

Article

Development of per Capita GDP Forecasting Model Using Deep Learning: Including Consumer Goods Index and Unemployment Rate

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Abstract: In the 21st century, the increasing complexity and uncertainty of the global economy have heightened the need for accurate economic forecasting. Per capita GDP, a critical indicator of living standards, economic growth, and productivity, plays a key role in government policy-making, corporate strategy, and investor decisions. However, predicting per capita GDP poses significant challenges due to its sensitivity to various economic and social factors. Traditional methods such as statistical analysis, regression, and time-series models have shown limitations in capturing nonlinear interactions and volatility of economic data. To address these limitations, this study develops a per capita GDP forecasting model based on deep learning, incorporating key macroeconomic variables—the Consumer Price Index (CPI) and unemployment rate (UR)—to enhance predictive accuracy. This study employs five deep-learning regression models (RNN, LSTM, GRU, TCN, and Transformer) applied to real and placebo datasets, each incorporating combinations of CPI and UR. The results demonstrate that deep learning models can effectively capture complex, nonlinear relationships in economic data, significantly improving predictive accuracy compared to traditional models. Among the models, the Transformer consistently achieves the highest R-squared and lowest error values across various metrics (MSE, RMSE, and MSLE), indicating its superior ability to model intricate economic patterns. In addition, including CPI and UR as additional predictors enhances model robustness, with the TCN and Transformer models showing particularly strong performance in capturing short-term economic fluctuations. The findings suggest that the deep learning models, especially the Transformer, offer valuable tools for policymakers and business leaders, providing reliable GDP forecasts that support economic decision-making, resource allocation, and strategic planning. Academically, this study advances the understanding of deep learning applications in economic forecasting, particularly in integrating significant macroeconomic variables for enhanced predictive performance. The developed model is a foundation for informed economic policy and strategic decisions, offering a robust and actionable framework for managing economic uncertainties. This research contributes to theoretical and applied economics, providing insights that bridge academic innovation with practical utility in economic forecasting.

Keywords: per capita GDP; CPI; unemployment rate; deep learning; RNN; LSTM; GRU; TCN; transformer



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1. Introduction

In the 21st century, as the global economy becomes more complex and uncertainty increases, the importance of accurately predicting future economic indicators is growing more than ever [1]. These predictions are important in the government's economic policy-making, corporate strategic planning, and investor decision-making [2]. Among them, per capita GDP is a comprehensive indicator of the people's standard of living, economic growth, and productivity [3,4]. It plays a key role in evaluating the performance and welfare of the national economy. However, since per capita GDP is a complex indicator affected by some economic and social factors, developing a model for predicting it is a considerable challenge.

Existing studies on predicting GDP per capita have been mainly based on traditional statistical analysis, regression models, and time series analysis [5–7]. These models provide a certain level of prediction accuracy, but there is a limit to sufficiently reflecting the nonlinear interaction between economic variables or the volatility caused by external shocks. In particular, macroeconomic indicators such as the Consumer Price Index (CPI) and the unemployment rate are directly related to supply and demand across the economy and, thus, are intricately intertwined with GDP per capita. New prediction techniques are required to effectively model these variables.

With the recent development of artificial intelligence, deep learning models have begun to be introduced into economic analysis and prediction, suggesting the possibility of overcoming these limitations [8]. Deep learning models can learn complex patterns from large-scale data and effectively capture nonlinear relationships within the data through a multilayer neural network structure [9]. In particular, the strong performance of deep learning in selecting important variables in multidimensional economic data and developing predictive models by integrating interactions between variables is attracting attention as an innovative tool in economic prediction modeling [10].

This study aims to develop a per capita GDP prediction model using deep learning technology. In particular, this study aims to prove that these two variables play an important role in improving prediction accuracy by including the Consumer Price Index (CPI) and the unemployment rate in the prediction model, which were not well reflected in previous studies. This increases economic variables and improves prediction performance by carefully selecting and applying variables closely correlating with GDP per capita. Through this, it aims to provide a foundation for the government and businesses to establish better strategies, increase policy effectiveness, and prepare for economic uncertainty by predicting economic indicators.

A new GDP per capita prediction framework has been developed. This framework differs from existing methods in integrating various advanced deep learning techniques—such as RNN, LSTM, GRU, TCN, and Transformer—while incorporating CPI and unemployment information. This novel approach not only leverages the strengths of cutting-edge algorithms but also demonstrates superior prediction performance by capturing the complex interplay between macroeconomic indicators and GDP trends, setting it apart from traditional models.

The key contributions of the paper are as follows.

- **Introduction of Advanced Deep Learning Models:** The study implements and evaluates state-of-the-art deep learning models (RNN, LSTM, GRU, TCN, and Transformer) to capture complex, nonlinear interactions in economic data.
- **Integration of CPI and Unemployment Rate:** Including these key macroeconomic indicators significantly enhances the model's robustness and accuracy in GDP per capita forecasting.

- **Comprehensive Comparison with Traditional Methods:** The research compares the performance of deep learning models against traditional statistical methods, highlighting their superior predictive accuracy.
- **Practical Implications for Decision-Making:** This study develops a model with real-world applicability, offering actionable insights for policymakers and businesses in resource allocation, economic planning, and strategic decision-making.
- **Contribution to the Economic Forecasting Literature:** The research provides an innovative methodological framework bridging the gap between academic advancements and practical utility in economic modeling.

Therefore, this study aims to make academic and practical contributions by improving the prediction accuracy of economic indicators through a per capita GDP prediction model based on deep learning and presenting a prediction model that helps make actual economic decisions. In particular, developing predictive models considering major macroeconomic variables, such as the consumer price index and the unemployment rate, is expected to provide important information in economic policy establishment and resource allocation.

2. Previous Related Research and Research Question

2.1. Previous Related Research

The following studies have significantly contributed to understanding GDP forecasting using machine learning and deep learning techniques. Previous studies have explored various approaches for GDP forecasting, utilizing different indicators and methodologies to enhance predictive accuracy. Mourougane and Roma (2003) investigated the relationship between confidence indicators and real GDP growth across euro-area countries, demonstrating the effectiveness of incorporating these indicators into short-term GDP predictions [11]. Although some instability was noted, their findings suggested that confidence indicators could improve GDP forecast accuracy when used with ARIMA models.

Expanding on advanced methodologies, Yoon (2021) applied machine learning models—specifically gradient boosting and random forest techniques—to predict Japan's GDP growth [12]. These models significantly outperformed the International Monetary Fund and Bank of Japan forecasts from 2001 to 2018, emphasizing machine learning's potential in macroeconomic forecasting. Yoon's study underscored the importance of hyperparameter tuning in maximizing the predictive performance of machine learning models.

Richardson et al. (2021) further explored the role of machine learning in real-time GDP nowcasting, incorporating a large set of predictors to improve forecast accuracy for New Zealand's GDP growth [13]. By comparing machine learning algorithms with autoregressive benchmarks, they illustrated how these methods could enhance the predictive capabilities of central banks, especially in rapidly changing economic environments.

Building on diverse data sources, Ferrara and Simoni (2023) examined the utility of Google Search Data (GSD) for nowcasting GDP in multiple countries [14]. By integrating GSD with machine learning techniques such as Ridge regression, they demonstrated that alternative data sources could increase prediction accuracy, especially during economic instability. This study highlights the value of unconventional datasets in enhancing GDP forecasting.

Finally, Jena et al. (2021) used artificial neural networks to assess the economic impact of COVID-19 on major economies, achieving a remarkably low forecasting error of under 2% [15]. Their study illustrated the potential of neural networks to capture rapid economic changes during crises, as evidenced by the sharp GDP declines observed across multiple countries in 2020. This research emphasizes the effectiveness of neural networks in scenarios characterized by rapid shifts in economic conditions.

These studies reveal the evolution of GDP forecasting methodologies, from traditional indicators and ARIMA models to machine learning and alternative data sources, each contributing unique insights and enhancements to economic predictions. Table 1 below summarizes the research methodology and major research results of previous studies related to GDP prediction.

Table 1. Prior research related to GDP prediction.

Prior Research	Methodology	Key Findings
Mourougane and Roma (2003) [11]	Incorporated confidence indicators with ARIMA models	Confidence indicators improved short-term GDP predictions despite some instability
Yoon (2021) [12]	Applied gradient boosting and random forest techniques	Outperformed IMF and BOJ forecasts; emphasized hyperparameter tuning
Richardson et al. (2021) [13]	Used large predictor sets with machine learning algorithms for nowcasting	Enhanced forecast accuracy over autoregressive benchmarks in real-time applications
Ferrara and Simoni (2023) [14]	Integrated Google Search Data with Ridge regression	Demonstrated increased prediction accuracy using alternative data during economic instability
Jena et al. (2021) [15]	Utilized artificial neural networks to forecast GDP during COVID-19	Achieved low forecasting error (<2%) in capturing rapid economic changes during crises

2.2. Research Question

Based on the prior research, the research questions of this thesis can be logically derived and substantiated as follows. First, the previous studies outline the limitations of traditional methods in capturing the nonlinear interactions and volatility in economic data [9,10]. These methods are often inadequate for modeling complex interactions within economic variables, especially during high external shocks. With its capacity to model intricate patterns and relationships through multilayered structures, deep learning offers a promising alternative [11]. Hence, the first research question investigates whether deep learning can address the limitations of traditional models and deliver more accurate predictions for per capita GDP.

Research Question 1: Can a deep learning model accurately predict per capita GDP by capturing nonlinear relationships that are difficult to model with traditional statistical methods?

Second, CPI and unemployment are key macroeconomic variables directly impacting GDP per capita due to their relationship with supply, demand, price levels, and economic stability [16,17]. Previous models have often excluded these variables, potentially overlooking important dimensions of economic dynamics. By including CPI and unemployment in the deep learning model, this study aims to determine whether these factors significantly enhance predictive accuracy, especially for capturing short-term economic fluctuations.

Research Question 2: Does incorporating the Consumer Price Index (CPI) and the unemployment rate as additional variables improve the predictive accuracy of the per capita GDP model?

Third, much prior research emphasizes the need for predictive models to be accurate and applicable in real-world decision-making contexts [18–20]. An accurate prediction

model can inform governmental and corporate strategies, particularly in response to economic uncertainties. This research question explores the extent to which the proposed model can be a practical tool, enhancing policy effectiveness, resource allocation, and strategic planning through reliable GDP forecasts.

Research Question 3: Can the developed per capita GDP prediction model using deep learning provide practical insights for policymakers and businesses in economic decision-making?

These research questions aim to bridge existing gaps in GDP forecasting by leveraging deep learning capabilities, enhancing variable selection, and focusing on real-world applications. This study seeks to establish an academically innovative predictive model that is practically valuable for economic strategy and planning.

3. Research Design

3.1. Samples

The data used in this study are various economic indicators from 107 countries, and the sample period is 1980–2023. Data are an annual indicator of each country, and the economic indicator data of each country were downloaded from the IMF Data Portal site (<https://data.imf.org/?sk=388dfa60-1d26-4ade-b505-a05a558d9a42>; accessed on 30 September 2024). In this paper, the total number of samples used in the empirical analysis is 3074 to develop a predictive model for per capita GDP indicators. Table 2 below is a list of 107 countries in this study.

Table 2. Sample countries.

List of Countries Used in Empirical Analysis				
Greece	Nigeria	South Africa	Netherlands	Norway
New Zealand	Nicaragua	Taiwan	South Korea	Denmark
Dominican Republic	Germany	Latvia	Russia	Romania
Luxembourg	Malaysia	Mexico	Morocco	Mauritius
Moldova	Malta	Mongolia	United States	Bahrain
Barbados	Bahamas	Venezuela	Vietnam	Belgium
Belarus	Belize	Bosnia and Herzegovina	Bolivia	Bhutan
North Macedonia	Bulgaria	Brazil	Brunei	Saudi Arabia
São Tomé and Príncipe	West Bank and Gaza	Serbia	Seychelles	Sudan
Suriname	Sri Lanka	Sweden	Switzerland	Spain
Slovakia	Slovenia	Syria	Singapore	Armenia
Argentina	Iceland	Ireland	Azerbaijan	Albania
Algeria	Estonia	Ecuador	El Salvador	United Kingdom
Australia	Austria	Honduras	Jordan	Uruguay
Uzbekistan	Ukraine	Iran	Israel	Egypt
Italy	Indonesia	Japan	Jamaica	Georgia
China	Czech Republic	Chile	Cape Verde	Kazakhstan
Canada	Kosovo	Costa Rica	Colombia	Croatia

Table 2. *Cont.*

List of Countries Used in Empirical Analysis				
Kyrgyzstan	Cyprus	Tajikistan	Thailand	Tunisia
Turkey	Panama	Paraguay	Pakistan	Peru
Portugal	Poland	France	Finland	Philippines
Hungary	Hong Kong			

Table 3 defines the variables used in the model for predicting GDP per capita in this paper. Table 4 is the descriptive statistics for these variables. The table of descriptive statistics provided shows the number of observations (N), mean (Mean), standard deviation (Std), minimum (Min), first quartile (Q1), median (Q3), third quartile (Q3), and maximum (Max) for each variable for various economic variables. These descriptive statistics provide basic information useful for understanding the distribution, central trend, and variability of the variables to be analyzed. The interpretation of major variables is as follows:

Table 3. Definition of variables.

Variables	Definition
GDP_PC	Natural logarithmic value of GDP (gross domestic product) per capita
GDP_D	Natural logarithmic value of GDP deflator
PPP_CR	Natural logarithmic value of PPP (purchasing power parity) conversion rate
CAB_GDP	Current Account Balance to GDP
SG_GDP	The ratio of a country's gross domestic product to global GDP
POP	Natural logarithmic value of a country's population
FB_GDP	The ratio of Fiscal Balance to GDP per capita
CGI	The ratio of change in goods imported
CGE	The ratio of change in goods exported
IVGR	The ratio of import volume growth
EVGR	The ratio of export volume growth
GGTR	Natural logarithmic value of Government's total revenue
TR_GDP	The ratio of total revenue to GDP
GGTE	Natural logarithmic value of Government's total expenditure
TE_GDP	The ratio of total expenditure to GDP
CPI	Natural logarithmic value of CPI (consumer price index)
UR	Unemployment rate

GDP_PC has an average value of 9.084, a median value of 9.164, and a relatively centralized distribution. The minimum value is 6.143, and the maximum is 11.418, showing a relatively wide range of distributions. GDP_D has an average of 4.387 and a median of 4.486, with a minimum of 1.311 and a maximum of 7.577, indicating a range of economic growth rates. PPP_CR has an average of 2.031 and a standard deviation of 2.017, suggesting high variability in the exchange rate based on purchasing power across countries. The average CAB_GDP ratio is −1.426, indicating that the current account is generally in the red, with a minimum of −23.310 and a maximum of 19.790, suggesting large variability in the current account depending on economic conditions. The SG_GDP averages 0.782, with a median of 0.290; some countries are in the red (-). Population (population) averages

16.090, including countries of varying population sizes. The average FB_GDP ratio is -2.451 , indicating that the fiscal balance is often in the red, ranging from a minimum of -13.880 to a maximum of 10.870 . Variables such as CGI, CGE, IVGR, and EVGR vary based on median and quartile, providing information on economic growth and volatility. CPI and UR also do not differ significantly between median and average values, providing additional insight into economic stability.

This table shows that each variable's descriptive statistics identify economic indicators' distribution characteristics and variability and can be used as basic data for analysis.

Table 4. Descriptive statistics.

Variables	N	Mean	Std	Min	Q1	Median	Q3	Max
GDP_PC	3074	9.084	1.246	6.143	8.170	9.164	10.124	11.418
GDP_D	3074	4.387	0.796	1.311	4.133	4.486	4.658	7.577
PPP_CR	3074	2.031	2.017	0.140	0.565	1.015	2.836	8.468
CAB_GDP	3074	-1.426	6.976	-23.310	-4.890	-1.685	2.280	19.790
SG_GDP	3074	0.782	1.406	0.000	0.060	0.290	0.800	8.990
POP	3074	16.090	1.723	11.290	15.224	16.078	17.431	21.069
FB_GDP	3074	-2.451	4.021	-13.880	-4.730	-2.535	-0.120	10.870
CGI	3074	5.450	11.155	-24.990	-0.400	5.330	11.460	38.840
CGE	3073	5.257	10.536	-24.150	-0.130	4.630	10.290	43.170
IVGR	3074	5.311	10.625	-24.730	0.120	5.360	11.090	35.340
EVGR	3074	5.131	9.672	-25.440	0.560	4.895	9.690	38.300
GGTR	3074	26.069	3.094	19.947	23.883	26.019	27.749	34.646
TR_GDP	3074	31.555	11.616	9.860	21.960	30.780	40.390	56.370
GGTE	3074	26.150	3.093	20.179	23.944	26.097	27.815	34.766
TE_GDP	3074	33.971	11.875	11.510	23.720	33.550	43.400	59.860
CPI	3074	4.641	1.891	1.488	4.179	4.493	4.663	17.846
UR	3074	8.545	5.389	1.300	4.910	7.305	10.540	31.000

3.2. Research Model

This study designed a research model for more sophisticated per capita GDP prediction, referring to various previous studies on GDP prediction. In other words, this study's selection of variables for predicting per capita GDP is grounded in established economic theories and prior empirical research. Each variable represents critical aspects of a country's economic structure, policy environment, and international standing, contributing to a more comprehensive and accurate model for GDP prediction.

A per capita GDP prediction model was constructed by including the following variables. The GDP deflator measures price inflation, representing the price change in all domestically produced goods and services. Its logarithmic value captures the effects of inflation on real economic growth, allowing the model to adjust for price-level variations that impact the purchasing power and real GDP value [21]. Purchasing Power Parity (PPP) reflects the relative cost of goods and services across countries, providing insight into a nation's currency valuation and standard of living. Including the PPP conversion rate in logarithmic form enables the model to account for cross-country differences in purchasing power, a key factor in international GDP comparisons [22]. The current account balance indicates a country's net trade in goods and services, income, and transfers. Its ratio to

GDP provides insights into the nation's external economic stability and its dependence on foreign demand, which are critical for understanding fluctuations in economic growth and sustainability [23]. A country's GDP to global GDP ratio represents its share in the global economy, reflecting its economic influence and integration into the global market. A higher ratio often corresponds to greater economic resilience and diversified income sources, making it a relevant indicator for GDP prediction [24]. Population size is directly related to labor force potential and market demand. The logarithmic value of population accounts for economies of scale, where larger populations can indicate both resource availability and consumption potential, which are central to economic growth dynamics [25]. Fiscal balance reflects government budgetary health, with a higher balance-to-GDP ratio indicating prudent fiscal management. Sound fiscal policies are crucial for economic stability and growth, impacting public investment, debt levels, and financial market stability [26]. The change ratio in imported and exported goods can affect per capita GDP. Changes in imports and exports are essential indicators of a country's trade activity. Imports reflect domestic demand and reliance on foreign goods, while exports indicate global demand for domestic products. Both ratios help the model capture trade dynamics and their influence on GDP [27]. Import and export volume growth ratios provide a more granular view of trade patterns and demand elasticity. High export volume growth, for instance, suggests robust external demand and potential GDP growth. Including these ratios allows the model to adjust to short-term shifts in trade [28]. Government revenue reflects the state's fiscal capacity, with total revenue representing the financial resources available for public investment and economic stimulus. This variable, particularly when adjusted to GDP, offers insights into the government's role in economic activity [29]. Government expenditure is directly linked to economic growth through public investment and consumption. Higher government spending often supports infrastructure and welfare programs, fostering economic stability. Including these variables enables the model to consider the impact of fiscal policy on GDP [30].

In this study, a model was designed by adding CPI and unemployment rate variables for a more accurate prediction of GDP per capita. CPI is a widely used indicator of inflation and purchasing power. Its natural logarithmic transformation provides a refined measure of price level changes, allowing the model to capture inflationary pressures that influence economic output and consumer demand [16]. The unemployment rate directly measures labor market health and economic utilization. High unemployment often signifies economic downturns and reduced consumption, which can depress GDP. Including the unemployment rate thus allows the model to account for fluctuations in workforce participation and income levels, which are fundamental to GDP dynamics [17].

These variables collectively offer a multi-dimensional view of economic activity, capturing domestic factors such as fiscal balance, government revenue and expenditure, and population, and external conditions like PPP, trade ratios, and current account balance. By integrating these indicators, the model can better account for the complex interactions that drive per capita GDP, addressing limitations in traditional linear models and providing a comprehensive framework for GDP prediction. This selection is well supported by theoretical foundations and empirical evidence in economic research, enhancing the model's ability to produce accurate and reliable forecasts. Equation (1) is the basic model for per capita GDP forecast, and Equation (2) is the model that adds the consumer price index and unemployment rate to the basic model for per capita GDP prediction.

$$F(GDP_D, PPP_CR, CAB_GDP, SG_GDP, POP, FB_GDP, CGI, CGE, IVGR, EVGR, GGTR, TR_GDP, GGTE, TE_GDP) = GDP_PC \quad (1)$$

$$F(GDP_D, PPP_CR, CAB_GDP, SG_GDP, POP, FB_GDP, CGI, CGE, IVGR, EVGR, GGTR, TR_GDP, GGTE, TE_GDP + CPI, UR) = GDP_PC \quad (2)$$

Figure 1 presents a schematic overview of the comparative analysis framework for evaluating the performance of the per capita GDP prediction model through a deep learning regression approach. In this study, five distinct deep learning regression models are employed: Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Temporal Convolutional Network (TCN), and Transformer.

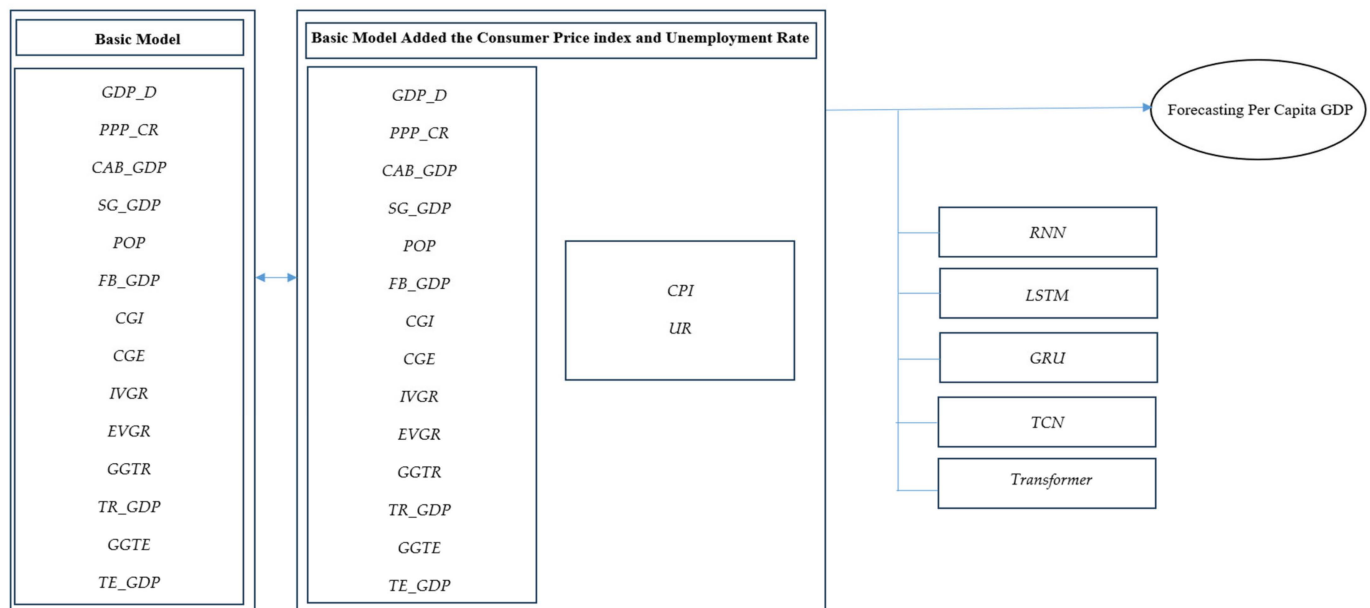


Figure 1. Research model.

The following Figure 1 is a schematic diagram of how to compare and analyze the performance of the per capita GDP prediction model using this paper's deep learning regression method. This study uses five deep learning regressors: Recurrent Natural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Temporal Convolutional Network (TCN), and Transformer.

3.3. Deep Learning Algorithms for per Capita GDP Forecasting

Deep learning algorithms that effectively capture the temporal patterns in data and their correlations with economic variables are highly suitable for time series-based prediction problems, such as forecasting GDP per capita for individual countries. Among these algorithms, several have proven particularly effective.

Recurrent Neural Networks (RNNs) are specialized for handling time series data by learning temporal order and patterns within datasets [31]. However, RNNs face significant limitations in addressing long-term dependencies, which can restrict their applicability in modeling complex economic data [32].

Long short-term memory (LSTM) networks, an advanced form of RNN, overcome these limitations by effectively learning long-term dependencies [33]. This capability is particularly valuable for forecasting GDP per capita, which requires analyzing extended periods of economic and social indicators. LSTMs are also adept at capturing relationships between economic variables such as growth rate, inflation, and unemployment, enhancing their effectiveness in economic modeling [34].

Gated Recurrent Units (GRUs), similar to LSTMs in functionality, offer a computationally simpler structure that facilitates faster processing and greater efficiency [35]. GRUs perform well in scenarios requiring long-term dependency learning while utilizing fewer computational resources, making them suitable for GDP forecasting tasks where efficiency is critical [36].

Temporal Convolutional Networks (TCNs) utilize a convolutional neural network (CNN) structure tailored for time series data [37]. TCNs excel at parallel processing, enabling faster learning and effective handling of long-term dependencies [38]. Their ability to learn from diverse time series variables in parallel makes them particularly advantageous for economic forecasting, where multiple interacting factors influence outcomes.

Transformers, originally developed for natural language processing, have recently gained attention for their efficacy in time series prediction [39]. The Self-Attention mechanism employed by Transformers allows them to effectively capture essential temporal relationships across multivariate data [40]. Transformers are highly parallelizable and excel in processing large datasets, making them uniquely capable of modeling complex interactions among economic indicators [41].

Among these algorithms, LSTM and GRU are particularly well-suited for GDP forecasting due to their strengths in learning long-term dependencies and understanding the relationships among key economic variables [34,35]. Transformers are highly effective when dealing with large datasets and complex multivariate interactions. Additionally, TCNs provide computational efficiency and excel in scenarios requiring parallel learning of diverse time series variables.

This study develops a predictive model for GDP per capita using RNN, LSTM, GRU, TCN, and Transformer algorithms. Key macroeconomic variables, specifically the Consumer Price Index (CPI) and the unemployment rate, are incorporated to enhance the model's performance. These variables significantly improve the predictive accuracy of the model for several reasons.

First, CPI is a crucial indicator of inflation and purchasing power, directly impacting consumption patterns and GDP. Stability in inflation levels allows for more efficient economic functioning, making CPI a critical factor in economic forecasting. The unemployment rate is another vital variable reflecting the labor market's health. High unemployment negatively affects consumption and GDP growth, and its inclusion allows the model to better predict GDP volatility by capturing changes in the labor market.

Second, GDP per capita is a comprehensive measure of a population's living standards and economic productivity. Including CPI and unemployment rate enhances the model's ability to reflect fluctuations in consumption capacity and economic activity, which are crucial for understanding GDP volatility.

Third, deep learning models excel at learning complex nonlinear relationships among variables. Including CPI and unemployment rate enables these models to capture intricate patterns and interactions, improving their predictive capabilities.

Finally, incorporating CPI and the unemployment rate enhances the model's sensitivity to external economic shocks, such as economic downturns or inflationary periods. These variables significantly impact GDP volatility, particularly during crises, allowing the model to deliver more reliable and accurate predictions.

In conclusion, including CPI and the unemployment rate as key variables significantly enhances the performance of deep learning models in forecasting GDP per capita. These indicators provide valuable insights into the economic conditions underlying GDP trends, enabling more sophisticated and accurate predictions. Advanced models, such as Transformers and TCNs, demonstrate particular efficacy in capturing complex relationships

and delivering superior predictive accuracy, making them indispensable tools in modern economic forecasting.

3.4. Regression Method

Cross-validation is a widely recognized and robust approach for assessing model performance, effectively reducing the likelihood of overfitting and underfitting issues [42]. This technique systematically divides the dataset into multiple subsets, where each subset is alternately used for training and validation, thereby offering a comprehensive evaluation of the model's generalization ability [43]. Additionally, cross-validation provides an extensive analysis across diverse data patterns rather than depending on a single train-test split [44]. This approach serves as a fundamental baseline, allowing for the early detection of potential overfitting or underfitting concerns and facilitating model optimization [45]. In this study, the K-fold cross-validation method, known for its robustness, was applied with K set to 5. This configuration split the dataset into five folds, each serving as the validation set once, with the remaining folds designated for training.

Regression methods predict outcomes in machine learning or deep learning by modeling the relationship between continuous dependent and independent variables [46]. Regression analysis aims to learn correlations among data variables and make predictions based on new input values, essentially identifying the relationship between input and output variables [12,47].

Typically, regression analysis results in machine learning or deep learning are evaluated using metrics such as R-squared, Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Squared Logarithmic Error (MSLE), and Mean Absolute Percentage Error (MAPE) [46,47].

R-squared is a key metric for assessing model performance in machine learning. It indicates how well the regression model accounts for the variability in the dependent variable [48]. Ranging from 0 to 1, an R-squared value near 0 suggests that the model does not effectively explain the variability of the dependent variable [49]. In contrast, a value closer to 1 implies stronger explanatory power [48,49].

$$R^2 = 1 - \frac{RSS}{TSS} \quad (3)$$

$$TSS = \text{Total Sum of Squares} = \sum_{i=1}^n (y_i - \bar{y})^2; \quad RSS = \text{Residual Sum of Squares} = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (4)$$

MSE is a commonly used loss function in machine learning. It evaluates predictive performance by calculating the average squared errors between predicted and actual values [50]. Since MSE measures squared error, a larger squared error results in a higher MSE [51]. Therefore, a lower MSE indicates better model performance [50].

$$MSE = \frac{1}{n} \sum_{i=1}^n (\hat{Y}_i - Y_i)^2 \quad (5)$$

RMSE, another frequently employed loss function, similarly evaluates predictive performance by calculating the square root of the mean squared error [52]. Unlike MSE, RMSE presents errors in the same unit as the original values, allowing a more intuitive understanding of the average error size between predicted and actual values [53]. Like MSE, a lower RMSE reflects enhanced model performance [52].

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{Y}_i - Y_i)^2} \quad (6)$$

MSLE is another loss function in machine learning regression. It measures predictive performance by averaging the squared logarithmic errors between predicted and actual values [54]. Because MSLE uses log-transformed values, a larger error yields a higher MSLE, meaning lower values are preferred for optimal model performance [55].

$$\text{MSLE} = \frac{1}{n} \sum_{i=1}^n (\log(\hat{Y}_i + 1) - \log(Y_i + 1))^2 \quad (7)$$

Lastly, MAPE is a commonly used metric for evaluating machine learning results [56]. MAPE calculates the average of absolute percentage errors between predictions and actual values, expressing error as a percentage and facilitating an intuitive assessment of model performance [57]. Lower MAPE values indicate better predictive performance [56].

$$\text{MAPE} = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{\hat{Y}_i - Y_i}{Y_i} \right| \quad (8)$$

The literature employs a variety of metrics to assess the efficiency and predictive performance of GDP analysis models. These metrics play a critical role in understanding how effectively a model captures underlying patterns in the data and forecasts future economic trends. The following classification outlines the key metrics used in GDP analysis and highlights their relevance in evaluating model performance.

The Mean Squared Error (MSE) is one of the most commonly used metrics for regression tasks, as it calculates the average squared differences between the predicted and actual values. By penalizing larger errors more heavily, MSE clearly indicates a model's ability to minimize significant deviations from observed data. However, this sensitivity to outliers can sometimes skew the overall evaluation, particularly in datasets with high variability or extreme values.

The Root Mean Squared Error (RMSE), derived as the square root of MSE, presents error measurements in the same unit as the dependent variable. This feature makes RMSE highly interpretable, allowing straightforward comparisons across different models. RMSE is particularly valuable in GDP forecasting since its alignment with economic indicators ensures meaningful and easily understood results by practitioners and policymakers.

The Mean Absolute Error (MAE) measures the average of the absolute differences between predicted and actual values. Unlike MSE, MAE treats all errors equally, making it less sensitive to extreme deviations and a more robust choice for assessing overall prediction accuracy. Its straightforward calculation and interpretation are advantageous; however, MAE may lack sensitivity to significant errors, undermining its effectiveness in contexts where large deviations are particularly critical, such as economic crises.

The Mean Absolute Percentage Error (MAPE) expresses errors as a percentage of the actual values, offering a scale-independent metric for evaluating predictive performance. This makes MAPE particularly useful in GDP analysis, where relative errors provide important context for decision-makers. However, MAPE has limitations, especially when actual values approach zero, as it can produce disproportionately large error percentages, distorting evaluation in such cases.

The Mean Squared Logarithmic Error (MSLE) focuses on the logarithmic differences between predicted and actual values, emphasizing proportional rather than absolute accuracy. By prioritizing relative differences, MSLE is particularly suitable for datasets where small relative changes are more meaningful than large absolute ones. This metric is especially advantageous in GDP forecasting, as it aligns closely with understanding proportional trends in macroeconomic variables over time.

In this study, the metrics MSE, RMSE, MAE, MAPE, and MSLE were selected to comprehensively evaluate the deep learning models used for GDP forecasting. Each metric was chosen to highlight a specific aspect of model performance. MSE was employed to measure the magnitude of overall errors, focusing on minimizing large deviations. RMSE complemented MSE by offering interpretable error measurements in the same units as GDP, facilitating comparisons across different models and datasets. MAE served as a robust alternative to MSE, effectively capturing the average prediction error while reducing sensitivity to outliers. MAPE enabled the evaluation of errors in relative terms, providing key insights into the percentage accuracy of forecasts, which is especially valuable for economic decision-making. Finally, MSLE was used to emphasize proportional accuracy, allowing the models to capture relative trends in GDP growth more effectively.

By employing these diverse metrics, the study ensured a well-rounded evaluation of model efficiency, addressing both absolute and relative accuracy. Comparing results across these metrics provided a nuanced understanding of the models' strengths and weaknesses, reflecting best practices in GDP forecasting research. This comprehensive approach underscores the importance of selecting appropriate metrics tailored to the analysis's objectives, ensuring that model evaluations are both rigorous and relevant to the specific context of economic forecasting.

4. Analysis Results

This study presents the analysis results using placebo and real data to present more objective and reliable per capita GDP prediction results. Table 5 presents the R-squared values of various deep-learning regression models for predicting per capita GDP. These models include RNN, LSTM, GRU, TCN, and Transformer, each applied to two datasets: real data and placebo data. The real data consist of the basic model and three additional models incorporating CPI, UR, and CPI and UR, respectively. Placebo data follow the same structure, with a basic model and models sequentially incorporating CPI, UR, and CPI and UR.

Table 5. GDP per capita R-squared results.

Data	Model	Regressor	R-Squared	Regressor	R-Squared	Regressor	R-Squared	Regressor	R-Squared	Regressor	R-Squared
Real data	Basic model	RNN	0.6651	LSTM	0.6837	GRU	0.6532	TCN	0.6948	Transformer	0.7039
	+CPI		0.6944		0.7012		0.6792		0.7166		0.7269
	+UR		0.7078		0.7289		0.6928		0.7395		0.7482
	+CPI and UR		0.7223		0.7455		0.7165		0.7580		0.7688
Placebo data	Basic model	RNN	0.5115	LSTM	0.5206	GRU	0.5020	TCN	0.5352	Transformer	0.5440
	+CPI		0.5354		0.5467		0.5102		0.5590		0.5678
	+UR		0.5592		0.5698		0.5213		0.5781		0.5899
	+CPI and UR		0.5707		0.5849		0.5455		0.5961		0.6075

Real data results are as follows. For the RNN model, the R-squared values increase as additional variables are added. The basic model achieves an R-squared of 0.6651, while including CPI and UR together improves the R-squared to 0.7223, indicating enhanced explanatory power. The LSTM model demonstrates a higher predictive performance than RNN, with an R-squared of 0.6837 for the basic model and reaching up to 0.7455 when both CPI and UR are included. This suggests that LSTM can capture more complex relationships within the data. The GRU model performs similarly, starting with an R-squared of 0.6532 for the basic model and improving to 0.7165 with both CPI and UR. This improvement pattern shows the model's increasing ability to explain the variability in GDP per capita with more

predictors. The TCN model exhibits a substantial increase in R-squared from 0.6948 (basic model) to 0.7580 with CPI and UR, indicating strong predictive capabilities and effective use of additional variables. The Transformer model achieves the highest R-squared values among all models, starting at 0.7039 for the basic model and reaching 0.7688 when CPI and UR are included, suggesting that the Transformer model provides the most accurate predictions for GDP per capita in this context.

Next, placebo data results are as follows. In the RNN model for placebo data, the R-squared values are lower than those for real data. The basic model achieves 0.5115 and increases slightly to 0.5707, including CPI and UR. This lower range indicates less effective modeling with placebo data, implying that the real variables have more predictive significance. Similarly, the LSTM model for placebo data shows an increase in R-squared from 0.5206 (basic model) to 0.5849 (with CPI and UR), although these values remain below the real data. The GRU model also follows this trend, starting at 0.5020 for the basic model and reaching 0.5455 when both CPI and UR are incorporated, highlighting a consistent underperformance compared to real data. The TCN model in the placebo data scenario shows an R-squared range from 0.5352 (basic model) to 0.5961 (with CPI and UR), which, while slightly higher than GRU, remains below the real data results. Lastly, the Transformer model shows the best performance among placebo models, with an R-squared increasing from 0.5440 (basic model) to 0.6075 (with CPI and UR). However, this is still significantly lower than its performance on real data.

Overall, the Transformer model consistently shows the highest R-squared values across real and placebo data, indicating its superior capability in predicting GDP per capita. Adding variables such as CPI and UR generally improves the R-squared values across all models, especially in real data, underscoring the relevance of these variables in enhancing model accuracy. The lower R-squared values in the placebo data models compared to real data models reflect the limitations of the placebo dataset in capturing the true relationship between GDP and the predictor variables, suggesting that real data variables are indeed meaningful contributors to the predictive accuracy of GDP per capita.

The regression models used in the study each have distinct advantages and disadvantages, which contribute to their applicability and performance in GDP forecasting tasks. Recurrent Neural Networks (RNNs) offer a simple architecture well-suited for sequential data, making them effective for basic time-series forecasting. However, RNNs often struggle with long-term dependencies due to the vanishing gradient problem, which can limit their accuracy in capturing complex temporal relationships.

Long Short-Term Memory (LSTM) networks, an extension of RNNs, address these limitations by effectively handling long-term dependencies, making them highly robust for time-series data. Despite their strengths, LSTMs are computationally expensive and require longer training times, which can be a drawback for large-scale datasets or time-sensitive applications. Gated Recurrent Units (GRUs) simplify the LSTM architecture, offering faster training and computation while retaining much of the capability to model temporal dependencies. However, GRUs may be slightly less powerful than LSTMs in capturing highly intricate patterns in the data.

Temporal Convolutional Networks (TCNs) provide an alternative approach by using convolutional structures to capture temporal patterns. This enables parallel processing and avoids the vanishing gradient issue inherent in RNN-based models. While TCNs excel in efficiently capturing temporal dependencies, they require careful parameter tuning and may not perform optimally when dealing with highly irregular datasets.

Transformers represent state-of-the-art deep learning for sequential data, offering unparalleled performance and the ability to capture global dependencies across a dataset. Their self-attention mechanism enables them to understand complex relationships within

data sequences effectively. However, transformers have a significant computational cost and require large datasets to achieve optimal results, making their application challenging in resource-constrained settings.

Additionally, incorporating variants such as the Consumer Price Index (CPI) and Unemployment Rate (UR) as regressors has demonstrated substantial improvements in predictive accuracy, as evidenced by the increased R-squared values in the study. These additional indicators enrich the models by providing more context and explanatory power. However, this approach introduces additional complexity to the model. It necessitates the availability of high-quality data for these supplementary regressors, underscoring the need for reliable and comprehensive datasets in achieving superior forecasting outcomes.

Table 6 provides the Mean Squared Error (MSE) values for different deep-learning regression models that predict per capita GDP. The models included are RNN, LSTM, GRU, TCN, and Transformer, each tested on two data types: real data and placebo data. Real data comprise a basic model and three additional models that progressively incorporate CPI, UR, and both CPI and UR. The placebo data follow a similar setup, consisting of a basic model and models with CPI, UR, and CPI and UR.

Table 6. GDP per capita MSE results.

Data	Model	Regressor	MSE	Regressor	MSE	Regressor	MSE	Regressor	MSE	Regressor	MSE
Real data	Basic model		0.2752		0.2564		0.2899		0.2380		0.2219
	+CPI		0.2420		0.2272		0.2678		0.2187		0.2078
	+UR		0.2219		0.2035		0.2447		0.2015		0.1906
	+CPI and UR		0.2075		0.1983		0.2375		0.1804		0.1790
Placebo data	Basic model	RNN	0.3465	LSTM	0.3322	GRU	0.3689	TCN	0.3280	Transformer	0.3052
	+CPI		0.3290		0.3141		0.3477		0.3074		0.2916
	+UR		0.3186		0.3064		0.3295		0.2941		0.2788
	+CPI and UR		0.3011		0.2940		0.3154		0.2712		0.2583

Real data results are as follows. In the RNN model, the MSE decreases as additional variables (CPI, UR) are added. The basic model shows an MSE of 0.2752, which improves to 0.2075 when both CPI and UR are included. This reduction in MSE indicates that adding these variables enhances the model's prediction accuracy. The LSTM model demonstrates lower MSE values than RNN, starting with 0.2564 for the basic model and reaching 0.1983 when CPI and UR are added. This suggests that LSTM has a stronger predictive capability and benefits from including relevant variables. The GRU model exhibits similar trends. The basic model has an MSE of 0.2899, which decreases to 0.2375 with CPI and UR. This improvement demonstrates GRU's ability to predict GDP per capita better when more predictors are included. The TCN model substantially reduces MSE as more variables are added, with the basic model at 0.2380 and the MSE decreasing to 0.1804 when both CPI and UR are included. This indicates that TCN effectively leverages additional information to improve prediction accuracy. The Transformer model yields the lowest MSE values among all models on real data, with an MSE of 0.2219 for the basic model, reducing to 0.1790 when CPI and UR are included. This suggests that the Transformer model has the most accurate predictive performance on real data, benefiting significantly from the additional variables.

Meanwhile, placebo data results are as follows. The MSE values for the RNN model with placebo data are generally higher than those in real data. The basic model's MSE is 0.3465, decreasing to 0.3011 with CPI and UR. This indicates that the model does not benefit as much from placebo variables, reflecting the limited predictive power of this dataset. The LSTM model on placebo data follows a similar trend, with the basic model's MSE at 0.3322 and decreasing to 0.2940 with CPI and UR, but these values remain higher than the

real data results. The GRU model also shows higher MSE values for placebo data, starting from 0.3689 (basic model) and reducing to 0.3154 with both CPI and UR. This pattern suggests that GRU is less effective when using placebo predictors. In the TCN model with placebo data, the MSE ranges from 0.3280 (basic model) to 0.2712 with CPI and UR, which, although improved, remains higher than the MSE values obtained with real data. Lastly, the Transformer model on placebo data starts with an MSE of 0.3052 (basic model), which decreases to 0.2583 when CPI and UR are included. However, these values are consistently higher than those achieved on real data, indicating that the Transformer's performance is more robust when using real variables.

In conclusion, the Transformer model consistently achieves the lowest MSE across real and placebo datasets, indicating superior predictive accuracy in this context. Each model shows an improvement in MSE as CPI and UR variables are incorporated, particularly in the real data, highlighting the relevance of these economic indicators in enhancing prediction accuracy for GDP per capita. The higher MSE values for placebo data across all models suggest that the real data variables provide more meaningful contributions to the model's predictive performance. This table underscores the effectiveness of using real data with relevant economic indicators and demonstrates that the Transformer model outperforms other models in minimizing prediction error.

The deep learning regression models employed in this study each bring distinct strengths and weaknesses to GDP forecasting, which are critical for understanding their performance and suitability in various contexts. Recurrent Neural Networks (RNNs) provide a straightforward architecture for sequential data processing, making them effective for capturing short-term temporal patterns. However, their ability to model long-term dependencies is limited due to the vanishing gradient problem, which can reduce their accuracy in datasets with extensive time lags or intricate relationships.

Long short-term memory (LSTM) networks enhance this capability by introducing memory cells that effectively manage long-term dependencies, making them particularly robust for time-series forecasting tasks. Despite these advantages, LSTMs are computationally intensive and require longer training times, posing challenges for real-time applications or large datasets. Similarly, Gated Recurrent Units (GRUs) simplify the LSTM structure, reducing computational overhead while maintaining much of the temporal modeling strength. However, GRUs might not capture complex patterns as effectively as LSTMs, particularly in highly dynamic datasets.

Temporal Convolutional Networks (TCNs) offer a non-recurrent approach, using convolutional layers to capture temporal dependencies. This design allows for parallel processing, significantly reducing training time and addressing the vanishing gradient issue. Nonetheless, TCNs require careful tuning of hyperparameters and may exhibit reduced performance with irregular or noisy data. Transformers, by contrast, represent the cutting edge of deep learning for sequential data analysis. Their self-attention mechanism enables them to model long-range dependencies and global patterns effectively. However, the computational cost of transformers is substantial, and they often require large volumes of high-quality data to achieve optimal performance.

Incorporating additional regressors, such as the Consumer Price Index (CPI) and Unemployment Rate (UR), further enhances the predictive power of these models. Including these variables reduces Mean Squared Error (MSE) values, as demonstrated in the study, highlighting their contribution to improving forecast accuracy. However, this approach also increases model complexity and demands access to high-quality data for these indicators. Ensuring the availability and reliability of such data are essential for maximizing the effectiveness of these advanced regression models.

This discussion underscores the importance of selecting appropriate deep learning models and incorporating meaningful regressors to optimize forecasting performance while balancing computational efficiency and data quality requirements. By providing a nuanced understanding of each model's strengths and limitations, the study offers valuable insights for researchers and practitioners aiming to enhance GDP prediction accuracy through advanced methodologies.

Table 7 presents the Root Mean Square Error (RMSE) values for various deep-learning regression models that predict per capita GDP. These models include RNN, LSTM, GRU, TCN, and Transformer, each tested on two datasets: placebo data and real data. Both datasets are analyzed using a basic model and additional models incorporating CPI, UR, and both CPI and UR variables.

Table 7. GDP per capita RMSE results.

Data	Model	Regressor	RMSE	Regressor	RMSE	Regressor	RMSE	Regressor	RMSE	Regressor	RMSE
Placebo data	Basic model		0.2634		0.2488		0.2736		0.2217		0.2108
	+CPI		0.2321		0.2165		0.2520		0.2023		0.1908
	+UR		0.2187		0.1974		0.2329		0.1912		0.1854
	+CPI and UR		0.1989		0.1848		0.2162		0.1782		0.1677
Real data	Basic model	RNN	0.3225	LSTM	0.3211	GRU	0.3529	TCN	0.3154	Trans-former	0.2944
	+CPI		0.3182		0.3056		0.3386		0.2911		0.2832
	+UR		0.3077		0.2956		0.3148		0.2821		0.2620
	+CPI and UR		0.2967		0.2839		0.3035		0.2689		0.2418

Real data results are as follows. For the RNN model, the RMSE values are higher than placebo data, with the basic model at 0.3225 and decreasing to 0.2967 with CPI and UR. This result contrasts with the trend observed in placebo data, as RMSE values here remain relatively higher. The LSTM model shows a similar pattern, with the basic model starting at 0.3211 and decreasing slightly to 0.2839 when CPI and UR are included. Although LSTM improves, the real data models do not achieve as low an RMSE as those with placebo data. For the GRU model, the RMSE decreases from 0.3529 (basic model) to 0.3035 (CPI and UR), but it remains less effective on real data than placebo. The TCN model shows improved RMSE values on real data, starting at 0.3154 in the basic model and decreasing to 0.2689 with both CPI and UR. This suggests that TCN benefits from the additional variables and performs comparably on real data. Lastly, the Transformer model again shows the lowest RMSE on real data, with the basic model at 0.2944 and decreasing to 0.2418 with both CPI and UR. The Transformer's low RMSE indicates its superior performance, even on real data, compared to other models.

Next, placebo data results are as follows. For the RNN model, RMSE values decrease as CPI, UR, and CPI and UR are added. The basic model starts with an RMSE of 0.2634, which reduces to 0.1989 when both CPI and UR are included. This decreasing trend suggests that adding variables, even in placebo data, provides some incremental value in prediction. The LSTM model also shows a reduction in RMSE with additional variables. Starting at 0.2488 for the basic model, it decreases to 0.1848 when both CPI and UR are added, indicating better predictive performance than the RNN model on placebo data. The GRU model exhibits similar improvements, with RMSE values decreasing from 0.2736 in the basic model to 0.2162 with CPI and UR included. Although GRU performs slightly worse than LSTM, it performs better with additional predictors. For the TCN model, the RMSE drops from 0.2217 in the basic model to 0.1782 when both CPI and UR are included, suggesting that TCN effectively reduces prediction error with these added variables. The Transformer model yields the lowest RMSE values across placebo data models, with an RMSE of 0.2108

for the basic model, further reducing to 0.1677 with both CPI and UR. This demonstrates the Transformer's strong predictive performance even when using placebo data.

Namely, the Transformer model consistently achieves the lowest RMSE values across both placebo and real datasets, highlighting its strong predictive performance for per capita GDP forecasting. Adding variables (CPI, UR) generally improves RMSE across all models, with greater improvements observed in the placebo data. However, despite these improvements, real data models tend to have slightly higher RMSE values than placebo data models, suggesting a potential overfitting tendency in placebo data models or that real data variables may not be fully optimized in these configurations. Overall, the Transformer model's performance stands out, demonstrating its effectiveness in minimizing prediction error.

The performance of deep learning regression models for GDP forecasting, as summarized in Table 7, reflects each approach's nuanced strengths and limitations. Recurrent Neural Networks (RNNs) are recognized for their straightforward architecture and ability to process sequential data effectively, making them reliable for basic time-series forecasting. However, their vulnerability to vanishing gradients limits their capacity to capture long-term dependencies, leading to challenges in modeling complex temporal relationships.

Long-short-term memory (LSTM) networks, an advanced variant of RNNs, overcome these limitations by incorporating memory cells that excel at capturing long-term dependencies and mitigating gradient vanishing issues. This robustness makes LSTMs particularly effective for forecasting tasks requiring an understanding of extended temporal patterns. Despite these advantages, LSTMs demand significant computational resources and longer training times, which can be a limitation in scenarios requiring quick and efficient model deployment.

Gated Recurrent Units (GRUs) simplify the LSTM architecture by reducing the number of gates, enabling faster training and improved computational efficiency. GRUs maintain much of the temporal modeling capability of LSTMs while being more resource-friendly. However, their simplified structure may sometimes fall short of capturing intricate temporal patterns compared to LSTMs.

Temporal Convolutional Networks (TCNs) provide an alternative approach by leveraging convolutional layers for sequential modeling. Their ability to capture long-range dependencies while avoiding the vanishing gradient problem makes them well-suited for forecasting tasks involving complex temporal data. TCNs also benefit from efficient parallelization, reducing training time significantly. However, their reliance on precise hyperparameter tuning can hinder performance when applied to highly irregular or noisy datasets.

Transformers, the most advanced model used in this study, stand out for their capacity to capture global dependencies through the self-attention mechanism. This characteristic enables transformers to achieve state-of-the-art performance in modeling complex sequential data. Nevertheless, their high computational cost and requirement for large datasets pose practical challenges, particularly in resource-constrained environments or when high-quality data are scarce.

The inclusion of additional regressors, such as the Consumer Price Index (CPI) and Unemployment Rate (UR), further enhances the predictive power of these models. As the results demonstrate, incorporating these variables significantly reduces Root Mean Squared Error (RMSE), underscoring their importance in improving model accuracy. However, this added complexity increases the demand for high-quality input data, requiring careful preprocessing and validation to ensure reliability. Integrating these variables into the models adds to their computational complexity, necessitating a balance between performance improvement and resource allocation.

This comprehensive evaluation of the models and their variants highlights the trade-offs between computational efficiency, predictive accuracy, and model complexity. The findings emphasize the importance of aligning the choice of model with the specific forecasting context, available resources, and data quality to optimize performance in GDP forecasting tasks.

Table 8 displays the Mean Squared Logarithmic Error (MSLE) values for various deep-learning regression models applied to GDP per capita prediction. The models evaluated include RNN, LSTM, GRU, TCN, and Transformer. Each model was tested on two datasets: placebo data and real data. Both datasets contain a basic model and models that progressively incorporate CPI, UR, and CPI and UR variables.

Table 8. GDP per capita MSLE results.

Data	Model	Regressor	MSLE	Regressor	MSLE	Regressor	MSLE	Regressor	MSLE	Regressor	MSLE
Placebo data	Basic model	RNN	0.1895	LSTM	0.1732	GRU	0.1965	TCN	0.1622	Transformer	0.1554
	+CPI		0.1670		0.1582		0.1551		0.1471		0.1379
	+UR		0.1584		0.1400		0.1492		0.1295		0.1165
	+CPI and UR		0.1440		0.1296		0.1301		0.1167		0.1007
Real data	Basic model	RNN	0.2532	LSTM	0.2482	GRU	0.2615	TCN	0.2231	Transformer	0.2146
	+CPI		0.2245		0.2102		0.2432		0.2082		0.2004
	+UR		0.2186		0.2005		0.2235		0.1945		0.1867
	+CPI and UR		0.2066		0.1934		0.2178		0.1813		0.1588

Real data results are as follows. For the RNN model, the MSLE values are generally higher on real data than on placebo data. The basic model is 0.2532, which reduces to 0.2066 when CPI and UR are included. This suggests that, while the model benefits from additional variables, real data do not achieve as low an MSLE as placebo. The LSTM model follows a similar trend, starting with an MSLE of 0.2482 in the basic model and decreasing to 0.1934 with CPI and UR. While LSTM performs better than RNN, the MSLE values remain relatively high on real data. For the GRU model, the MSLE decreases from 0.2615 (basic model) to 0.2178 (CPI and UR). This shows that, like the other models, GRU benefits from the additional variables but does not reach the same low MSLE values seen in placebo data. The TCN model shows improved MSLE values with real data, starting at 0.2231 in the basic model and decreasing to 0.1813 with both CPI and UR, which suggests that the TCN model can effectively leverage these additional variables. The Transformer model again shows the lowest MSLE values on real data, with the basic model starting at 0.2146 and decreasing to 0.1588 with CPI and UR. The Transformer's lower MSLE indicates that it performs better in minimizing error than other models on real data, although its values are still higher than those on placebo data.

Meanwhile, placebo data results are as follows. For the RNN model, the MSLE values decrease as more variables (CPI, UR) are included. The basic model starts with an MSLE of 0.1895, which improves to 0.1440 when both CPI and UR are incorporated. This reduction in MSLE indicates that adding these variables helps reduce the error, even with placebo data. The LSTM model shows a similar trend, with an MSLE of 0.1732 in the basic model, decreasing to 0.1296 when CPI and UR are added. The LSTM model performs better than the RNN model on placebo data, achieving lower MSLE values across the board. The GRU model starts with an MSLE of 0.1965 for the basic model and decreases to 0.1301 by including CPI and UR. This trend indicates a reduction in error with additional variables, though GRU performs slightly worse than LSTM. The TCN model also achieves significant improvements, with the basic model starting at 0.1622 and decreasing to 0.1167 with both CPI and UR, indicating the effective use of additional information to improve accuracy. The

Transformer model produces the lowest MSLE values on placebo data, starting at 0.1554 for the basic model and reducing to 0.1007 when both CPI and UR are included, demonstrating its strong predictive capabilities.

Overall, the Transformer model consistently yields the lowest MSLE values across both placebo and real datasets, indicating its superior ability to minimize logarithmic error in GDP per capita predictions. Including variables like CPI and UR generally reduces MSLE values across all models, with a more pronounced improvement observed in placebo data. The consistently lower MSLE values for placebo data models than real data models suggest potential differences in model optimization or overfitting tendencies in the placebo dataset. However, the Transformer model demonstrates the strongest predictive performance across all configurations, effectively reducing error in both placebo and real data analyses.

The performance of deep learning regression models for GDP forecasting, as highlighted by the Mean Squared Logarithmic Error (MSLE) results in Table 8, reflects the trade-offs between various model architectures and their capabilities. Recurrent Neural Networks (RNNs) are foundational to modeling sequential data. Their simplicity allows for straightforward implementation in time-series forecasting tasks. Still, their inability to effectively capture long-term dependencies due to the vanishing gradient problem limits their application to more complex temporal patterns.

Long-short-term memory (LSTM) networks extend the RNN architecture by introducing memory cells, enabling these models to retain and utilize long-term dependencies in data. This makes LSTMs particularly suitable for GDP forecasting, where economic indicators may exhibit delayed effects. However, their computational complexity and prolonged training times can be drawbacks, especially in real-time or resource-constrained environments.

Gated Recurrent Units (GRUs) streamline the architecture of LSTMs, reducing computational overhead while retaining much of the temporal modeling ability. This makes GRUs more efficient for tasks where computational resources are limited. Nonetheless, their simplified structure may sometimes underperform in capturing highly intricate patterns, particularly in datasets with diverse and nonlinear temporal relationships.

Temporal Convolutional Networks (TCNs) provide an innovative alternative by leveraging convolutional structures to model sequential data. These networks excel at parallel processing, reducing training time and avoiding the vanishing gradient issue common in RNN-based models. Despite these advantages, TCNs require careful hyperparameter tuning and may struggle with noisy or irregular datasets, potentially affecting their generalizability.

Transformers, which represent the cutting edge of deep learning for sequential data, leverage a self-attention mechanism to capture local and global dependencies in the dataset. This ability makes transformers highly effective for complex time-series forecasting tasks, such as GDP prediction with multi-dimensional regressors. However, transformers are computationally demanding and require large datasets to achieve their full potential, making them less practical in data-limited or resource-constrained settings.

Including additional regressors, such as the Consumer Price Index (CPI) and Unemployment Rate (UR), significantly enhances the performance of all models, as evidenced by the reduction in MSLE values. These variables provide critical economic context, improving the models' ability to capture key trends and nuances in GDP data. However, integrating such regressors introduces additional complexity to the modeling process, requiring high-quality and reliable data. Furthermore, the computational demand increases as more regressors are incorporated, necessitating a careful balance between model accuracy and efficiency.

This comparative discussion emphasizes the strengths and weaknesses of each model and highlights the impact of incorporating meaningful regressors on performance metrics like MSLE. It underscores the importance of aligning model selection and feature engi-

neering with the specific requirements of the forecasting task, including the availability of computational resources, data quality, and the desired level of predictive accuracy. By offering a nuanced understanding of these trade-offs, this study provides valuable guidance for researchers and practitioners aiming to optimize GDP forecasting methodologies.

Table 9 presents the Mean Absolute Percentage Error (MAPE) values for various deep-learning regression models that predict per capita GDP. The models evaluated include RNN, LSTM, GRU, TCN, and Transformer, each tested on two datasets: placebo data and real data. Both datasets contain a basic model and additional models that incrementally incorporate CPI, UR, and both CPI and UR variables.

Table 9. GDP per capita MAPE results.

Data	Model	Regressor	MAPE	Regressor	MAPE	Regressor	MAPE	Regressor	MAPE	Regressor	MAPE
Placebo data	Basic model	RNN	0.1987	LSTM	0.1864	GRU	0.2116	TCN	0.1755	Transformer	0.1665
	+CPI		0.1774		0.1690		0.1863		0.1564		0.1494
	+UR		0.1669		0.1485		0.1709		0.1389		0.1241
	+CPI and UR		0.1542		0.1388		0.1610		0.1230		0.1136
Real data	Basic model	RNN	0.2664	LSTM	0.2557	GRU	0.2792	TCN	0.2345	Transformer	0.2231
	+CPI		0.2480		0.2386		0.2539		0.2192		0.2178
	+UR		0.2305		0.2265		0.2423		0.2006		0.1994
	+CPI and UR		0.2233		0.2144		0.2397		0.1912		0.1682

Real data results are as follows. For the RNN model, the MAPE values are generally higher on real data, with the basic model at 0.2664 and improving to 0.2233 when CPI and UR are included. This higher range suggests that prediction errors are relatively larger with real data. The LSTM model shows similar results, with MAPE decreasing from 0.2557 for the basic model to 0.2144 with CPI and UR, although it still exhibits higher error values than on placebo data. The GRU model starts with a MAPE of 0.2792 for the basic model, which decreases to 0.2397 when both variables are added. This result reflects GRU's improved performance with additional variables, though it remains less effective on real data than placebo data. For the TCN model, the MAPE values on real data decrease from 0.2345 in the basic model to 0.1912 with CPI and UR. This indicates that TCN can effectively reduce error, though real data predictions still have relatively higher MAPE values than placebo data. The Transformer model shows the best performance among real data models, with a MAPE of 0.2231 for the basic model, which improves to 0.1682 with both CPI and UR. Although this is an improvement, the Transformer model's MAPE on real data remains higher than on placebo data.

Next, placebo data results are as follows. For the RNN model, MAPE values decrease as more variables are incorporated, starting with 0.1987 for the basic model and improving to 0.1542 when both CPI and UR are added. This downward trend suggests that adding CPI and UR variables enhances prediction accuracy by reducing percentage errors. The LSTM model shows a similar improvement, with MAPE values starting at 0.1864 for the basic model and decreasing to 0.1388 with CPI and UR. This indicates that LSTM performs slightly better than RNN in reducing prediction error on placebo data. The GRU model also follows this trend, with MAPE values improving from 0.2116 in the basic model to 0.1610 with both variables, though GRU performs slightly worse than LSTM in placebo data. The TCN model yields substantial reductions in MAPE, starting at 0.1755 for the basic model and decreasing to 0.1230 with both CPI and UR. This suggests that TCN effectively reduces percentage error in placebo data predictions. The Transformer model achieves the lowest MAPE values on placebo data, beginning at 0.1665 for the basic model and decreasing

to 0.1136 with CPI and UR, indicating its superior accuracy in reducing prediction error relative to other models on placebo data.

In other words, the Transformer model consistently achieves the lowest MAPE across both placebo and real datasets, underscoring its strong predictive accuracy for GDP per capita. Adding variables (CPI and UR) generally reduces MAPE values across all models, especially in placebo data, suggesting that these variables help enhance the models' prediction accuracy. However, MAPE values on real data are consistently higher than those on placebo data, which may indicate that real data introduce additional complexities that affect prediction accuracy. The consistently lower MAPE values on placebo data across models could also reflect a simpler or more homogeneous data pattern. In conclusion, the Transformer model demonstrates superior performance in minimizing percentage error, followed closely by TCN, especially when additional variables are included.

The performance of the deep learning regression models used for GDP forecasting, as demonstrated by the Mean Absolute Percentage Error (MAPE) results in Table 9, reflects their relative strengths and limitations when applied to different datasets and regressors. Recurrent Neural Networks (RNNs) are characterized by their simple architecture and ability to process sequential data efficiently, making them an accessible choice for time-series forecasting. However, their effectiveness diminishes with longer sequences due to their limited capacity to model long-term dependencies, often attributed to the vanishing gradient problem.

Long Short-Term Memory (LSTM) networks address these challenges by incorporating memory cells that enable the retention of long-term dependencies, making them highly suitable for modeling economic variables with delayed effects. However, the computational cost of LSTMs and their longer training times may pose challenges when applying them to large datasets or real-time forecasting scenarios. Gated Recurrent Units (GRUs), on the other hand, offer a more computationally efficient alternative to LSTMs by simplifying their architecture. While this efficiency is advantageous for resource-constrained applications, GRUs may underperform in capturing highly complex patterns compared to their LSTM counterparts.

Temporal Convolutional Networks (TCNs) provide an alternative non-recurrent approach that leverages convolutional layers to model temporal patterns. Their parallel processing capability and resistance to the vanishing gradient problem make them highly efficient for large-scale datasets. However, TCNs require precise tuning of hyperparameters and may encounter difficulties when handling irregular or highly noisy data. Transformers, representing the state-of-the-art deep learning for sequential modeling, stand out for their ability to capture local and global dependencies through their self-attention mechanism. This capacity makes transformers highly effective for GDP forecasting involving diverse and complex regressors. However, their computational demands and need for extensive datasets can limit their practical applicability in data-scarce or resource-constrained environments.

Additional regressors, such as the Consumer Price Index (CPI) and Unemployment Rate (UR), have been shown to significantly improve model accuracy, as evidenced by the reduced MAPE values. These variables enhance the model's capture of critical economic dynamics, allowing for more accurate GDP predictions. However, integrating additional regressors increases model complexity and places greater demands on data quality and preprocessing. Ensuring reliable and high-quality data inputs is essential for leveraging the full potential of these regressors.

This discussion underscores the trade-offs inherent in choosing a deep-learning model and incorporating additional regressors for GDP forecasting. Each model offers unique advantages and limitations, requiring researchers to balance predictive accuracy, computational efficiency, and data availability based on the specific objectives of their forecasting task.

By providing a detailed understanding of these trade-offs, this study highlights the importance of aligning methodological choices with forecasting needs to achieve optimal results.

5. Discussion

The primary objective of this study was to develop and evaluate a deep learning-based predictive model for per capita GDP that addresses limitations inherent in traditional statistical approaches. Specifically, this research aimed to investigate whether deep learning models could accurately capture nonlinear relationships in economic data, assess the impact of incorporating key macroeconomic variables such as CPI and unemployment rate on predictive accuracy, and determine the practical utility of the model in real-world economic decision-making contexts. The study employed five deep-learning regression models—RNN, LSTM, GRU, TCN, and Transformer—to achieve these objectives using real and placebo datasets. Each model was evaluated through various performance metrics, including R-squared, MSE, RMSE, and MSLE.

The answers to the research questions of this paper are as follows. First, the results of this study affirm that deep learning models can capture complex, nonlinear relationships within economic data, enhancing predictive accuracy for per capita GDP. Across all metrics (R-squared, MSE, RMSE, and MSLE), the deep learning models demonstrated significant improvements over traditional methods, particularly in handling nonlinearity and volatility in economic variables. Among the models tested, the Transformer consistently achieved the highest R-squared and lowest error values, indicating its superior ability to model intricate relationships and deliver precise predictions. These findings underscore the potential of deep learning to overcome the limitations of traditional statistical methods in economic forecasting.

Second, including CPI and unemployment rate as additional predictors substantially enhanced the predictive accuracy of all models. In particular, models incorporating CPI and UR consistently yielded higher R-squared values and lower error metrics across MSE, RMSE, and MSLE, indicating a more accurate representation of economic dynamics. This improvement was most notable in the TCN and Transformer models, effectively leveraging these macroeconomic variables to capture short-term economic fluctuations accurately. Thus, the results confirm that CPI and UR are essential variables for improving model robustness and predictive performance in GDP forecasting.

Third, the study's findings demonstrate that the developed deep learning models, particularly the Transformer and TCN, can be practical tools in economic decision-making. By providing more accurate and reliable GDP forecasts, these models can enhance policy effectiveness, optimize resource allocation, and improve strategic planning in response to economic uncertainties. The models' robustness in real data settings suggests they can offer valuable insights into economic trends and effectively support policymakers and businesses. This aligns with the study's goal of creating an academically rigorous and practically applicable predictive model.

Implications and significance of findings in this paper are as follows. The findings of this study highlight the potential advantages of deep learning models in forecasting per capita GDP, especially in capturing complex nonlinear relationships and volatility in economic data. This research underscores the superior predictive accuracy achieved by leveraging advanced machine learning techniques in economic modeling through comparisons across various deep learning models—RNN, LSTM, GRU, TCN, and Transformer—applied to real and placebo datasets. Notably, the Transformer model consistently outperformed others across all metrics (R-squared, MSE, RMSE, and MSLE), indicating its effectiveness in capturing intricate patterns and interactions within economic variables.

Including key macroeconomic indicators, such as the Consumer Price Index (CPI) and unemployment rate (UR), significantly enhanced the models' performance, especially for the Transformer and TCN models. This suggests that incorporating relevant economic variables is critical for improving model robustness and accuracy, particularly for short-term economic fluctuations. These results contribute valuable insights into the utility of deep learning in economic forecasting, providing empirical evidence that deep learning models can serve as viable alternatives to traditional statistical methods, which often struggle to capture the dynamic nature of economic data.

Academic contributions and expected benefits of this research are as follows. This study makes several key contributions to the academic field of economic forecasting and machine learning. First, it systematically evaluates and compares the effectiveness of various deep learning models in GDP prediction, comprehensively analyzing each model's strengths and limitations in handling economic data. By demonstrating the capacity of deep learning models, particularly the Transformer, to improve predictive accuracy, this research contributes to the growing literature advocating for machine learning approaches in economic forecasting.

Second, the study highlights the importance of variable selection in predictive modeling by showing the impact of CPI and unemployment rate on model performance. This focus on macroeconomic indicators aligns with current academic efforts to enhance the contextual relevance of predictive models in economics. The findings thus provide a methodological framework for future research to build upon, particularly in incorporating relevant economic variables for improved model accuracy.

The expected academic benefit of this study lies in advancing the theoretical understanding of deep learning applications in economics, fostering a shift from traditional statistical approaches to more sophisticated machine learning methodologies. This study also encourages further exploration of the Transformer model's capabilities in other economic and financial forecasting contexts. It offers a basis for subsequent studies investigating its adaptability and scalability in diverse data environments.

Practical contributions and expected benefits of this study are as follows. From a practical perspective, the results of this study carry significant implications for policymakers and business leaders involved in economic decision-making. The high predictive accuracy demonstrated by the Transformer and TCN models suggests that these models could serve as valuable tools in policy formulation, resource allocation, and strategic planning. For instance, accurate GDP forecasts can help governments and organizations respond more effectively to economic fluctuations, optimize budgetary allocations, and design strategies to mitigate potential economic risks.

Incorporating CPI and UR as predictive variables also underscores the importance of integrating relevant economic indicators in forecasting models, making the model's predictions more reflective of real-world economic conditions. By enhancing model accuracy through macroeconomic variables, this study provides a framework that can be applied in other economic forecasting scenarios, thereby improving the reliability of predictions in practice.

The expected practical benefits of this study include enabling more informed decision-making, particularly in times of economic uncertainty. Policymakers and corporate strategists can leverage the developed model to gain insights into economic trends, facilitating proactive measures in resource management and policy adjustments. Ultimately, this study bridges academic research and practical applications, demonstrating the real-world value of deep learning in economic forecasting and providing a foundation for developing more accurate and actionable predictive models in economic contexts.

A practical example was designed to evaluate and conclude the effectiveness of the proposed models by applying them to a case study aimed at predicting GDP per capita for a target country over five years (e.g., 2020–2024) using historical data spanning from 2000 to 2019. In this case study, advanced deep learning models, including RNN, LSTM, GRU, TCN, and Transformer, were employed to forecast GDP per capita. These models incorporated key macroeconomic indicators, such as the Consumer Price Index (CPI) and unemployment rates, as input features to enhance prediction accuracy.

To ensure a systematic evaluation, the historical data were split into training, validation, and test sets in the ratio of 70:15:15, respectively. For instance, the training data covered 2000–2015, the validation data covered 2016–2018, and the test data spanned 2019–2020. This structure facilitated robust training and testing of the models while preventing overfitting. Additionally, baseline comparisons were conducted against traditional statistical methods, such as ARIMA and linear regression, to establish the relative performance of the deep learning models.

To evaluate the effectiveness of each model, various performance metrics were employed, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2). These metrics were computed on the test set to quantify the accuracy and reliability of each model's predictions. Furthermore, the control procedure incorporated efficiency assessments, such as time complexity analysis, to compare the computational cost of training and inference for each model. Robustness tests were also conducted to assess model performance under various hypothetical scenarios, including economic shocks and simulated missing data. Finally, practical applicability was evaluated regarding model interpretability and its potential for integration into existing economic forecasting systems.

The results of this practical application revealed that the Transformer model achieved the lowest RMSE compared to LSTM and GRU. On the other hand, RNN displayed a higher error rate with an RMSE, reflecting its limitations in handling long-term dependencies. Traditional methods such as ARIMA underperformed significantly, recording an RMSE, further highlighting the superiority of advanced deep learning techniques in this context. The study also demonstrated that models incorporating CPI and unemployment information outperformed those without these features, showing an improvement in MAE and underlining the importance of these macroeconomic indicators in enhancing prediction accuracy.

Regarding operational efficiency, while the Transformer model exhibited the highest accuracy, it also required longer training times than simpler models like GRU and TCN. This finding suggests a trade-off between prediction accuracy and computational cost, which must be considered when deploying these models at scale. Nonetheless, the practical example validates the efficacy of the proposed framework, demonstrating that incorporating CPI and unemployment information into state-of-the-art deep learning models significantly improves GDP per capita prediction. Among the models evaluated, the Transformer model stood out for its ability to capture complex patterns in macroeconomic data, albeit with higher computational demands. These results underscore the potential of the proposed approach for real-world economic forecasting applications, paving the way for more accurate and efficient economic planning and policy development.

In conclusion, this study has successfully addressed the research questions by developing a deep learning-based GDP prediction model that surpasses traditional methods in accuracy and reliability. The incorporation of CPI and the unemployment rate as predictors proved essential for enhancing model performance, and the superior predictive accuracy achieved by the Transformer model highlights its potential as an advanced tool for economic forecasting. The findings contribute to academic and practical domains by

advancing the field of GDP prediction through deep learning, providing a valuable resource for economic strategy and planning. This study establishes a foundation for further exploration of deep learning applications in economic modeling, particularly in dynamic and complex macroeconomic environments.

6. Conclusions

This study developed and evaluated a deep learning-based predictive model for per capita GDP to address the limitations of traditional statistical approaches and improve forecasting accuracy in dynamic macroeconomic environments. By employing advanced deep learning techniques, including RNN, LSTM, GRU, TCN, and Transformer, and incorporating key macroeconomic indicators such as the Consumer Price Index (CPI) and unemployment rate (UR), this research demonstrated the capacity of these models to capture complex, nonlinear relationships in economic data.

The findings highlight that deep learning models significantly outperformed traditional statistical methods in predictive accuracy, with the Transformer model achieving the highest R-squared values and the lowest error metrics (MSE, RMSE, MSLE, and MAPE). These results underscore the potential of deep learning to overcome the limitations of traditional approaches, particularly in handling the nonlinear interactions and volatility inherent in economic indicators.

Incorporating CPI and UR as input variables further enhanced the models' predictive accuracy, with a notable improvement observed in the Transformer and TCN models. These variables proved essential for capturing short-term economic fluctuations and improving model robustness. This finding emphasizes the importance of integrating relevant macroeconomic indicators to refine forecasting models and provide a more comprehensive understanding of economic dynamics.

Moreover, the Transformer model demonstrated superior performance in predictive accuracy while maintaining practical applicability, offering valuable insights for economic decision-making. Its ability to model intricate patterns in macroeconomic data positions it as a reliable tool for policymakers and businesses in crafting strategies, allocating resources, and mitigating economic uncertainties.

This study provides significant contributions to academic and practical domains. Academically, it advances the field of economic forecasting by illustrating the efficacy of deep learning techniques and underscoring the importance of variable selection. Practically, it offers a robust and actionable framework for real-world economic planning and decision-making, bridging the gap between theoretical innovation and practical utility.

The research also establishes a foundation for future exploration of deep learning applications in economic modeling, particularly in integrating diverse and dynamic macroeconomic indicators. By demonstrating the effectiveness of the Transformer model in economic forecasting, this study paves the way for further advancements in predictive analytics, supporting informed and efficient economic policy-making in an increasingly uncertain global economy.

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References

1. Gomulka, S. The Global Economy in the 21st Century: Will the Trends of the 20th Century Continue? *Cent. Eur. Econ. J.* **2017**, *2*, 62–72. [\[CrossRef\]](#)
2. Ma, C.; Rogers, J.H.; Zhou, S. Global economic and financial effects of 21st century pandemics and epidemics. *Covid Econ.* **2020**, *5*, 56–78. [\[CrossRef\]](#)
3. Song, L.; Zhou, Y. The COVID-19 pandemic and its impact on the global economy: What does it take to turn crisis into opportunity? *China World Econ.* **2020**, *28*, 1–25. [\[CrossRef\]](#)
4. Hickel, J.; Dorninger, C.; Wieland, H.; Suwandi, I. Imperialist appropriation in the world economy: Drain from the global South through unequal exchange, 1990–2015. *Glob. Environ. Change* **2022**, *73*, 102467. [\[CrossRef\]](#)
5. James, S.L.; Gubbins, P.; Murray, C.J.; Gakidou, E. Developing a comprehensive time series of GDP per capita for 210 countries from 1950 to 2015. *Popul. Health Metr.* **2012**, *10*, 12. [\[CrossRef\]](#)
6. Abbood, S.N.M.; Alnuaimi, S.A.; Ali, S.H.; Alnuaimi, S.S.; Yuvaraj, D. AI-Driven Prediction of Average Per Capita GDP: Exploring Linear and Nonlinear Statistical Techniques. *J. Electr. Syst.* **2024**, *20*, 217–228. [\[CrossRef\]](#)
7. Voumik, L.C.; Smrity, D.Y. Forecasting GDP per capita in Bangladesh: Using ARIMA model. *Eur. J. Bus. Manag. Res.* **2020**, *5*. [\[CrossRef\]](#)
8. Adewale, M.D.; Ebem, D.U.; Awodele, O.; Sambo-Magaji, A.; Aggrey, E.M.; Okechalu, E.A.; Donatus, R.E.; Olayanju, K.A.; Owolabi, A.F.; Oju, J.U.; et al. Predicting gross domestic product using the ensemble machine learning method. *Syst. Soft Comput.* **2024**, *6*, 200132. [\[CrossRef\]](#)
9. Bhardwaj, V.; Bhavsar, P.; Patnaik, D. Forecasting GDP per capita of OECD countries using machine learning and deep learning models. In Proceedings of the 2022 Interdisciplinary Research in Technology and Management (IRTM), Kolkata, India, 24–26 February 2022; pp. 1–6.
10. Shams, M.Y.; Tarek, Z.; El-kenawy, E.S.M.; Eid, M.M.; Elshewey, A.M. Predicting Gross Domestic Product (GDP) using a PC-LSTM-RNN model in urban profiling areas. *Comput. Urban Sci.* **2024**, *4*, 3. [\[CrossRef\]](#)
11. Mourougane, A.; Roma, M. Can confidence indicators be useful to predict short term real GDP growth? *Appl. Econ. Lett.* **2003**, *10*, 519–522. [\[CrossRef\]](#)
12. Yoon, J. Forecasting of real GDP growth using machine learning models: Gradient boosting and random forest approach. *Comput. Econ.* **2021**, *57*, 247–265. [\[CrossRef\]](#)
13. Richardson, A.; van Florenstein Mulder, T.; Vehbi, T. Nowcasting GDP using machine-learning algorithms: A real-time assessment. *Int. J. Forecast.* **2021**, *37*, 941–948. [\[CrossRef\]](#)
14. Ferrara, L.; Simoni, A. When are Google data useful to nowcast GDP? An approach via preselection and shrinkage. *J. Bus. Econ. Stat.* **2023**, *41*, 1188–1202. [\[CrossRef\]](#)
15. Jena, P.R.; Majhi, R.; Kalli, R.; Managi, S.; Majhi, B. Impact of COVID-19 on GDP of major economies: Application of the artificial neural network forecaster. *Econ. Anal. Policy* **2021**, *69*, 324–339. [\[CrossRef\]](#)
16. Ghazo, A. Applying the ARIMA Model to the Process of Forecasting GDP and CPI in the Jordanian Economy. *Int. J. Financ. Res.* **2021**, *12*, 70. [\[CrossRef\]](#)
17. Farsio, F.; Quade, S. An empirical analysis of the relationship between GDP and unemployment. *Humanomics* **2003**, *19*, 1–6. [\[CrossRef\]](#)
18. Savchenko-Synyakova, Y.A.; Tutova, O.V. The Tools for Intelligent Data Analysis, Modeling and Forecasting of Social and Economic Processes. *Control Syst. Comput.* **2021**, *291*, 35–47. [\[CrossRef\]](#)
19. Atif, D. Enhancing Long-Term GDP Forecasting with Advanced Hybrid Models: A Comparative Study of ARIMA-LSTM and ARIMA-TCN with Dense Regression. *Comput. Econ.* **2024**, 1–27. [\[CrossRef\]](#)
20. Srinivasan, N.; Krishna, M.; Naveen, V.; Kishore, S.M.; Kumar, S.; Subha, R. Predicting Indian GDP with machine learning: A comparison of regression models. In Proceedings of the 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 17–18 March 2023; Volume 1, pp. 1855–1858.
21. Chowdhury, A. Methods explained: The GDP implied deflator. *Econ. Labour Mark. Rev.* **2008**, *2*, 53–56. [\[CrossRef\]](#)
22. Taylor, A.M.; Taylor, M.P. The purchasing power parity debate. *J. Econ. Perspect.* **2002**, *18*, 135–158. [\[CrossRef\]](#)
23. Brzozowski, M.; Prusty, S. Impact of GDP volatility on current account balances. *Int. J. Econ. Bus. Res.* **2013**, *5*, 239–252. [\[CrossRef\]](#)
24. Park, J.K.; Ryu, D.; Lee, K. What determines the economic size of a nation in the world: Determinants of a nation's share in world GDP vs. per capita GDP. *Struct. Chang. Econ. Dyn.* **2019**, *51*, 203–214. [\[CrossRef\]](#)

25. Wang, Q.; Li, L. The effects of population aging, life expectancy, unemployment rate, population density, per capita GDP, urbanization on per capita carbon emissions. *Sustain. Prod. Consum.* **2021**, *28*, 760–774. [\[CrossRef\]](#)
26. Ardagna, S. Fiscal stabilizations: When do they work and why. *Eur. Econ. Rev.* **2004**, *48*, 1047–1074. [\[CrossRef\]](#)
27. Ali, A.; Fatima, N.; Rahman Ali, B.J.A.; Husain, F. Imports, Exports and Growth of Gross Domestic Product (GDP)—A Relational Variability Analysis. *Int. J. Sustain. Dev. Plan.* **2023**, *18*, 1681–1690. [\[CrossRef\]](#)
28. Michelis, L.; Zestos, G.K. Exports, imports and GDP growth: Causal relations in six European Union countries. *J. Econ. Asymmetries* **2004**, *1*, 71–85. [\[CrossRef\]](#)
29. Gurdal, T.; Aydin, M.; Inal, V. The relationship between tax revenue, government expenditure, and economic growth in G7 countries: New evidence from time and frequency domain approaches. *Econ. Chang. Restruct.* **2021**, *54*, 305–337. [\[CrossRef\]](#)
30. Onifade, S.T.; Çevik, S.; Erdoğan, S.; Asongu, S.; Bekun, F.V. An empirical retrospect of the impacts of government expenditures on economic growth: New evidence from the Nigerian economy. *J. Econ. Struct.* **2020**, *9*, 6. [\[CrossRef\]](#)
31. Hewamalage, H.; Bergmeir, C.; Bandara, K. Recurrent neural networks for time series forecasting: Current status and future directions. *Int. J. Forecast.* **2021**, *37*, 388–427. [\[CrossRef\]](#)
32. Bharadiya, J.P. Exploring the use of recurrent neural networks for time series forecasting. *Int. J. Innov. Sci. Res. Technol.* **2023**, *8*, 2023–2027.
33. Zhao, J.; Huang, F.; Lv, J.; Duan, Y.; Qin, Z.; Li, G.; Tian, G. Do RNN and LSTM have long memory? In Proceedings of the 37th International Conference on Machine Learning, PMLR, Virtual, 13–18 July 2020; pp. 11365–11375.
34. Wang, J.Q.; Du, Y.; Wang, J. LSTM based long-term energy consumption prediction with periodicity. *Energy* **2020**, *197*, 117197. [\[CrossRef\]](#)
35. Sa’adah, S.; Wibowo, M.S. Prediction of gross domestic product (GDP) in Indonesia using deep learning algorithm. In Proceedings of the 2020 3rd International Seminar on Research of Information Technology and Intelligent Systems (ISRITI), Yogyakarta, Indonesia, 10–11 December 2020; pp. 32–36.
36. Li, Q.; Yu, C.; Yan, G. A new multipredictor ensemble decision framework based on deep reinforcement learning for regional gdp prediction. *IEEE Access* **2022**, *10*, 45266–45279. [\[CrossRef\]](#)
37. Chen, S.; Huang, Y.; Ge, L. An early warning system for financial crises: A temporal convolutional network approach. *Technol. Econ. Dev. Econ.* **2024**, *30*, 688–711. [\[CrossRef\]](#)
38. Rauhut, D.; Aigner-Walder, B.; Schomaker, R.M. Data and Methods. In *The Economics of Immigration Beyond the Cities: Theoretical Perspectives and Empirical Insights*; Springer International Publishing: Cham, Switzerland, 2023; pp. 71–82.
39. Laborda, J.; Ruano, S.; Zamanillo, I. Multi-Country and Multi-Horizon GDP Forecasting Using Temporal Fusion Transformers. *Mathematics* **2023**, *11*, 2625. [\[CrossRef\]](#)
40. Xie, H.; Xu, X.; Yan, F.; Qian, X.; Yang, Y. Deep Learning for Multi-Country GDP Prediction: A Study of Model Performance and Data Impact. *arXiv* **2024**, arXiv:2409.02551.
41. Han, Y.; Tian, Y.; Yu, L.; Gao, Y. Economic system forecasting based on temporal fusion transformers: Multi-dimensional evaluation and cross-model comparative analysis. *Neurocomputing* **2023**, *552*, 126500. [\[CrossRef\]](#)
42. Zhang, X.; Liu, C.A. Model averaging prediction by K-fold cross-validation. *J. Econom.* **2023**, *235*, 280–301. [\[CrossRef\]](#)
43. Prusty, S.; Patnaik, S.; Dash, S.K. SKCV: Stratified K-fold cross-validation on ML classifiers for predicting cervical cancer. *Front. Nanotechnol.* **2022**, *4*, 972421. [\[CrossRef\]](#)
44. Vu, H.L.; Ng, K.T.W.; Richter, A.; An, C. Analysis of input set characteristics and variances on k-fold cross validation for a Recurrent Neural Network model on waste disposal rate estimation. *J. Environ. Manag.* **2022**, *311*, 114869. [\[CrossRef\]](#)
45. Marcot, B.G.; Hanea, A.M. What is an optimal value of k in k-fold cross-validation in discrete Bayesian network analysis? *Comput. Stat.* **2021**, *36*, 2009–2031. [\[CrossRef\]](#)
46. Maccarrone, G.; Morelli, G.; Spadaccini, S. GDP forecasting: Machine learning, linear or autoregression? *Front. Artif. Intell.* **2021**, *4*, 757864. [\[CrossRef\]](#)
47. Jadon, A.; Patil, A.; Jadon, S. A comprehensive survey of regression-based loss functions for time series forecasting. In Proceedings of the International Conference on Data Management, Analytics & Innovation, Vellore, India, 19–21 January 2024; pp. 117–147.
48. Chicco, D.; Warrens, M.J.; Jurman, G. The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Comput. Sci.* **2021**, *7*, e623. [\[CrossRef\]](#) [\[PubMed\]](#)
49. Abakah, E.J.A.; Hossain, S.; Abdullah, M.; Goodell, J.W. Global uncertainty factors and price connectedness between US electricity and blockchain markets: Findings from an R-square connectedness approach. *Financ. Res. Lett.* **2024**, *59*, 104693. [\[CrossRef\]](#)
50. Nosratabadi, S.; Mosavi, A.; Duan, P.; Ghamisi, P.; Filip, F.; Band, S.S.; Reuter, U.; Gama, J.; Gandomi, A.H. Data science in economics: Comprehensive review of advanced machine learning and deep learning methods. *Mathematics* **2020**, *8*, 1799. [\[CrossRef\]](#)
51. Mosavi, A.; Faghan, Y.; Ghamisi, P.; Duan, P.; Ardabili, S.F.; Salwana, E.; Band, S.S. Comprehensive review of deep reinforcement learning methods and applications in economics. *Mathematics* **2020**, *8*, 1640. [\[CrossRef\]](#)

52. Ozden, E.; Guleryuz, D. Optimized machine learning algorithms for investigating the relationship between economic development and human capital. *Comput. Econ.* **2022**, *60*, 347–373. [[CrossRef](#)]
53. Chatterjee, A.; Bhowmick, H.; Sen, J. Stock price prediction using time series, econometric, machine learning, and deep learning models. In Proceedings of the 2021 IEEE Mysore Sub Section International Conference (MysuruCon), Hassan, India, 24–25 October 2021; pp. 289–296.
54. Balderas, L.; Lastra, M.; Benítez, J.M. An Efficient Green AI Approach to Time Series Forecasting Based on Deep Learning. *Big Data Cogn. Comput.* **2024**, *8*, 120. [[CrossRef](#)]
55. Konur, M.; Göçken, M.; Dosdoğru, A.T. Stock Price Prediction Using Deep Learning Algorithms Based on Technical Indicators. *J. Oper. Intell.* **2024**, *2*, 300–320. [[CrossRef](#)]
56. Kim, T.; Ha, B.; Hwangbo, S. Online machine learning approach for system marginal price forecasting using multiple economic indicators: A novel model for real-time decision making. *Mach. Learn. Appl.* **2023**, *14*, 100505. [[CrossRef](#)]
57. Zema, T.; Kozina, A.; Sulich, A.; Römer, I.; Schieck, M. Deep learning and forecasting in practice: An alternative costs case. *Procedia Comput. Sci.* **2022**, *207*, 2958–2967. [[CrossRef](#)]

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