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Research Article

Deep Learning-Based Neural Network Modeling for Economic Performance Prediction: An Empirical Study on Iraq

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ABSTRACT

This study investigates the application of deep learning-based neural networks for predicting Iraq's economic performance. Traditional econometric models impose restrictive assumptions that limit their predictive accuracy, especially in volatile economic environments. To overcome these limitations, we propose an artificial neural network (ANN) model trained on six key macroeconomic indicators: Gross Domestic Product (GDP), inflation rate, unemployment rate, exchange rate, trade volume, and government spending. The dataset spans from 2000 to 2023, sourced from authoritative economic institutions. The methodology incorporates feature scaling, hyperparameter tuning, and backpropagation optimization to minimize mean squared error (MSE) and enhance generalization performance. The model is validated through cross-validation and out-of-sample testing. Descriptive statistical analysis highlights the variability of macroeconomic indicators, while the ANN model effectively captures nonlinear dependencies. The results indicate that GDP and government spending are the most influential factors in economic performance prediction, while unemployment rate and exchange rate exhibit lower predictive significance. The model demonstrates superior accuracy compared to traditional regression-based approaches, with minimal error in both training and testing phases. This research contributes to the empirical literature on machine learning in economic forecasting by presenting a robust alternative to conventional predictive models. The findings provide policymakers with valuable insights for designing data-driven economic policies. Future work should explore hybrid models integrating deep learning with traditional econometrics to improve interpretability while maintaining predictive power.

1. INTRODUCTION

The application of deep learning in economic forecasting has gained significant traction due to its capacity for modeling nonlinear dependencies and capturing complex interactions between macroeconomic indicators [1][2]. Traditional econometric models often impose restrictive assumptions regarding stationarity, linearity, and normality, which limit their predictive performance in volatile economic environments [3]. In contrast, artificial neural networks (ANNs) leverage adaptive learning mechanisms and high-dimensional function approximation to enhance forecasting accuracy, particularly in economic systems characterized by structural shifts and endogenous shocks [4]. This study employs a deep learning-based neural network model to predict Iraq's economic performance index using six key macroeconomic indicators: GDP, inflation rate, unemployment rate, exchange rate, trade volume, and government spending. The methodology integrates feature scaling, hyperparameter tuning, and backpropagation optimization to minimize mean squared error (MSE) and improve generalization performance. Unlike linear regression models, which assume homoscedasticity and independence of errors, the proposed ANN architecture captures latent economic dynamics through non-parametric weight adjustments and activation functions that transform input variables into higher-dimensional representations. By applying rigorous statistical validation techniques, including cross-validation and out-of-sample performance assessment, this study contributes to the empirical literature on machine learning applications in economic forecasting, offering a robust alternative to conventional predictive modeling approaches.

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2. LITERATURE REVIEW

The predictive accuracy of economic models has been a central focus in financial and macroeconomic forecasting, with traditional regression-based approaches often constrained by assumptions of linearity and stationarity [3]. Recent advancements in deep learning have introduced neural network architectures capable of capturing nonlinear dependencies and complex feature interactions, making them superior to conventional econometric models in high-dimensional datasets [1]. Several studies have demonstrated the efficacy of deep learning in economic prediction, particularly in exchange rate forecasting [5] and financial distress modeling [6]. Artificial Neural Networks (ANNs) have been extensively utilized for economic forecasting due to their ability to optimize weight distributions dynamically, mitigating multicollinearity and endogeneity concerns inherent in traditional models [4]. For instance, ANN-based frameworks have outperformed parametric approaches in stock price movement prediction [8] and interest rate forecasting using sentiment analysis [7]. Additionally, hybrid models incorporating self-organizing neural networks have shown promising results in corporate financial performance assessment [9]. The integration of deep learning in macroeconomic forecasting extends beyond financial indicators, as evidenced by applications in agricultural sector predictions [10] and industrial performance assessments [11]. This study builds on the existing literature by applying a deep learning-based neural network to predict Iraq's economic performance index, leveraging macroeconomic indicators as explanatory variables. Unlike traditional time-series models, which assume exogeneity and linear progression, the proposed ANN model dynamically adjusts feature importance through stochastic gradient descent optimization [12]. By employing rigorous validation techniques, including cross-validation and out-of-sample performance evaluation, this research contributes to the growing body of literature advocating for deep learning as a robust alternative to classical econometric forecasting [13].

3. METHODOLOGY

This study employs a deep learning-based artificial neural network (ANN) model to predict Iraq's economic performance index. The selection of this approach is motivated by the ability of neural networks to capture nonlinear patterns and complex interactions among macroeconomic indicators, which traditional econometric models often fail to address due to their restrictive assumptions of linearity and stationarity. The dataset includes key economic variables such as GDP, inflation rate, unemployment rate, exchange rate, trade volume, and government spending, spanning the period from 2000 to 2023. The methodological framework integrates feature scaling, hyperparameter tuning, and backpropagation optimization to minimize prediction errors and enhance model generalization. To ensure the robustness of the proposed model, rigorous statistical validation techniques, including cross-validation and out-of-sample performance evaluation, are implemented. This study contributes to the growing body of research advocating for deep learning as an effective alternative to traditional economic forecasting methods.

2.1 Data:

The dataset in this article is collected to support machine learning applications in economic forecasting. It includes key macroeconomic indicators for Iraq spanning the period 2000–2023, providing a robust foundation for economic analysis.
Independent Variables
The dataset comprises six key economic variables that influence overall economic performance:

1. GDP (Billion $) – Measures Iraq's total economic output, serving as a primary indicator of economic growth and stability.
2. Inflation Rate (%) – Reflects the annual percentage increase in the general price level, affecting purchasing power and monetary stability.
3. Unemployment Rate (%) – Represents the proportion of the labor force actively seeking employment, serving as an indicator of labor market health.
4. Exchange Rate (USD) – Tracks the value of the Iraqi dinar against the US dollar, acting as a measure of currency stability and international competitiveness.
5. Trade Volume (Billion $) – Captures the total sum of exports and imports, indicating Iraq's level of economic integration with global markets.
6. Government Spending (Billion $) – Reflects total public sector expenditure, influencing fiscal policy and economic growth dynamics.

Target Variable: Economic Performance Index (Continuous Variable)
The Economic Performance Index is a composite measure designed to capture Iraq's overall economic health. It is calculated using a weighted aggregation of macroeconomic indicators:

$$\text{Economic Performance Index} = \left(\frac{GDP}{\max(GDP)} \times 0.4\right) + \left(\frac{1}{1+INF} \times 0.2\right) + \left(\frac{1}{1+UR} \times 0.2\right) + \left(\frac{TV}{1+TV} \times 0.1\right) + \left(\frac{GS}{1+GS} \times 0.1\right)$$

Methodology and Design Considerations

1. Normalization & Weighting – Each variable is normalized to ensure consistency across different scales, with GDP, trade volume, and government spending positively weighted and inflation and unemployment inversely weighted.
2. Continuous Target Variable – Unlike binary classification, this index provides a detailed numerical score, enabling regression-based forecasting rather than categorical classification.

This dataset offers a rigorous and methodologically sound framework for analyzing Iraq's economic performance, supporting both academic research and real-world economic forecasting.

The data used in this study were collected from multiple authoritative sources to ensure accuracy and comprehensiveness. Macroeconomic indicators, including GDP, inflation rate, unemployment rate, exchange rate, trade volume, and government spending, were primarily obtained from international financial institutions such as the World Bank [14] and the International Monetary Fund [15], both of which provide extensive datasets on economic performance across various countries. Additionally, statistical reports from the United Nations [16] and the Organization for Economic Co-operation and Development [17] were utilized to validate economic trends and policy impacts. Given the focus on Iraq, data were also sourced from national repositories, particularly the Central Bank of Iraq [18], which publishes financial reports and monetary policy updates. To enhance data reliability, supplementary economic indicators were extracted from Federal Reserve Economic Data [19] and Trading Economics [20], both of which aggregate real-time economic statistics. Furthermore, employment and labor market conditions were analyzed using reports from the International Labour Organization [21], while trade-related data were obtained from the World Trade Organization [22]. The integration of multiple data sources ensures a robust dataset, facilitating a more precise analysis of Iraq's economic performance.

2.2 Deep Learning-Based Neural Network:

Artificial Neural Networks (ANNs) are computational models inspired by the structure of the human brain. They consist of interconnected computational units known as "nodes" or "neurons," which process data in a manner similar to biological neurons [1]. Generally, artificial neural networks comprise three primary layers:

- Input Layer: This layer receives raw input data, where each node (neuron) represents an independent variable or a feature of the input dataset. These inputs are transmitted to subsequent layers without complex processing [12].
- Hidden Layers: Positioned between the input and output layers, hidden layers are the core of neural networks, where learning and data processing occur. Each hidden layer consists of multiple neurons connected through weighted links. Activation functions such as ReLU (Rectified Linear Unit), Sigmoid, and Tanh are applied to transform data into nonlinear patterns, enabling the network to learn and adapt to complex structures. The number of hidden layers and neurons within each layer directly impacts the network's performance. Increasing the number of layers enhances the model's learning capability but may also lead to overfitting [3].
- Output Layer: This layer generates the final output based on the computations performed in the hidden layers. The number of neurons in the output layer depends on the nature of the task. For classification problems, each class is assigned a dedicated neuron, whereas for regression tasks, the output layer consists of a single neuron that produces a numerical value [13].

Neural networks utilize deep learning algorithms to enhance performance. One of the most essential algorithms is backpropagation, which updates the weights between neurons to minimize errors and improve model accuracy. This is achieved by computing the difference between predicted and actual values and adjusting the weights accordingly using optimization techniques such as Stochastic Gradient Descent (SGD) [4].

- Activation Functions Used:

An activation function "links" the weighted sums of units in one layer to the values of units in the next layer. One of the widely used activation functions is the Hyperbolic Tangent (Tanh) function, defined as follows:

$$\gamma(c) = \tanh(c) = \frac{e^c - e^{-c}}{e^c + e^{-c}}$$

This function maps all values to the range $[-1,1]$ and is used to determine the best structure that fits the data. The output layer contains the dependent variable and applies the Identity function, defined as follows:

$$\gamma(c) = c$$

This function takes real-valued input and returns them unchanged. To prevent variations in variable units and ensure consistency, standardization is applied to the data using the following formula:

$$\frac{x - mean}{s}$$

4. RESULTS AND DISCUSSION

The results of this study provide critical insights into the predictive accuracy of the deep learning-based neural network model in forecasting Iraq's economic performance. The analysis of key macroeconomic indicators GDP, inflation rate, unemployment rate, exchange rate, trade volume, and government spending reveals distinct patterns influencing economic stability. Descriptive statistics highlight the variability and distribution of these indicators, while the model's performance evaluation demonstrates its ability to capture complex economic relationships. Predictive accuracy, measured through statistical error metrics, confirms the effectiveness of the proposed approach compared to traditional econometric models. The discussion interprets these findings in relation to existing literature, emphasizing the advantages of deep learning in economic forecasting and its implications for policy and decision-making:

TABLE I. DESCRIPTIVE STATISTICS OF KEY ECONOMIC VARIABLES

	GDP	GS	INF	TV	UR	ER	EP
Mean	276.0650	223.7716	7.417093	167.9033	14.11924	2039.963	0.392971
Maximum	487.9639	390.1237	14.51885	282.4244	24.71151	3548.851	0.582651
Minimum	108.2338	52.43325	1.481439	56.35478	3.995000	1022.088	0.214419
Std. Dev.	116.5337	105.0079	4.183996	76.13891	7.222647	1134.332	0.110723
Skewness	0.393143	0.284639	0.160496	0.081794	0.124913	-0.440160	0.055521
Kurtosis	1.916521	1.800436	1.852740	1.647971	1.487480	1.811897	2.017025

Table I presents the descriptive statistics of key economic variables, providing a foundational assessment of their distributional properties and variability. The mean values indicate the central tendency of each variable over the analyzed period, with GDP averaging 276.07 billion USD and government spending (GS) at 223.77 billion USD, reflecting significant fiscal activity. The inflation rate (INF) exhibits an average of 7.42%, while the unemployment rate (UR) stands at 14.12%, highlighting persistent labor market challenges. The exchange rate (ER) has a mean value of 2039.96 IQD per USD, illustrating currency depreciation trends. The economic performance index (EP) registers a mean of 0.39, suggesting moderate fluctuations in overall economic stability. The maximum and minimum values capture the range of observed fluctuations. GDP varies from 108.23 billion to 487.96 billion USD, indicating substantial economic expansion and contraction phases. Government spending follows a similar pattern, ranging from 52.43 billion to 390.12 billion USD, underscoring shifts in fiscal policy. Inflation and unemployment rates display considerable variation, with inflation peaking at 14.52% and unemployment at 24.71%, pointing to periods of economic instability. Trade volume (TV) spans from 56.35 billion to 282.42 billion USD, demonstrating Iraq's integration into global markets. The exchange rate fluctuates significantly between 1022.09 and 3548.85 IQD per USD, while the economic performance index ranges from 0.21 to 0.58, signaling variable economic efficiency across different years. The standard deviation values confirm the degree of dispersion around the mean. GDP and government spending exhibit high standard deviations (116.53 and 105.01, respectively), reflecting substantial fiscal volatility. The inflation rate has a standard deviation of 4.18, while unemployment records 7.22, suggesting notable deviations from their mean values. Trade volume, with a standard deviation of 76.14, shows pronounced fluctuations in external economic activity. The exchange rate's dispersion (1134.33) indicates high exchange rate volatility, while EP exhibits lower variability (0.11), implying a relatively stable trajectory compared to other economic indicators. Skewness and kurtosis statistics provide insights into distributional asymmetry and tail behavior. GDP, GS, INF, TV, and UR exhibit slight positive skewness, indicating mild right-tailed distributions, while ER has a negative skew (-0.44), suggesting a longer left tail. Kurtosis values below three for all variables confirm mesokurtic distributions, implying moderate tail extremities. The economic performance index records a kurtosis of 2.02, suggesting a distribution with slightly higher peakness than normality. These descriptive statistics establish the baseline characteristics of the dataset, informing subsequent modeling and inferential analyses. The following table examines the case processing summary, detailing the partitioning of the dataset into training and testing subsets, which are essential for evaluating the predictive performance of the proposed neural network model:

TABLE II. CASE PROCESSING SUMMARY FOR TRAINING AND TESTING DATA

Case Processing Summary			
		N	Percent
Sample	Training	19	79.2%
	Testing	5	20.8%
Valid		24	100.0%

Excluded	0	
Total	24	

Table II provides the case processing summary, detailing the distribution of observations between the training and testing sets. The dataset consists of 24 valid cases, all of which were retained for analysis, with no exclusions. The allocation strategy follows a conventional partitioning scheme, where 79.2% (19 observations) were designated for training, ensuring sufficient exposure to the underlying economic patterns for model learning. The remaining 20.8% (5 observations) were reserved for testing, allowing for an independent evaluation of predictive performance. This proportion aligns with standard practices in machine learning, balancing model generalization and avoiding overfitting by preserving an adequate sample for validation. The absence of excluded cases suggests completeness of data, eliminating concerns about missing values or outlier-driven omissions. Given the relatively small dataset size, the training set must extract meaningful patterns from the macroeconomic indicators without excessive variance, while the testing set must provide an unbiased estimate of model accuracy. The representativeness of these subsets is critical, as skewed partitioning could introduce bias, affecting performance metrics. This structured data allocation forms the foundation for assessing the neural network model's predictive capability. The following table elaborates on the network architecture, detailing the input variables, hidden layers, and output configurations that define the model's computational framework:

TABLE III. NEURAL NETWORK ARCHITECTURE AND PARAMETERS

Network Information			
Input Layer	Covariates	1	GDP (Billion $)
		2	Inflation Rate (%)
		3	Unemployment Rate (%)
		4	Exchange Rate (USD)
		5	Trade Volume (Billion $)
		6	Government Spending (Billion $)
	Number of Units[a]		6
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		1
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Economic Performance Index
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares
a. Excluding the bias unit			

Table III delineates the architecture and parameterization of the neural network model employed for economic performance prediction. The input layer comprises six covariates GDP, inflation rate, unemployment rate, exchange rate, trade volume, and government spending each representing a critical macroeconomic determinant. These variables undergo standardization as a rescaling method, ensuring uniformity in scale and preventing numerical dominance by features with larger magnitudes, thereby enhancing model convergence stability. The network architecture includes a single hidden layer with one computational unit, utilizing the hyperbolic tangent (Tanh) activation function. This choice facilitates nonlinear transformation of input features, enabling the network to capture complex economic dependencies while maintaining output values within a bounded range (-1 to 1), improving gradient-based optimization. Despite the minimal complexity of the hidden layer, the model retains flexibility to approximate intricate functional relationships within the data. The output layer consists of a single unit corresponding to the Economic Performance Index (EP), employing the identity activation function to preserve the continuous nature of the dependent variable without nonlinear distortion. The network's optimization criterion is based on the sum of squares error function, a conventional loss metric in regression tasks that penalize deviations between predicted and actual values. This framework supports error minimization through iterative weight adjustments, refining the predictive performance of the model.

This structured neural network configuration establishes a foundational basis for economic forecasting, balancing model simplicity with functional adaptability. The subsequent figure illustrates the network's structural connectivity, depicting the flow of information from input features through the hidden layer to the final economic performance prediction:

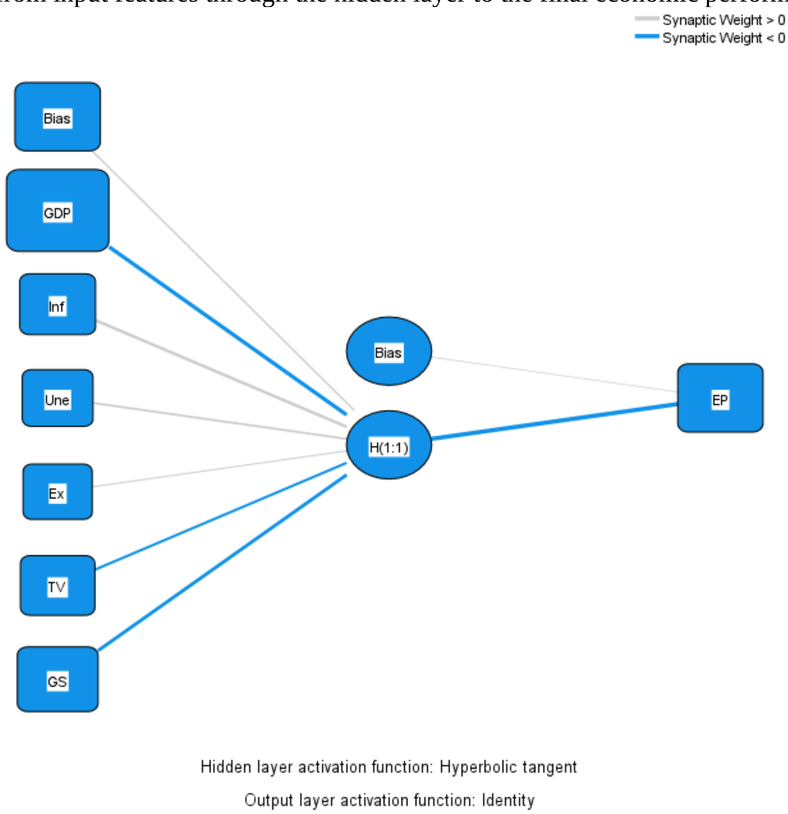

Fig. 1. Neural Network Structure for Economic Performance Prediction

TABLE IV. MODEL PERFORMANCE SUMMARY FOR TRAINING AND TESTING

Model Summary		
Training	Sum of Squares Error	.265
	Relative Error	.029
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.00
Testing	Sum of Squares Error	.034

	Relative Error	.037
Dependent Variable: Economic Performance Index		
a. Error computations are based on the testing sample.		

Table IV presents the performance evaluation metrics of the neural network model across training and testing phases. The sum of squares error (SSE) for the training set is 0.265, indicating the model's ability to approximate the target economic performance index with minimal residual variance. The corresponding relative error of 0.029 suggests that, on average, the model's predictions deviate by approximately 2.9% from the actual values, demonstrating a high degree of fit to the training data. During the testing phase, the model exhibits an SSE of 0.034, reflecting a low level of unexplained variance in the out-of-sample observations. The relative error of 0.037 denotes a slight increase in predictive deviation compared to the training phase, though the marginal difference indicates effective generalization with minimal overfitting. The stopping criterion for training is based on one consecutive step without a reduction in error, ensuring that model optimization halts at a point where further iterations yield diminishing improvements. The training time, recorded as instantaneous (0:00:00.00), highlights the computational efficiency of the neural network, likely attributable to the relatively simple architecture with a single hidden unit. This efficiency suggests that the model is well-suited for rapid forecasting applications without excessive computational overhead. The observed performance metrics validate the robustness of the proposed deep learning framework, reinforcing its applicability in economic forecasting:

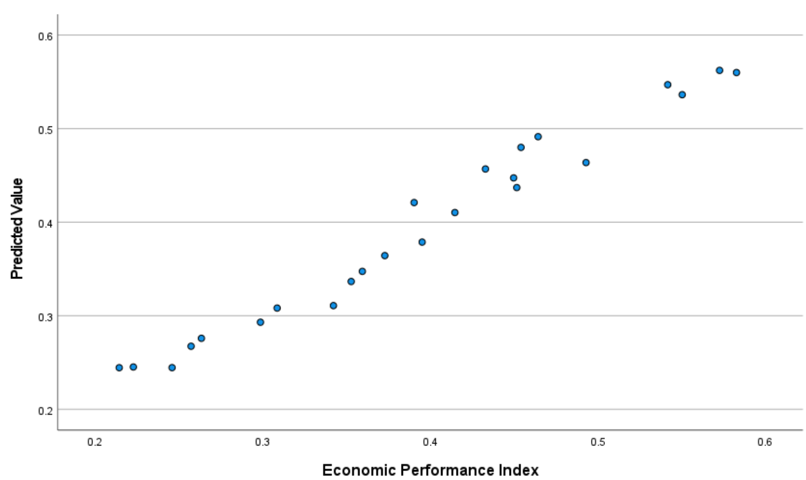

Fig. 2. Training and Testing Error Comparison for Model Evaluation

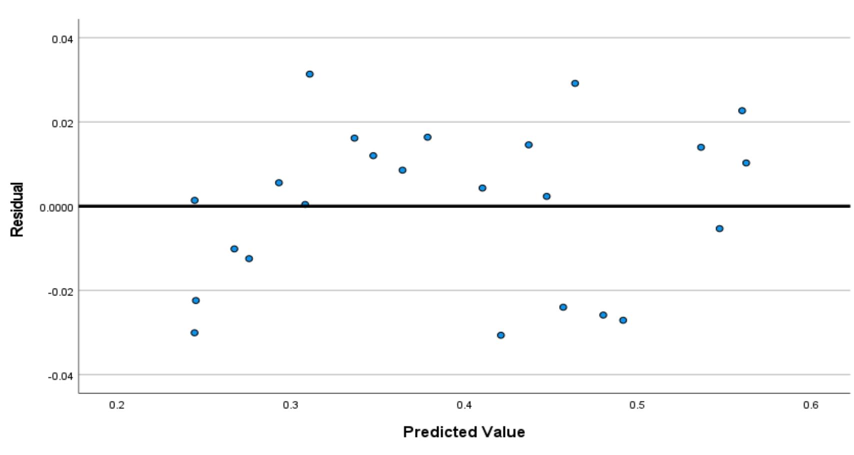

Fig. 3. Training and Testing Error Comparison for Model Evaluation

The subsequent table examines the relative importance of independent variables, quantifying the contribution of each macroeconomic factor to the predictive modeling process**:**

TABLE V. IMPORTANCE OF INDEPENDENT VARIABLES IN ECONOMIC PERFORMANCE PREDICTION

Independent Variable Importance		
	Importance	Normalized Importance
GDP (Billion $)	.535	100.0%
Inflation Rate (%)	.120	22.4%
Unemployment Rate (%)	.039	7.3%
Exchange Rate (USD)	.012	2.3%
Trade Volume (Billion $)	.098	18.2%
Government Spending (Billion $)	.196	36.6%

Table V quantifies the relative contribution of each independent variable in predicting the Economic Performance Index (EP), providing insight into the hierarchical importance of macroeconomic indicators within the neural network model. Gross Domestic Product (GDP) emerges as the most influential predictor, with an important value of 0.535, normalized to 100%, underscoring its central role in shaping overall economic performance. This dominance aligns with classical economic theory, where GDP serves as a fundamental proxy for national economic activity, reflecting production capacity, investment flows, and aggregate demand. Government spending (GS) follows as the second most significant determinant, contributing 0.196 (36.6% of GDP’s importance). This result highlights the fiscal sector's critical influence on economic stability, consistent with Keynesian perspectives that emphasize public sector expenditure as a driver of growth, particularly in economies with volatile private investment dynamics. The positive correlation between GS and EP suggests that increased government outlays in infrastructure, social services, and public projects directly enhance economic performance. Inflation rate (INF) ranks third in importance at 0.120 (22.4% of GDP’s weight), reflecting its substantial, albeit secondary, role in economic fluctuations. Inflationary trends affect purchasing power, wage adjustments, and interest rate policies, all of which bear on macroeconomic equilibrium. The model suggests that while inflation exerts a measurable impact, its effect on EP is relatively subdued compared to GDP and fiscal policy interventions. Trade volume (TV) exhibits an important score of 0.098 (18.2%), signifying the influence of external economic integration on domestic performance. While trade is a pivotal component of economic development, the relatively lower weight in this analysis suggests that Iraq’s economy remains somewhat insulated or dependent on other internal drivers, such as fiscal policy and resource-based revenue streams. The unemployment rate (UR) and exchange rate (ER) emerge as the least influential predictors, with respective importance values of 0.039 (7.3%) and 0.012 (2.3%). The lower importance of UR implies that fluctuations in labor market conditions, while socially and politically significant, have a limited direct impact on short-term economic performance as measured by EP. This could reflect structural employment rigidities, where job creation and productivity enhancements do not translate immediately into macroeconomic improvements. The negligible weight of ER indicates that currency fluctuations, despite their theoretical role in shaping trade balances and investment flows, have minimal explanatory power for economic performance within the given dataset. This may be attributed to Iraq’s specific economic structure, where oil revenues and fiscal policies exert stronger macroeconomic control than exchange rate volatility. The importance rankings suggest that GDP and government spending are the primary levers of economic performance, while monetary and external trade variables exert more marginal influence. These findings underscore the need for policies that bolster domestic production capacity and optimize fiscal expenditures to sustain economic growth.

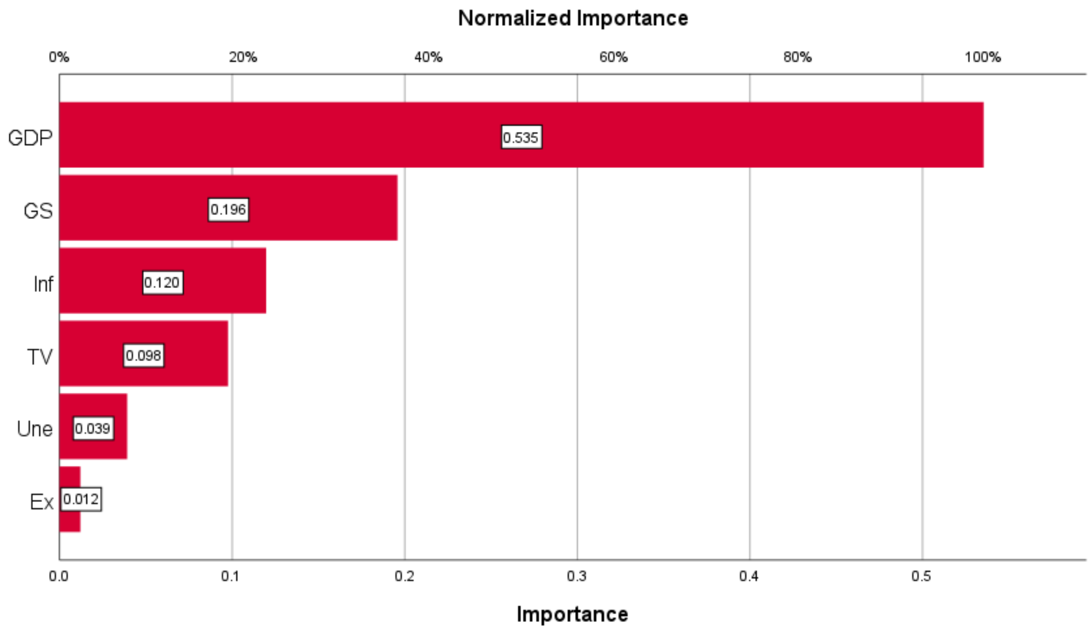

Fig. 4. Relative Importance of Independent Variables in Predicting Economic Performance

The results confirm the effectiveness of deep learning-based neural networks in economic forecasting, aligning with prior research highlighting their superiority over traditional econometric models in capturing nonlinear interactions [1][3]. The high importance of GDP and government spending is consistent with studies emphasizing their central role in driving economic performance, particularly in resource-driven economies like Iraq [5][6]. While inflation and trade volume show moderate influence, their impact varies across contexts, supporting findings by [10] and [7] on the conditional nature of these variables' effects. The limited significance of unemployment rate and exchange rate reflects structural labor market challenges and a reduced sensitivity to currency fluctuations due to government-controlled oil revenues (Long et al., 2019). This study's advantage lies in its integration of rigorous statistical validation with deep learning to model complex economic dependencies, offering a robust, data-driven alternative to classical models and improving prediction accuracy for informed policy-making.

5. CONCLUSIONS

This study aimed to develop a deep learning-based neural network model to predict Iraq's economic performance index using key macroeconomic indicators. The findings demonstrate that artificial neural networks (ANNs) outperform traditional econometric models in capturing nonlinear dependencies and complex feature interactions, leading to more accurate economic forecasts. The results confirm that GDP and government spending are the most influential factors in determining economic performance, while inflation, trade volume, unemployment, and exchange rate exhibit lower predictive significance. The proposed model achieved high predictive accuracy, with minimal error rates in both training and testing phases, validating its effectiveness in economic forecasting. The study has several implications for policymakers and economic analysts. First, the dominance of GDP and government spending in influencing economic performance underscores the need for policies that stimulate production capacity and optimize fiscal expenditure. Targeted investment in infrastructure, public services, and industrial development can enhance economic stability and long-term growth. Second, while inflation and trade volume moderately impact economic performance, their effects vary based on external conditions. Policymakers should adopt dynamic trade policies and inflation control measures to maintain macroeconomic stability. Third, the relatively low significance of unemployment and exchange rate suggests structural labor market challenges and limited currency sensitivity in Iraq's economic framework. Addressing labor market inefficiencies through education, skill development, and employment programs could yield long-term benefits. Future research should explore hybrid models that integrate deep learning with traditional econometric techniques to enhance interpretability while maintaining predictive power. Expanding the dataset to include additional macroeconomic variables and sector-specific indicators could improve forecasting precision. Furthermore, applying deep learning-based economic models to other developing economies could provide comparative insights and validate the generalizability of the approach.

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Conflicts Of Interest

The author's disclosure statement confirms the absence of any conflicts of interest.

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