Establishment of Economic Analysis Model Based on Artificial Intelligence Technology

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***Abstract*—With the continuous evolution of artificial intelligence technology, its integration into economic analysis models is becoming increasingly prevalent. This paper employs the Lasso Back Propagation neural network method to conduct financial analysis and prediction for major global economies, focusing on total Gross Domestic Product, combined Gross Domestic Product growth rate, and Consumer Price Index. The real Gross Domestic Product of the top 30 countries in the global ranking is meticulously analyzed and categorized into various economic types. This categorization, coupled with the utilization of neural network multi-hidden layer variable analysis, facilitates the analysis and prediction of national economic trends. The findings reveal that overall economic growth among the top 30 countries is sluggish, albeit showing a growth trajectory. However, the driving force for economic growth remains notably inadequate. Moreover, employing a single time series model effectively predicts Gross Domestic Product and Consumer Price Index growth rates, alongside other macroeconomic indicators. Notably, the absence of autocorrelation in the fitting residual series underscores the applicability of the time series method for combined forecasting, affirming the robustness of the predictive framework.**

Keywords—Artificial intelligence; lasso regression; BP neural network; economic analysis model; major global economies; multi-hidden layer variable analysis; economic trends

I. Introduction

The paper is structured into eight sections to elucidate the research findings. Section I delineates the significance of macroeconomic dynamic forecasting, identifies deficiencies in existing forecasting models, and underscores the considerable potential of artificial intelligence (AI) technology in economic analysis. Section II comprises a comprehensive literature review, delving into the utilization of AI technology in economic analysis across various industries and elucidating the associated challenges. Following this, Section III offers an in-depth exploration of the theory and application of Lasso regression and Back Propagation (BP) neural network models, providing the theoretical underpinning for the economic forecasting model in this paper. Section IV expounds on the research framework, encompassing variable selection amalgamated with economic theory, hierarchical classification of multilevel economies, methodological innovations in forecasting, and the application of combined forecasting techniques. Section V delineates the specific procedures involved in model construction, encompassing the selection of key factors based on Lasso regression and the hierarchical clustering analysis of diverse economic categories. Subsequently, Section VI presents the outcomes of constructing the BP neural network forecasting model and substantiates its efficacy through empirical analysis. Section VII conducts empirical analysis on the combined forecasting of Gross Domestic Product (GDP) and Consumer Price Index (CPI), evaluating the accuracy and robustness of the model in predicting macroeconomic indicators. Finally, section VIII encapsulates the entirety of the paper, underscoring the contribution of this paper to macroeconomic analysis and proposing avenues for future research endeavors.

Macroeconomic dynamic forecasting technology has emerged as a pivotal theoretical domain within macroeconomic forecasting analysis. It entails a systematic approach that integrates scientific, reliable, and comprehensive historical statistics, investigative data, and pertinent macroeconomic information. This process aims to unveil the fundamental historical laws governing economic phenomena and employs the most scientific, practical, and efficacious economic theories and methodologies. The overarching goal is to offer timely, insightful, and accurate qualitative and quantitative insights into the objective state of social and economic activities. By enhancing public comprehension of the inherent dynamics of human economic endeavors, this approach aids in discerning economic phenomena and forecasting future industry developments [1], [2], [3], [4], [5]. The significance of forecasting macroeconomic trends cannot be overstated, as it underpins the sustained, stable, and efficient functioning of the national economy while bolstering policy decision-making [6], [7], [8].

In the realm of macroeconomic forecasting, numerous economic prediction models have been developed and scrutinized by professional researchers. These include the Autoregressive Moving Average (ARMA) model [9], [10], error correction model [11], [12], vector adaptive regression model [13], [14], mechanism conversion model [15], [16], ensemble models [17], [18] and dynamic factor model [19], [20]. While each of these models can yield favorable prediction outcomes under specific conditions, they may also exhibit significant errors at times. For instance, the traditional large-scale simultaneous equation model often falls short compared to simpler models like the Autoregressive Integrated Moving Average (ARIMA) model in short-term predictions. Conversely, the vector error correction model excels in predicting non-stationary time series with co-integration relationships. Hence, the applicability of various time series models varies depending on the context and environment. Nevertheless, relying solely on a single time series prediction method has its drawbacks. It may fail to fully leverage the information embedded in the data and can lead to unstable prediction results, particularly when influenced by outliers or anomalous data points. Thus, a judicious approach to model selection and integration is imperative to enhance the accuracy and robustness of macroeconomic predictions.

Considerable research has delved into the theory and practical applications of combined forecasting, yielding several noteworthy methodologies [21], [22], [23], [24], [25]. Samuels and Sekkel [26], for instance, introduced a model confidence set approach wherein model sets are pruned before constructing an average combination forecasting model. This method thoroughly evaluated the statistical significance of prediction performance across samples, enhancing forecasting accuracy, particularly beyond the sample range. Empirical investigations focusing on forecasting macroeconomic indicators in the United States have underscored the efficacy of this model correction technique. Similarly, Kotchoni et al. [27] explored four distinct weight-setting methods, including pruning average and inverse average, to average forecasts from five individual models. These diverse approaches to combined forecasting hold promise for refining prediction outcomes and enhancing the reliability of economic forecasts.

Numerous economic forecasting endeavors have demonstrated that combined forecasting models typically outperform single forecasting models in terms of accuracy [28], [29], [30]. However, while many mixed forecasting methods offer various model combinations, they often lack in-depth discussions on the relationship between the number of combined forecasting methods and the forecast results, as well as the robustness of combined models compared to single forecasting models. In this paper, the Lasso model identifies key factors influencing national GDP output, while the BP neural network model establishes an economic forecasting model. Through macro quantitative correlation research, the analysis focuses on the correlation between the actual average GDP growth rate of China and nearly 30 countries ranking in the top five of global GDP. Additionally, it considers current and future trends in global political and economic development. This analysis is supported by a multidimensional correlation data environment, enabling predictions of GDP growth rates and future development trends for over 30 countries and the corresponding international community. The paper conducts macro trend research, trend analysis, and predictions of global changes, employing quantitative and multidimensional correlation model empirical analyses. This approach further enriches the understanding of macroeconomic policy theories and research frameworks, providing valuable insights into observed phenomena and theoretical frameworks through extensive academic verification.

II. Literature Review

A. Application of AI Technology in Economic Analysis

The application of AI techniques in economic analysis has garnered considerable attention and exploration in academic discourse. Biju et al. (2024) contended that the utilization of machine learning and AI for predictive processes is marred by severe flaws stemming from algorithmic biases, particularly prevalent in domains such as insurance, credit scoring, and mortgage lending [31]. This study underscores the imperative for academia to pivot strategically toward embracing disruptive and innovative forces that are reshaping the future of finance. Liao et al. (2022) identified a key limitation hindering the widespread adoption of AI in chemical production: the absence of a quantitative understanding of the potential benefits and risks associated with various AI applications [32]. They underscored the necessity for future research endeavors to address data challenges in assessing the impact of AI and to develop AI-enhanced tools conducive to supporting sustainable development within the chemical industry. Chen et al. (2022) harnessed decision tree algorithms of AI to devise an environmental cost control system tailored for manufacturing companies, facilitating the internalization of environmental costs [33]. Dauvergne (2022) delved into the ramifications of AI applications within global supply chains (GSCs) on environmental sustainability, revealing that while AI yields micro-level benefits, it fails to mitigate the adverse environmental consequences of GSCs [34]. He posited that framing AI as a catalyst for sustainable development serves to rationalize conventional business operations, fortify corporate responsibility narratives, attenuate the necessity for heightened national regulation, and endow multinational corporations with global governance prowess. Wilson et al. (2022) explored the impact of AI on reverse logistics within the circular economy, spotlighting the technology's potential as a significant force shaping entrepreneurial opportunities and processes within corporate ecosystems [35]. Ronaghi et al. (2023) delved into the influence of AI on circular economy practices, unveiling that technological characteristics, organizational capabilities, and external task environments collectively influence AI adoption, thereby positively impacting circular economy practices [36]. Their findings underscored AI technology's potential to revolutionize production processes and mitigate industries' deleterious environmental footprint. Onyeaka et al. (2023) investigated the capacity of AI technology to combat food waste and bolster the circular economy, asserting that leveraging AI technology can optimize resource utilization efficiency, curtail environmental impacts, and foster a more sustainable and equitable food system [37]. Bochkay et al. (2021) scrutinized the nexus between macro-uncertainty and analysts' forecasting accuracy, emphasizing the criticality of accounting for uncertainty in economic analyses [38]. Bousdekis et al. (2021) delved into big data-driven macroeconomic forecasting models, offering a behavioral analysis of decision-making in the Industry 4.0 era [39]. Additionally, Tilly et al. (2021) showcased the potential of non-traditional data sources such as news, sentiment, and narratives in economic analyses, suggesting that AI techniques hold immense promise in enhancing economic efficiency, curbing resource wastage, and fostering sustainable development [40]. Although challenges and risks accompany the application of AI techniques in economic analysis, meticulous evaluation and effective management can maximize their advantages and foster sustainable economic development and innovation. Hence, while the use of AI techniques for economic analysis is indeed feasible, it necessitates cautious implementation in practice and adaptable application across diverse contexts to yield optimal results and societal benefits.

B. Lasso Regression and BP Neural Network Modeling

Least Absolute Shrinkage and Selection Operator (Lasso) regression serves as a regression method adept at handling data with multicollinearity. It accomplishes this by introducing an L1 regularization term, compressing insignificant regression coefficients towards zero, and facilitating variable selection. Notably, this approach not only enhances model interpretability but also mitigates the risk of model overfitting. In economic analysis, Lasso regression finds widespread utility across various forecasting domains, including macroeconomic indicator prediction and financial market analysis. For instance, Deng and Liang et al. (2023) utilized Lasso regression to refine a semiparametric ARMA-TGARCH-EVT model, enhancing the robustness of portfolio optimization in their study [41]. BP neural network represents a multilayer feed-forward neural network trained via a backward propagation algorithm, proficient in discerning intricate relationships between input and output data. Given its adeptness in pattern recognition and time series forecasting, BP neural networks have found extensive application in economic forecasting. Sedighi et al. (2022) harnessed BP neural networks to predict the Standard & Poor's 500 index stock market, underscoring its utility within the financial realm [42]. The BP neural network model serves as a potent tool for economic forecasting, leveraging historical data to capture nonlinear relationships and dynamic shifts among economic indicators. Integrating Lasso regression with BP neural networks enables the synergistic utilization of their respective strengths. Specifically, the variable selection prowess of Lasso regression reduces the input dimension of BP neural networks, enhancing their training efficiency and predictive performance. Concurrently, the formidable nonlinear fitting capability of BP neural networks adeptly addresses intricate relationships potentially overlooked by Lasso regression. This amalgamation holds considerable promise in economic forecasting, augmenting forecast accuracy and reliability.

C. Research Positioning

In comparison to existing studies, the economic analysis model proposed in this paper, based on Lasso regression and BP neural network, possesses distinctive characteristics:

1) Integration of variable selection and economic theory: This paper not only employs Lasso regression for variable selection but also amalgamates economic theory with theoretical interpretation and variable screening. This fusion enhances the economic significance of the model by integrating domain knowledge with statistical techniques.

2) Hierarchical classification of economies: Through hierarchical clustering analysis, the paper categorizes the top 30 global GDP countries into distinct economic types. This classification approach facilitates a more accurate capture of diverse economic characteristics, enabling targeted forecasting.

3) Innovative forecasting methodology: The paper adopts the BP neural network model for forecasting and enhances its nonlinear fitting capability by designing multiple hidden layers. This innovation in modeling contributes to improved forecasting accuracy.

4) Application of combined forecasting: This paper incorporates cross-validation of time series and inverse root mean square error for combined forecasting. This approach significantly enhances forecasting accuracy compared to using a single forecasting model alone.

In summary, this research program offers new perspectives and tools for macroeconomic analysis through methodological innovation and theoretical deepening while building upon existing research foundations.

III. Lasso-BP Neural Network Model

A. Lasso Regression

The Lasso compressed regression estimation model utilized in this paper offers a refined approach to regression analysis. By reconstructing the penalty function, this model effectively compresses certain regression coefficients, allowing for a more abstract and nuanced estimation of the underlying structure. Notably, it enables the compression of coefficients to zero, thereby addressing multicollinearity issues and retaining the advantageous features of subset shrinkage regression models. This flexibility allows for independent data processing, enhancing the model's utility in handling complex datasets.

The principle of the Lasso model is outlined as follows: Let matrix x represent the independent variables, and y denote the dependent variable. Following n sampling operations, the standardized values of the paired data (x, y) can be computed, where matrix x is an $n \times P$ matrix ($n>p$), and y is set to an n×1 matrix. The data for the i-th observation in matrix $x$is denoted as $x_i = (x_{i1}, x_{i2}\ldots, x_{ip})^T$, where $i \in [1,2 \cdots. n]$, and each observation is independent of the others. Similarly, $y = (y_1, y_2\ldots, y_n)^T$. The regression model of y with respect to x can be expressed as:

$$y_i = \hat{\alpha} + \sum \beta_j x_{ij} + \varepsilon_i \tag{1}$$

In the Eq. (1), $\varepsilon \sim N$ (0, σ^2), and α in the definition $\hat{\alpha}$ is defined as $\hat{\alpha}=\bar{y}$. The standardized data $\bar{y}=0$; therefore, Eq. (1) can be rearranged as follows:

$$y = \beta x + \varepsilon \tag{2}$$

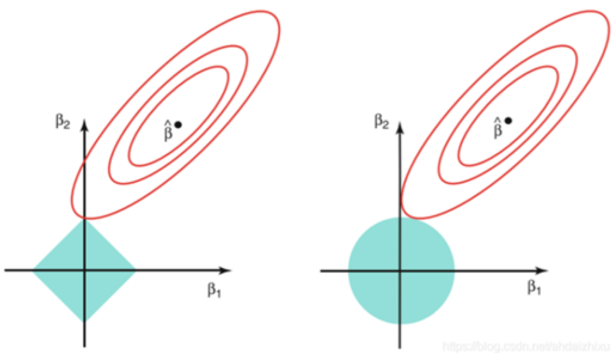
In Eq. (1), $\varepsilon \sim N$ (0, σ 2), β signifies the n-dimensional parameter vector, and ε denotes the random disturbance term. To screen out variables with significant influence, a condition needs to be added to Eq. (2), expressed as Eq. (3):

$$arg \min_{\{\beta_1,\beta_2,\cdots,\beta_n\}} \|y-\beta x\|^2 \qquad s.t \sum_j \frac{|\beta|}{\sum \beta_0^j} \le s \tag{3}$$

In Eq. (3), the value range of S is generally [0, 1] as the t value is also a tunable parameter $t \geq 0$. The Lasso regression model entails reducing the regression coefficient of the entire model by continuously adjusting the value of the t parameter and progressively compressing the regression coefficient of the model, excluding non-significant variables until it reaches zero.

The objective function's first line closely resembles that of the traditional linear regression model. However, the most significant and fundamental distinction between Elastic Net and linear regression lies in the constraint: in Elastic Net, there are both lasso and ridge penalties, whereas in linear regression, only the lasso penalty is present. Both linear regression and Elastic

Net regulate the magnitude of the coefficients of the independent variables within the range controlled by *t*. This feature allows the Elastic Net model to automatically adjust the complexity of variables. Moreover, the Lasso regression model can automatically filter variables and modify the complexity of variables concurrently.



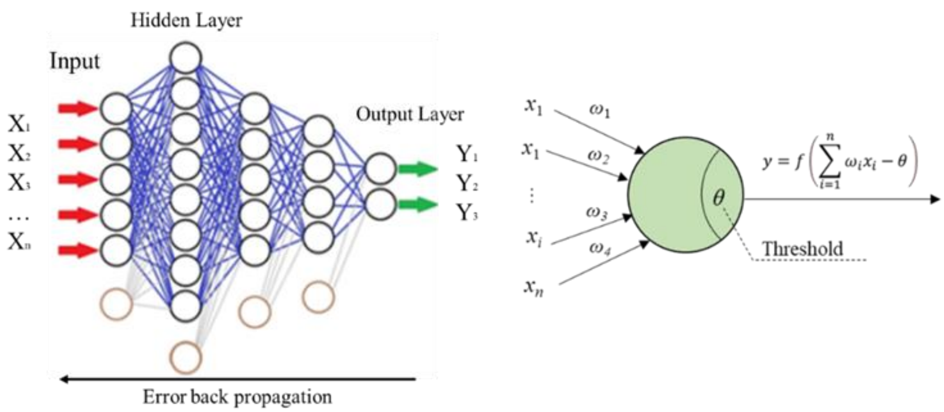
(a) (b)

Fig. 1. (a) Estimation plot for Lasso regression (b) Estimation plot for ridge regression.

As depicted in Fig. 1, suppose the coefficients corresponding to a two-dimensional model are denoted as β_1 and β_2, then $\hat{\beta}$ represents the point where the sum of squared errors is minimized, yielding the independent variable coefficients obtained by traditional linear regression. However, this coefficient point must fall within the blue square, leading to the existence of a series of potential coefficients, denoted as $\hat{\beta}$. The first point that intersects the blue square is the point that adheres to the constraint and minimizes the sum of squared errors. This point represents the independent variable coefficients obtained by Lasso regression. Due to the constraint being a square, the intersection points between the square's vertices and a concentric elliptical surface always lie on the same square vertex. When the vertex intersects the coordinate axis, it implies that only one value of the independent variable coefficient meeting the constraint conditions can be precisely less than 0. Consequently, in this scenario, traditional linear regression yields effective models for both β_1 and β_2, whereas Lasso regression results in only β_2 being effective, thereby illustrating Lasso regression's capability to screen variables.

B. BP Neural Network Model

The main concept of the BP neural network model is illustrated in Fig. 2. Learning samples are input into the input layer, and multiple adjustment calculations and simulation training are conducted for the deviation signal within the network through error backpropagation, aiming to minimize the error between the output value and the expected value of the signal.



(a) BP neural network model (b) Neuron topology

Fig. 2. Typical structure of neural networks.

Kang et al. [43], Zhang et al. [44], and Zhi et al. [45] have explained the operational principle of the BP neural network and proposed enhancements to its applicability. The BP neural network serves as a prevalent computer algorithm across various domains. The operational principle of the BP neural network model is outlined as follows: Consider a training set represented by X= (X_1, X_2, X_3, ⋯, X_r X_n) where the training sample set comprises input values X_r= (X_{r0}, X_{r1}, X_{r2}, ⋯, X_{rq}), real input value y_r= (y_{r1}, y_{r2}, y_{r3}, ⋯, y_{r0}), and predicted value s_r= ($s_{r1,}$ sr_2, s_{r3}, ⋯, s_{r0}). Assuming thresholds and weights between the input-hidden layer and the output-hidden layer are denoted as v_{oj} and v_{ij}, respectively, and thresholds and weights between the hidden input layer and the hidden output layer are represented by u_{ok} and u_{jk}, with the expected precision *b* and the number of iterations denoted as *m*, the mathematical expression is as follows:

$$z_j = f(I_j) = f(\textstyle\sum_{i=0}^{q} v_{ij} x_{rj}) \tag{4}$$

$$z_k = f(I_k) = f(\textstyle\sum_{i=0}^{p} v_{jk} x_{rj}) \tag{5}$$

Here, I_j represents the input in the hidden input layer, I_k denotes the input in the hidden output layer, z_j signifies the output in the hidden output layer, s_k indicates the output in the hidden output layer, and *f* refers to the transfer function.

The sum of error energy is given by Eq. (6):

$$E(m) = \frac{1}{2}\textstyle\sum_{k=1}^{0}[y_{rk}(m) - s_{rk}(m)]^2 \tag{6}$$

The criterion for meeting accuracy requirements is $E(m)<b$. If this criterion is not satisfied, error backpropagation is necessitated. Here, a new parameter, η, is introduced. The iterative process is expressed as Eq. (7):

$$v_{ij}(m+1) = v_{ij}(m) - \eta \frac{\partial E(m)}{\partial v_{ij}} \quad (7)$$

In Eq. (7), η denotes the learning rate. The calculation method for u_{jk} (m+1) mirrors that of Eq. (7).

The above calculation process is reiterated until the error is confined within an allowable range or the maximum number of iterations is reached.

C. Role of AI Technology in Economic Modeling

The integration of AI technology into economic modeling is poised to redefine the role of human economists. Firstly, the widespread adoption of AI will empower economists to process and analyze vast and intricate economic datasets with greater precision, facilitating a more nuanced understanding and prediction of economic phenomena. Traditionally, economists invest substantial time and effort in data collection, organization, and analysis. However, AI-driven models can automate these tasks, allowing economists to dedicate their expertise to higher-level analysis and decision-making. Secondly, AI technology enhances economists' ability to identify economic patterns and trends, including those elusive to human observation. Leveraging machine learning algorithms, economic models can unearth hidden correlations and patterns within extensive datasets, thereby furnishing economists with deeper insights and predictive capabilities. This capability enables economists to comprehend the intricacies of the economic ecosystem more comprehensively and respond adeptly to forthcoming challenges and opportunities. Furthermore, AI-based economic models facilitate the generation of timelier and more accurate forecasts, equipping economists with the agility to formulate policies and make decisions expeditiously. With ongoing algorithmic refinement and model updates, these models progressively enhance prediction accuracy and reliability, empowering economists to navigate economic fluctuations and mitigate risks more effectively.

In essence, AI-driven economic models elevate the role of economists to one that is more specialized and intellectually adept. Economists can leverage technology more effectively to elucidate and interpret economic phenomena, thereby crafting more impactful economic policies and strategies for governments, businesses, and society at large. Nonetheless, while the proliferation of AI technology presents immense opportunities for economists, they must continue to uphold their comprehension of and adaptability to technology. This ensures the preservation of human values and ethics in economic decision-making, safeguarding against the potential pitfalls of unchecked technological advancement.

IV. Model Construction

A. Identification of Key Influencing Factors Based on Lasso Regression

Currently, the world can be divided into 233 groups of major economic countries and one economic region, with more than 197 countries in one group and 36 countries in regional groups. The most important factors that can affect the composition of the GDP of each country in the world may vary significantly, including the intricate relationships with other global variables such as world politics, economy, humanities, geographical conditions, and the environment. Therefore, it is challenging for research to swiftly and accurately analyze all these factors simultaneously and conduct a comprehensive macroeconomic global correlation analysis closely related to almost all specific economic variables. To ensure reliable, accurate, timely, and comprehensive financial data and forecasts of the total GDP, changes, and trends of the top 40 and 30 major countries in the euro area, it is imperative to consider the absolute height and availability of relevant economic data information of existing countries in the euro area. Moreover, it is necessary to minimize confusion in relevant macroeconomic data information and reduce the untrustworthiness and dimensionality of economic-related data. In this paper, the Lasso regression analysis is employed to identify key factors affecting performance. Considering four main aspects that may simultaneously influence China's regional economy's overall rapid and sustainable development and operation process, five key reference factors with potentially significant impacts on the current changes in the average annual GDP level of the countries in the above regions are selected: national fiscal revenue, actual nominal utilization of international foreign capital, legal money supply in a broad sense of society, total amount of expenditure income within the fiscal budget, and total amount of investment projects completed in fixed asset infrastructure. Additional indicators include the average social share of countries with different industrial development rates, agricultural population, labor force participation rate, consumer price index, gross national product, total energy, and the proportion of total foreign trade income and expenditure. It gives the details on the proportion of tax revenue, exchange rate, foreign debt, added value of real economy, and the total social and economic output of various virtual countries in the total nominal GDP of a virtual country.

The aforementioned 15 variables serve as independent variables, with total GDP employed as the dependent variable for Lasso regression analysis. With a K value of 0.05, the model achieves an R-squared value of 0.973, indicating that the 15 factors identified in the paper can account for 97.3% of the variations in total GDP. Consequently, these 15 factors hold predictive power over real GDP within a defined scope, as confirmed by correlation analysis.

B. Classification of Different Types of Economies

Hierarchical data clustering analysis stands as a prominent statistical classification method for hierarchically clustering information data, widely acclaimed for its extensive study, familiarity, and effectiveness. It finds frequent application in in-depth analysis and the mining of information data, as well as in professional fields involving biological gene diversity analysis and expression. Unlike traditional methods, this statistical analysis does not mandate a priori knowledge of the total categories of the information data or the need for manual data division based on predetermined category numbers. Instead, it yields results in the form of nested partition structures at each layer, offering a comprehensive understanding of the data organization. Generally, the model-based clustering framework encompasses three primary structural components.

Firstly, the model parameters of each Expectation-Maximization algorithm undergo initialization and optimization using the model-based aggregation and clustering segmentation methods. Secondly, these model parameters are employed to estimate and optimize the parameter values with maximum likelihood. Thirdly, the model and the number of categories are selected based on the Bayesian Information Criterion (BIC) approximation of Bayesian factors. The model adopts the classification likelihood objective function, represented by Eq. (8).

$$l_{CL}(\theta_k, \gamma_i; x_i) = \prod_{i=1}^{n} f_{y_i}(x_i; \theta_i) \quad (8)$$

In Eq. (8), γ_i is the classification mark of the i-th observation point. If x_i belongs to the k-th component, γ_i=k. In the mixed model, the number of observation points included in each element follows a polynomial distribution to the n-th power, with probability parameters π_1, π_2, up to π_c.

The model-based aggregation clustering method aims to maximize the likelihood function of classification, treating each point as a single class, with the algorithm initialized in this state.

During each iteration, the algorithm merges the two types of functions exhibiting the fastest growth rate in the classification likelihood functions. This iterative process continues until all observation points are integrated into the same group.

Utilizing data collected via Python, the top 30 countries are categorized into various types of economies for systematic and scientific induction and analysis of large-scale, dynamic, multi-dimensional, and heterogeneous data. SPSS software is employed for cluster analysis, with hierarchical clustering utilized to classify and summarize the data, as depicted in Fig. 3.

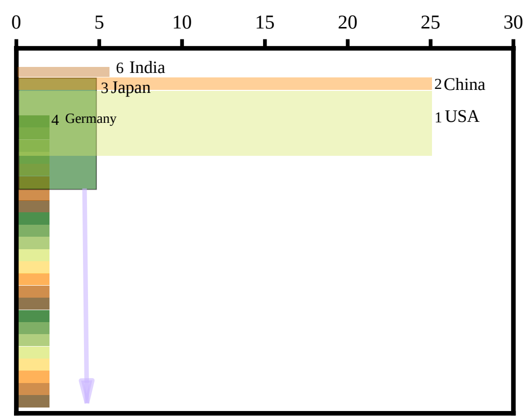


Fig. 3. Cluster analysis of 30 countries.

The graphical representation reveals the division of the top 30 countries in the global GDP ranking into five distinct categories: the United States, China, Japan, India, and other countries. Utilizing hierarchical clustering, countries with analogous eigenvalues are identified, facilitating the systematic and scientific categorization of diverse nations. This classification framework serves as a foundational step towards the precise prediction of the top 30 countries, employing the BP neural network multi-hidden layer variable method.

C. Results of BP Neural Network Prediction Model Construction

For the period spanning 2001 to 2021, thirty-five key influencing factors pertaining to Germany are selected as the anticipated inputs for the BP neural network system. The GDP measured in USD serves as the predicted total output. A neural network machine learning system based on the BP network is constructed as a sample. The system's network structure is approximately 12-5-1, with training and learning objectives reaching up to 300,000 times per day. The annual learning rate is set at around 0.01, with the minimum prediction error range for training objectives typically maintained at 10-5. Following thorough training and design, the BP neural network model demonstrates its efficacy in predicting the error range of the tested sample target. On average, the relative prediction error range of the results stand at approximately 0.48%. These findings underscore the suitability of the BP neural network model for GDP prediction. The fitting between the GDP output obtained using the neural network model and the corresponding yearly production is illustrated in Fig. 4.

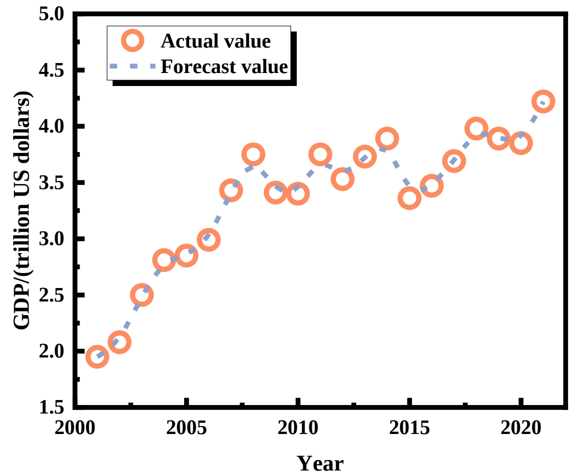


Fig. 4. BP neural network training result diagram.

V. Empirical Analyses

A. Forecast and Analysis of GDP Output of Major Global Economies

Cluster analysis effectively divides the global economies into five distinct types. Leveraging the BP neural network method, the paper delves into the economic and technological development revolutions, innovations in new technology industries and organizations, labor input and productivity, national fiscal revenue, utilization of foreign capital, broad-based social currency supply, total budgetary expenditure, fixed assets, and overall social investment. Additionally, the analysis scrutinizes social population demographics, labor force participation rates, consumer price indices, gross national products, energy resources, total foreign trade volumes, tax revenues, exchange rates, foreign debts, real economy value-added, and the share of virtual and network economies in the GDP of each major country. This examination extends to significant economic variables and influential factors exchanged among governments of nations with varying income levels. Furthermore, the financial aggregate data of China's GDP spanning from the 1990s to 2021, alongside data from other major industrialized nations, is integrated into the BP neural network for comprehensive analysis.

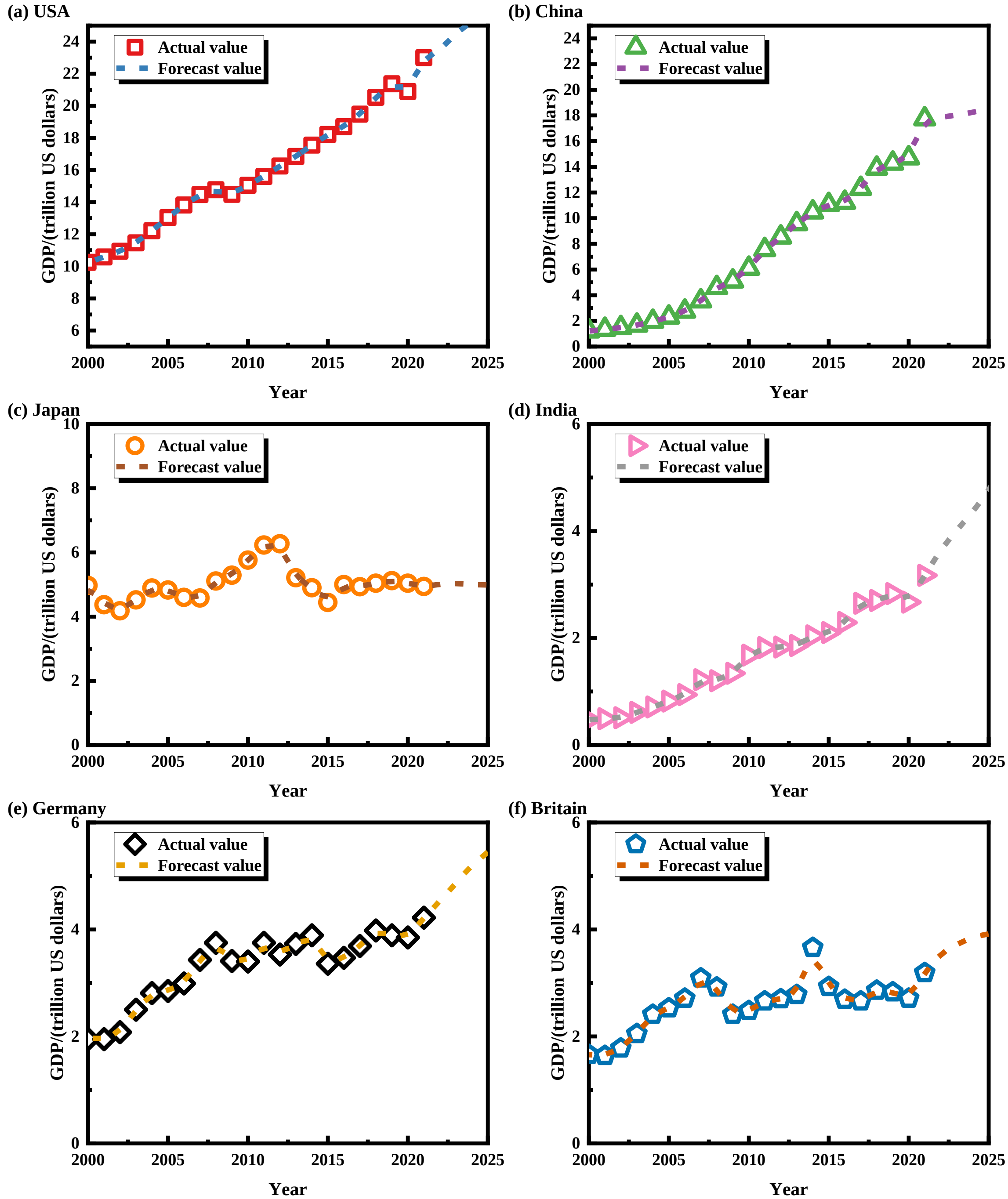


Fig. 5. Neural network forecast of GDP of major global economies.

As depicted in Fig. 5 (a), the United States has sustained a relatively high and continuous growth rate in total GDP, indicative of a robust economic trajectory. However, as the economy progresses past the mid-2020s, a shift from accelerated to moderated growth becomes evident. This transition can be attributed to several factors. Firstly, given the substantial size of the United States' economy on the global stage, further significant growth becomes increasingly challenging, compounded by the mature and well-established economic and cultural landscape. Secondly, the existing market structure may lack new avenues for economic expansion, limiting potential growth opportunities. Moreover, ongoing global transformations and advancements introduce new complexities, including cross-border investment and trade frictions. These emerging dynamics pose systemic risks to the market, thereby hindering the rapid and stable development of the United States' economy. As the world undergoes continual evolution, addressing these challenges becomes imperative for sustaining economic growth and stability.

As illustrated in Fig. 5 (b), a promising outlook emerges for China's economic development in the foreseeable future. The analysis suggests that China is poised to sustain its momentum and advance the reform of comprehensive mechanisms driving economic growth. Notably, recent policy adjustments, including supply-side structural reforms and initiatives to mitigate trade protectionism, have contributed to significant economic adjustments from late 2018 to 2020. Despite initial challenges, it is anticipated that China's economy will undergo a resurgence following the completion of comprehensive economic and technological transformations. As China enters the new decade, the gradual culmination of these transformations, coupled with ongoing industrial innovation and technological advancements, is expected to propel the nation's digital economy to new heights. This resurgence is projected to follow a ladder-type growth trajectory, reflecting the dynamic nature of China's economic landscape and its capacity for adaptation and innovation.

As depicted in Fig. 5 (c), Japan has confronted a prolonged period of economic stagnation, which commenced in the mid-1990s, nearly a century after China's integration into the global economy. Although a resurgence or rapid growth in its economy occurred in the early to mid-2000s, such recoveries often ensued after periods of swift expansion. This trend may be attributed to Japan's current economic landscape, which grapples with the repercussions of a pronounced slowdown in global economic growth, protracted sluggishness in overall wage growth, and a persistent, tepid growth trajectory in production rates. Moreover, the nation contends with significant demographic challenges, including a rapidly aging population. Looking ahead, Japan's economic growth prospects remain contingent upon its ability to address these entrenched issues effectively. Failure to implement timely and comprehensive policy measures to tackle these challenges in the short term may dampen Japan's economic outlook in the years to come.

As illustrated in Fig. 5 (d), India's economy experienced robust growth post-2018, primarily propelled by its demographic dividend. India's development paradigm prioritizes consumption over investment, domestic demand over exports, services over manufacturing, and high-tech industries over labor-intensive ones with low technological content. This strategic orientation renders the Indian economy more resilient to global economic downturns, fostering sustained and resilient economic expansion over extended cycles. Projections indicate that India's economy will sustain rapid growth beyond 2020.

Fig. 5 (e) depicts the swift economic advancement witnessed in Germany post-2020, largely attributed to China's timely structural economic reforms. While such reforms do not yield immediate results, the policies and trends implemented during this phase have significantly propelled the nation's economic growth. Consequently, substantial development opportunities are anticipated for Germany's GDP in the forecast model.

In Fig. 5 (f), the British economy faced adversity in the aftermath of the COVID-19 pandemic in 2019. However, the country was among the earliest adopters of herd immunity strategies. With the evolving landscape of the COVID-19 pandemic, Britain gradually reopened its economy, fostering recovery. Model predictions suggest that Britain's GDP will continue to exhibit significant developmental momentum post-2022.

B. *Forecast and Analysis of GDP Output in the Remaining Countries*

As depicted in Fig. 6, the GDP growth trajectory of the remaining countries spanning from the onset of 2018 to 2025, alongside the annual growth rates projected by the International Monetary Fund, may exhibit a fluctuating upward trend. This pattern can be attributed to several factors. Primarily, the persisting macro uncertainties affecting global long-term regional economic development and growth prospects may exert influence. The anticipated slowdown in the average growth of the global gross factor of production could contribute to heightened overall downward pressure on the economy. According to reports from Xinhua News Agency and Bloomberg News International Economic Department, significant global economic development indices have experienced a rapid deceleration in growth rates since the first quarter of 2018, gradually reaching the lowest levels observed since the onset of the global financial crisis in the summer of 2008.

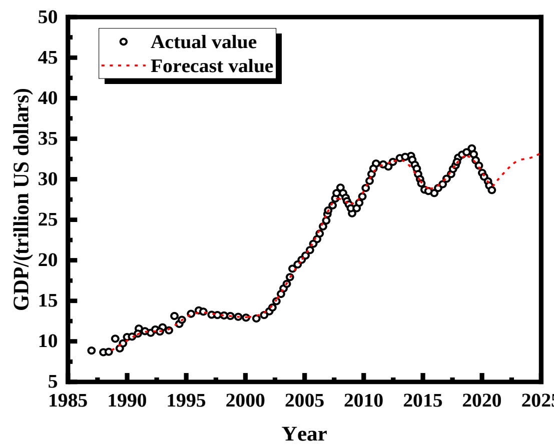


Fig. 6. Network forecast of GDP in the remaining countries.

VI. GDP AND CPI COMBINATION FORECAST

A. *Empirical Analysis of GDP Growth Rate Combination Forecast*

As illustrated in Fig. 7, the establishment of a neural network model is highly sensitive to parameter selection, with different parameter values significantly impacting model prediction outcomes. This paper utilizes the NNE function in the R language to determine the number of hidden nodes based on the principles of minimum Akaike Information Criterion (AIC) and BIC, identifying the optimal number of hidden nodes as 3. Given the nonlinear nature of the neural network model, explicit fitting formulas are unnecessary, as the focus lies on prediction accuracy and robustness, primarily evaluated through observation of the residual sequence predicted by the model. Given that the neural network model deviates from traditional time series methods, the variance of parameter estimates cannot be obtained, thereby precluding calculation of prediction intervals. Consequently, this paper provides only the predicted level values for the following four quarters: 6.1667, 6.2278, 6.2031, and 6.1530, with the predicted range falling between 6.1% and 6.3%.

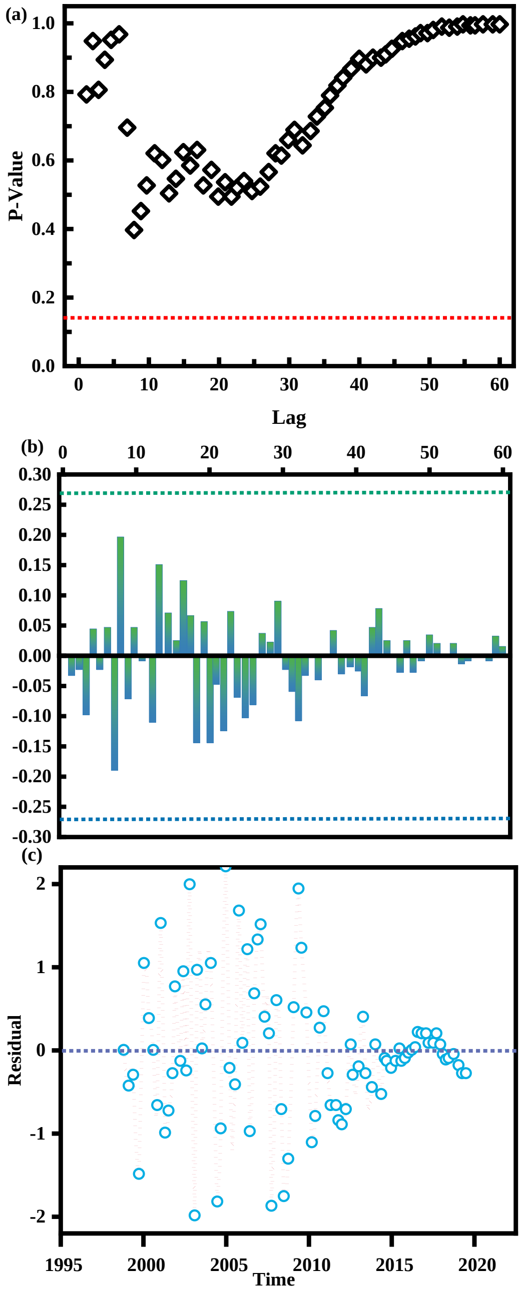


Fig. 7. (a) Ljung Box test chart of neural network model predicting GDP growth rate; (b, c) Residual autocorrelation diagram and residual sequence diagram of neural network model predicting GDP growth rate.

B. *Empirical Analysis of CPI Growth Rate Combination Forecast*

As depicted in Fig. 8, the neural network model's performance is notably sensitive to parameter selection, underscoring the importance of optimal parameter estimation to enhance predictive accuracy, aligning with GDP growth rate predictions. Utilizing the NNE function in the R language, the number of hidden nodes is determined based on the AIC and BIC minimization principles, yielding an optimal count of seven hidden nodes for predicting the CPI growth rate. Given the nonlinear nature of the model and the focus on prediction results, the intricate process of fitting a model formula akin to the ARIMA model is obviated. Instead, emphasis is placed on assessing the model's predictive accuracy through residual analysis.

Examination of the Ljung Box test chart and residual autocorrelation chart reveals a lack of autocorrelation in the residual sequence, accompanied by minimal fluctuation around the zero value. These findings indicate the neural network model's robust predictive performance within the sample. Given the model's departure from traditional time series methodologies, the estimation of parameter variance remains unattainable, precluding the calculation of prediction intervals. However, the predicted CPI growth rates for the subsequent four quarters are furnished: 103.5839%, 103.2596%, 103.0759%, and 102.6257%. Exhibiting a downward trend, these predicted values fall within a range of 2.6% to 3.6%.

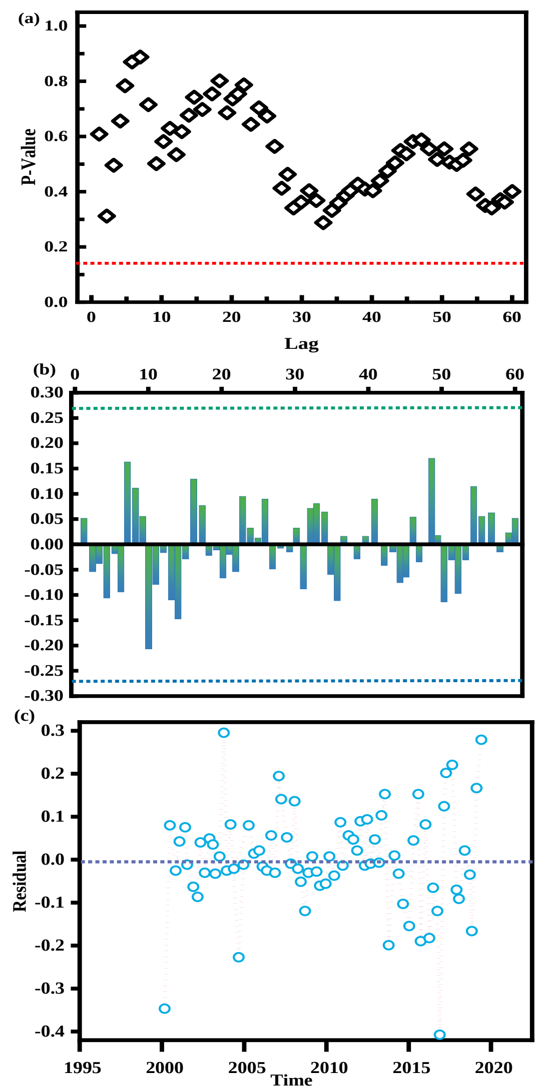


Fig. 8. (a) Ljung Box test chart of neural network model predicting CPI growth rate; (b, c) Residual autocorrelation diagram and residual sequence diagram of neural network model predicting CPI growth rate.

C. *Summary of this Chapter*

Real-life economic phenomena arise from the intricate interplay of numerous internal factors and external dynamics, embodying both inherent complexity and potential regularity. Relying solely on a single time series method proves inadequate for uncovering internal patterns or data insights, often leading to unstable prediction outcomes. Thus, continuous model refinement is imperative to enhance the prediction of future economic indicators, necessitating the exploration of more robust and effective prediction methodologies. Drawing upon the theoretical foundations of forecasting GDP and CPI growth rates, this chapter integrates time series cross-validation with inverse root mean square error to address shortcomings observed in combined forecasting approaches. By meticulously considering prediction accuracy across various time points within the sample, this methodology forecasts GDP and CPI growth rates in tandem. In contrast to prevailing methods such as the equal weight approach and inverse root mean square error weight method commonly employed in literature, this novel approach markedly enhances the accuracy of combined forecasting, underscoring the efficacy of this model in practical combined forecasting endeavors.

VII. Discussion

This study provides a comprehensive analysis and prediction of the real GDP of the top 30 countries in the global GDP ranking through the construction of a Lasso BP neural network model based on AI technology. By comparing the findings of this paper with existing research, its significance can be elucidated from diverse viewpoints. Firstly, in terms of economic forecasting model establishment, Alaminos et al. (2022) underscored the efficacy of non-traditional computational methods, exemplified by evolutionary computation, in handling intricate economic data for macroeconomic forecasting [46]. This aligns with the utilization of the BP neural network model in this paper. Functioning akin to the human brain, this algorithm adeptly processes and analyzes vast and complex economic datasets, thereby augmenting forecast accuracy. Secondly, the validation of the Lasso regression model in screening pivotal influencing factors resonates with the findings of Deng and Liang (2023), who leveraged a semi-parametric ARMA-TGARCH-EVT model combined with a hybrid Copula. Their study underscored the significance of advanced statistical methodologies in managing uncertainty and risk [47]. Similarly, the 15 independent variables identified by the Lasso model in this paper elucidate 97.3% of GDP change causality, affirming the necessity of multifactor consideration in economic analysis. Furthermore, in the realm of economy classification and forecasting, the generalized dynamic factor model proposed by Trucíos et al. (2021) offers a fresh perspective on identifying and estimating macroeconomic variables [48]. The utilization of hierarchical cluster analysis in this paper to categorize the top 30 global GDP countries into distinct economic types mirrors Trucíos et al.'s research ethos. Both endeavors aim to bolster forecasting relevance and accuracy through classification methodologies.

This paper delineates that the top 30 global economies are poised for sluggish growth between 2020 and 2025, notwithstanding prevailing growth trajectories, indicative of inadequate economic growth drivers. This finding correlates with the uncertainty and complexity inherent in the contemporary global economic landscape. Moreover, the paper predicts that China, the United States, and India will persist as the primary engines propelling economic growth among these nations. Lastly, the findings reported here underscore the efficacy of a single time series model in forecasting macroeconomic indicators such as GDP growth rate and Consumer Price Index (CPI) growth rate, with no autocorrelation in the fitted residual series. This underscores the viability of the time series approach in portfolio forecasting, aligning with the observations of Wei et al. (2021), who advocated for a combined forecasting model predicated on model confidence sets, accentuating the significance of statistical significance in forecasting performance assessment [49].

In essence, this paper not only furnishes a novel perspective for macroeconomic analysis but also furnishes an efficacious tool for global economy classification and forecasting. Future research avenues may delve deeper into the interplay between disparate economies and explore enhanced strategies for navigating economic fluctuations and risks through the prism of AI techniques.

VIII. Conclusion

In this section, a thorough examination of the principal challenges encountered during the research endeavors is conducted, delving into their nuances. Firstly, the substantial challenge of data quality and availability is grappled with. The intricate and fluctuating nature of macroeconomic data often renders it incomplete and time-lagged, impinging upon the precision and predictive capacity of the model. Rigorous data preprocessing and cleansing measures are implemented to ensure the integrity and uniformity of the input data. Secondly, during model construction, the complexities inherent in variable selection and parameter optimization are confronted. Amidst myriad factors influencing GDP, accurately identifying and selecting pivotal variables, along with determining the optimal network structure and parameters for the neural network model, emerge as pivotal technical quandaries. Leveraging Lasso regression for variable screening and multiple iterations of BP neural network training, these challenges are effectively navigated. Thirdly, the interpretability of the model emerges as a focal point of concern. Despite the commendable prediction accuracy of AI models, their decision-making processes often lack transparency. Future research endeavors aim to delve deeper into the decision logic embedded within the model, aiming to integrate economic theories more seamlessly into its framework. Lastly, the generalization capability and robustness of the model represent critical performance benchmarks. While the model's adaptability to diverse economies and temporal contexts is bolstered through cross-validation and the incorporation of multiple economic indicators, enhancing its stability and reliability in the face of dynamic economic landscapes remains a paramount focus for future research endeavors. In summary, each challenge encountered during the research journey is meticulously addressed, employing methodological rigor and innovative strategies to propel the investigation forward. These endeavors underscore a commitment to advancing the frontiers of economic analysis and forecasting, laying a robust foundation for future scholarly inquiry.

This paper employs the Lasso BP neural network model, leveraging AI technology, to construct an economic analysis model aimed at analyzing and forecasting the real GDP of the top 30 countries in the global GDP ranking. Firstly, the Lasso regression model is deployed to discern the key factors influencing each country's GDP output. Through the variable screening functionality of the Lasso model, 15 independent variables are selected, elucidating 97.3% of the causative factors behind GDP fluctuations, thereby establishing a robust foundation for the ensuing model. Furthermore, hierarchical cluster analysis categorizes the top 30 countries based on global GDP into distinct economic types, facilitating more accurate predictions of each economy's developmental trajectory. Subsequently, leveraging the BP neural network model, the identified influencing factors undergo training to predict GDP. The model architecture, structured as 12-5-1, undergoes extensive iterative training to achieve a learning rate of 0.01, while maintaining prediction error within a controlled range of 10^{-5}, indicative of favorable fitting performance. Secondly, the paper analyzes the prediction outcomes of the BP neural network model, encompassing forecasts of GDP growth trends for countries such as the United States, China, Japan, and India. Potential factors influencing these predictions are scrutinized. To enhance forecasting accuracy, a combined forecasting approach is adopted, amalgamating time series cross-validation and inverse root mean square error considerations. This approach evaluates forecasting accuracy across different time points within the sample, encompassing combined forecasts of GDP growth rate and CPI growth rate. Lastly, the model's forecasting performance is validated through the Ljung-Box test and residual autocorrelogram. Test results indicate the absence of autocorrelation within the residual series, with fluctuations around the value of 0 minimized, affirming the neural network model's adeptness in sample prediction. This paper has yielded several notable research findings, summarized as follows:

1) *Economic growth outlook (2020-2025):* The economic growth trajectory of the top 30 global economies during the period from 2020 to 2025 is anticipated to exhibit relative sluggishness. Despite an observable growth trend, the impetus for economic expansion remains notably inadequate, with some nations even experiencing stagnation or regression. This trend is attributed primarily to deep-seated structural challenges impeding these economies from achieving sustained recovery and growth.

2) *Key drivers of economic growth:* Analysis underscores that China, the United States, and India continue to serve as the principal drivers of economic growth among the top 30 countries from 2020 to 2025. However, the economies of these nations, along with others, are poised to grapple with emerging uncertainties, such as the surge in anti-globalization sentiments and trade protectionism. Consequently, their economic development trajectories are expected to align closely with global economic trends, characterized by subdued growth and feeble recovery trajectories, accompanied by heightened instability and uncertainty in the near term.

3) *Prediction accuracy of macroeconomic indicators:* The predictive outcomes for GDP growth rate and CPI growth rate highlight the efficacy of the single time series model in accurately forecasting these macroeconomic indicators. Notably, the residual series exhibit no autocorrelation, with the GDP growth rate residual series approximating zero. These findings underscore the suitability of time series methodologies for combined forecasting, affirming their reliability in predicting key economic metrics.

This paper employs the Lasso BP neural network model, grounded in AI technology, to construct an economic analysis model aimed at analyzing and forecasting the real GDP of the top 30 countries in the global GDP ranking. Initially, the Lasso regression model is deployed to discern the pivotal factors influencing each country's GDP output. Leveraging the variable screening functionality of the Lasso model, 15 independent variables are selected, elucidating 97.3% of the causative factors behind GDP fluctuations, thus establishing a robust foundation for the model. Additionally, hierarchical cluster analysis categorizes the top 30 countries based on global GDP into distinct economic types, facilitating more precise predictions of each economy's developmental trajectory. Subsequently, employing the BP neural network model, the identified influencing factors undergo training to predict GDP. The model structure, configured as 12-5-1, undergoes extensive iterative training to achieve a learning rate of 0.01, while maintaining prediction error within a controlled range of 10^{-5}, showcasing favorable fitting efficacy. Furthermore, the paper analyzes the prediction outcomes of the BP neural network model, encompassing forecasts of GDP growth trends for countries such as the United States, China, Japan, and India. Potential factors influencing these predictions are scrutinized. To enhance forecasting accuracy, the paper adopts a combined forecasting method, amalgamating time series cross-validation and inverse root mean square error considerations. This approach evaluates forecasting accuracy across different time points within the sample, encompassing combined forecasts of GDP growth rate and CPI growth rate. Lastly, the model's forecasting performance is validated through the Ljung-Box test and residual autocorrelogram. Test results indicate the absence of autocorrelation within the residual series, with fluctuations around the value of 0 minimized, affirming the neural network model's adeptness in sample prediction.

Competing of Interests

The authors declare no competing of interests.

Authorship Contribution Statement

Jiqing Shi: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.

Data Availability

On Request

Declarations

Not applicable

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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