and R2 of 0.91, with accuracy and F1 score decreasing by 8% and 12%, respectively. Compared to the complete model, MSE and MAE increase by 52% and 83%. These results highlight the critical importance of the MS-TCN and Multimodal Learning modules in capturing multi-scale dependencies and integrating multi-source data.When the MS-TCN and Reinforcement Learning (RL) modules are removed, the model's MSE rises to 0.033, MAE to 0.021, and R2 drops to 0.92, with accuracy and F1 score decreasing by 6% and 9%. Compared to the full model, MSE and MAE increase by 43% and 75%, indicating the indispensable role of the MS-TCN and RL modules in capturing long-term economic trends, short-term market fluctuations, and optimizing decision strategies.Removing the Multimodal Learning and RL modules results in an MSE of 0.027, MAE of 0.018, and R2 of 0.93, with accuracy and F1 score declining by 4% and 7%. These findings suggest that the combination of Multimodal Learning and RL modules jointly enhances the model's financial risk prediction capability, particularly in multi-source data fusion and decision strategy optimization.Similar trends are observed on the FRED dataset. Removing the MS-TCN and Multimodal Learning modules increases MSE and MAE by 52% and 100%, respectively, relative to the complete model. Excluding the MS-TCN and RL modules raises MSE by 38% and MAE by 80%, while removing the Multimodal Learning and RL modules results in MSE and MAE increases of 19% and 50%. These experimental results demonstrate that the combined contributions of the MS-TCN, Multimodal Learning, and RL modules are crucial for improving model performance.These findings suggest that the combination of Multimodal Learning and RL modules jointly enhances the model's financial risk prediction capability, particularly in multi-source data fusion and decision strategy optimization.Similar trends are observed on the FRED dataset. By removing the MS-TCN and Multimodal Learning module increases MSE and MAE by 52% and 100% respectively. Excluding the MS-TCN and RL modules, MSE by 38%, MAE by 80%, while removing the Multimodal Learning and RL modules results in MSE and MAE increases of 19% and 50%. The results of these experiments that MS-TCN, Multimodal Learning, RL shows that the combined contribution of the module is essential to improve model performance.

Overall, the results of the ablation experiment show that the MS-TCN, Multimodal Learning, and RL modules are essential to improve the prediction accuracy, risk assessment, and decision optimization capabilities of the MS-RL DeepSeek model. Each module plays an indispensable role in the model, and removing each module combination results in a significant power fluctuation. In addition, these results confirm the synergy effects and interdependencies between the modules and support the development of the MS-RL DeepSeek model.

5. Conclusion and Discussion

The MS-RL DeepSeek model learns multimodally to systematically address business cycle forecasting and financial risk assessment. The integration of MS-TCN and RL enhances its capabilities. Experimental results show that MS-RL DeepSeek outper forms existing reference models on the Yahoo Finance and FRED datasets across several evaluation metrics. The model specifically addresses the challenge of short term dependencies in multi-source data and time series. Ablation studies confirm the important role of each module in the model. The MS-TCN and multimodal learning modules are crucial in balancing long-term trends and short-term fluctuations in time series.

There MS-RL DeepSeek are some limitations on the model despite the promising performance in economic cycle prediction and financial risk assessment. First, the mod eling process is relatively complex, especially in large scale financial data processing IT Resources are required. Second, multimodal learning and reinforcement learning allow for effective fusion of data from multiple sources and optimization of decision making, but it is necessary to further improve the rigidity of the model in extreme economic conditions and sudden events. Future research may focus on Algorithms optimization, increased data, and other strategies to improve the accuracy and prediction accuracy of models in a more unstable market environment.

In conclusion, the MS-RL DeepSeek model combines advanced deep learning, in tensive learning, and multimodal data fusion techniques to provide new methods for business cycle forecasting and financial risk assessment. They effectively improve the accuracy of forecasts and the effectiveness of decisions. Thanks to continuous tech nological advances and enhanced computing capacity, models offer wider possibilities for use in different areas and can continue to stimulate the development of intelligent economic analysis and financial risk management.

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Conflicts of Interest

The author confirms that there are no conflicts of interest.

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