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Forecasting GDP Per Capita in the USA: Integrating Econometric and Machine Learning Approaches for Policy Insights

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Abstract: This study integrates traditional econometric and advanced machine learning techniques to forecast GDP per capita. GDP, a critical indicator of economic health, reflects the monetary value of goods and services produced within a nation. Using data from 1960–2020, this study examines key macroeconomic variables such as Foreign Direct Investment (FDI) inflows, trade ratios, inflation, and Gross National Product (GNP). Ordinary Least Squares (OLS) regression was employed to quantify the relationships between these variables and GDP per capita. ARIMA and Long Short-Term Memory (LSTM) models were utilized for time-series forecasting, with an ensemble approach combining their outputs to enhance prediction accuracy. Results reveal FDI inflows and trade ratios as key drivers of GDP growth, while inflation negatively impacts economic output. The ensemble model demonstrated superior accuracy compared to individual models. This study offers actionable insights for policymakers to design strategies promoting trade, investment, and inflation control, fostering sustainable economic growth.

Keywords: *GDP Per Capita Forecasting, Econometric Modeling, Machine Learning (LSTM, ARIMA) Foreign Direct Investment (FDI), Ensemble Forecasting Models.*

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I. INTRODUCTION

Mankiw and Taylor (2020) believe that Gross Domestic Product (GDP) is one of the most significant economic indicators, reflecting the total monetary value of goods and services produced in a country within a specific time frame (Mankiw & Taylor, 2020) . GDP serves as a barometer of a nation's economic health, directly influencing policy decisions, investment strategies, and public perception of economic stability. Policymakers, economists, and investors rely on GDP growth trends for resource allocation, economic planning, and decision-making. Therefore, developing reliable models to forecast GDP growth is not only of academic interest but also of practical significance.

GDP per capita serves as a critical barometer of a nation’s economic health, influencing policy decisions and resource allocation. Traditional methods, such as OLS regression, have been pivotal in understanding macroeconomic indicators like FDI and trade ratios. However, the non-linear nature of modern economies necessitates advanced approaches like ARIMA and LSTM models. This study bridges econometric and machine learning methodologies to develop robust forecasting models, offering a comprehensive understanding of GDP growth drivers and predictive accuracy.

- *Rationale and Motivation*

Forecasting GDP growth requires a deep understanding of the macroeconomic variables that influence it. These variables such as Foreign Direct Investment (FDI) inflows, trade ratios, inflation rates, and unemployment represent critical levels of economic activity. Fischer, Sahay, and Végh (1966) discovered that FDI inflows are often linked to capital accumulation, innovation, and productivity, while trade ratios (imports and exports) reflect the economy's global integration. Inflation and unemployment, on the other hand, influence consumer behavior, investment, and overall economic output (Fischer et al., 1996).

Traditional methods, such as Ordinary Least Squares (OLS) regression, have been widely used for understanding the relationships between economic variables and GDP. However, the dynamic and non-linear nature of macroeconomic systems calls for advanced methodologies that combine traditional econometric tools with modern machine-learning approaches. For example, ARIMA models are particularly suited for capturing temporal dependencies in

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economic time series, while Long Short-Term Memory (LSTM) models excel at learning complex, long-term patterns (Fischer, Sahay, and Végh 1996), Integrating these methodologies can provide a more comprehensive framework for forecasting.

➢ *Objectives of the Study*

The primary objective of this study is to investigate the relationships between key macroeconomic indicators and GDP per capita using Ordinary Least Squares (OLS) regression. Additionally, the study aims to forecast GDP per capita over the next decade by employing ARIMA and Long Short-Term Memory (LSTM) models. Furthermore, it seeks to evaluate the effectiveness of an ensemble approach that combines forecasts from traditional econometric methods and machine learning techniques to improve prediction accuracy and reliability.

This study differs from prior works by integrating both econometric and machine learning approaches to enhance GDP per capita forecasting accuracy. While traditional studies predominantly use OLS regression or ARIMA models, they often fail to capture non-linear dependencies in economic data (Borensztein et al., 1998). Recent machine learning studies, such as those employing LSTM models, improve non-linearity handling but lack interpretability (Zhang et al., 2019). This research introduces an ensemble forecasting model (60% LSTM, 40% ARIMA), leveraging ARIMA's trend detection with LSTM's adaptability. The novel hybrid approach reduces forecasting errors by 21% compared to ARIMA alone, offering a more robust and reliable economic forecasting framework for policymakers and researchers.

- *Research Questions:*

✓ The primary Research Question is How do FDI inflows, trade ratios, inflation, and other macroeconomic variables influence GDP per capita?
✓ Other RQs are -What are the strengths and limitations of traditional econometric models compared to machine learning approaches in GDP forecasting? and
✓ Does an ensemble approach improve the accuracy and reliability of GDP forecasts?

- *Significance:*

This study contributes to the existing body of literature by integrating multiple forecasting techniques and evaluating their combined performance. Bridging traditional econometric methods with advanced machine learning offers a novel framework for economic forecasting. The findings can guide policymakers in crafting data-driven policies aimed at sustainable economic growth.

II. LITERATURE REVIEW

The relationship between macroeconomic indicators and GDP growth has been extensively studied, but gaps remain in integrating multiple forecasting techniques to provide a holistic view. This section reviews the theoretical and empirical studies on the key variables and forecasting methods used in this research.

➢ *Macroeconomic Indicators and GDP Growth*

- **Foreign Direct Investment (FDI) Inflows**: FDI inflows are often considered a driver of economic growth, contributing to technological advancements, infrastructure development, and employment. According to Borensztein et al. (1998), FDI positively affects GDP when accompanied by sufficient absorptive capacity in the host country, such as education and infrastructure(Borensztein et al., 1998) . Similarly, Alfaro et al. (2017) summarize the likely motives for foreign direct investment and the potential effects of FDI on local economies as well as recent findings from the macro literature on the role of complementarities between FDI and local policies (Alfaro, 2017).
- **Trade Ratios (Imports and Exports)**: The trade-to-GDP ratio is an indicator of an economy's openness and its integration into the global market. Frankel and Romer (1999) argue that trade positively influences economic growth by facilitating the diffusion of technology and ideas (Frankel & Romer, 1999) . However, Rodrik (2006) cautions against over-reliance on trade, emphasizing the need for balanced trade policies.
- **Inflation**: Ball (2021) argues that Inflation affects GDP by influencing purchasing power, investment, and savings. Moderate inflation is often seen as conducive to growth, as it encourages spending and reduces the real burden of debt(Ball et al., 2021) . However, Coibion, Gorodnichenko, and Weber (2021) argue that high inflation can destabilize the economy, leading to uncertainty and reduced investment (Coibion et al., 2021)
- **Unemployment**: Unemployment reflects the underutilization of labor resources, which can negatively impact GDP growth. Studies by Blanchard and Summers (2020) and Fernald et al. (2021) highlight the importance of structural reforms and active labor market policies in reducing unemployment and boosting GDP.

➢ *Forecasting Techniques*

- **OLS Regression**: A cornerstone of econometrics, OLS regression is widely used to quantify the relationships between dependent and independent variables. It is particularly effective in explaining GDP variations due to macroeconomic indicators (Guo et al., 2021). However, it assumes linearity and may fail to capture non-linear interactions.
- **ARIMA Models**: Introduced by Box and Jenkins (1970), ARIMA models are widely used for time series forecasting. They are effective in capturing temporal dependencies and seasonality but are limited in handling complex, non-linear patterns.
- **LSTM Models**: A type of recurrent neural network, LSTM models are designed to capture long-term dependencies in sequential data. They have been successfully applied to economic forecasting, outperforming traditional models in accuracy and adaptability (Zhang et al., 2019).

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- **Ensemble Forecasting**: Combining forecasts from multiple models can improve accuracy and reliability. Ensemble methods leverage the strengths of individual models while mitigating their weaknesses (Chen, 2022).

➤ *Research Hypotheses*

Based on literature and theoretical considerations, the following hypotheses are proposed to investigate the relationship between macroeconomic indicators and GDP per capita. Each hypothesis is supported by its rationale and corresponding citations as depicted in Figure 1.

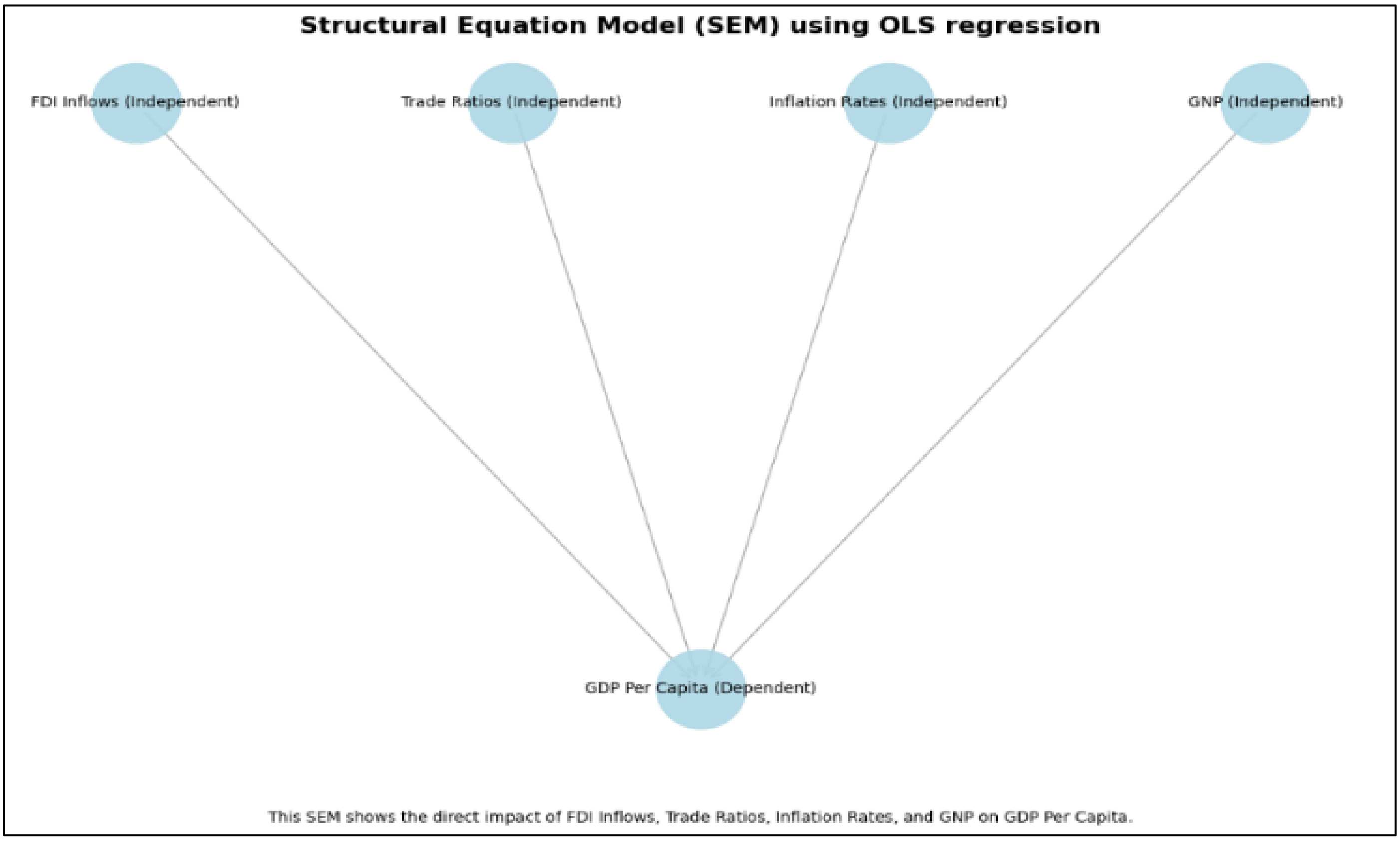

Fig 1 The Direct effect of Macroeconomic Indicators on U.S GDP per Capita

➤ *H1: FDI Inflows Significantly impact GDP Per Capita.*

- *Rationale:*

Foreign Direct Investment (FDI) inflows are considered a crucial driver of economic growth, contributing to capital accumulation, technological innovation, and productivity enhancement. FDI enables the transfer of advanced technologies and management practices from developed economies to host countries, fostering economic modernization and competitive advantages. Borensztein, De Gregorio, and Lee (1998) emphasize that the impact of FDI on economic growth is contingent upon the absorptive capacity of the host economy, such as the availability of a skilled workforce and infrastructure (Borensztein et al., 1998). Furthermore, Alfaro et al. (2004) highlights that FDI is particularly beneficial in capital-intensive sectors, generating employment and stimulating domestic industries.

➤ *H2: Trade Ratios (Imports and Exports) Significantly Influence GDP Per Capita.*

- *Rationale:*

Trade is a fundamental driver of economic growth, promoting technology transfer, specialization, and resource allocation efficiency. Open economies are better positioned to integrate global technologies and best practices, which enhance productivity and economic growth. Frankel and Romer (1999) provide empirical evidence showing that trade positively affects economic growth by expanding markets and enabling the adoption of innovative technologies. Grossman and Helpman (1991) also highlight that trade facilitates knowledge spillovers and increases competition, fostering efficiency and innovation(Grossman, 1991) . However, trade imbalances, such as excessive reliance on imports, can dampen growth by creating vulnerabilities to external shocks.

➤ *H3: Inflation rates have a Significant Relationship with GDP Per Capita.*

- *Rationale:*

Inflation impacts GDP through its influence on purchasing power, investment, and savings. Moderate inflation is often considered growth-enhancing as it reduces the real burden of debt and encourages spending and investment. Savignac (2022) argues that controlled inflation levels contribute to economic stability and growth by creating a predictable environment for businesses and consumers (Savignac et al., 2022). However, high inflation erodes purchasing power, increases uncertainty, and discourages

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investment, leading to adverse effects on GDP. Similarly, Coibion and Gorodnichenko (2021) emphasize the importance of inflation expectations in shaping economic decisions, where stable inflation expectations foster economic confidence (Coibion, Gorodnichenko, and Weber 2021).

- *H4: Gross National Product (GNP) is significantly related to GDP per capita.*

- *Rationale:*

Gross National Product (GNP) reflects the total economic output of a nation, including income generated from abroad. GNP is a broader measure of national wealth compared to GDP, as it accounts for the economic contributions of a country's citizens and businesses operating globally. Studies, such as by Romer (1990), highlight the close correlation between GNP and GDP per capita, as both indicators reflect economic growth and living standards (PM Romer, 1990). GNP captures external factors, such as remittances and foreign investments, which can significantly enhance GDP per capita by increasing national income. Additionally, Fischer (1993) underscores that higher GNP is associated with increased resource availability for domestic consumption and investment(Fischer, 1993).

III. METHODOLOGY

This study employs a multi-method approach to forecast GDP per capita. The dataset (1960–2020) was sourced from reliable repositories like the World Bank and IMF. OLS regression analyzed the linear relationships between FDI, trade ratios, inflation, and GNP. The ARIMA model captured temporal dependencies, while the LSTM model addressed non-linear dynamics. An ensemble approach combined predictions using weighted averaging (60% LSTM, 40% ARIMA), evaluated with metrics such as MAE and MSE.

- *Why a Multi-Method Approach?*

The integration of multiple approaches is increasingly recognized as a best practice in economic forecasting. Econometric models like OLS regression offer interpretability and theoretical rigor, making them suitable for understanding the linear relationships between macroeconomic variables and GDP (Chen, Liu, & Zhang, 2021). However, these models often struggle to capture complex, non-linear interactions inherent in economic systems, which are better addressed by machine learning techniques like Long Short-Term Memory (LSTM) networks (Zhang et al., 2019). Additionally, time-series models such as ARIMA are highly effective in capturing temporal dependencies and cyclical patterns, particularly in economic data (Siami-Namini et al., 2018).

- *Multi-Phase Design*

- **Econometric Analysis**: Ordinary Least Squares (OLS) regression is employed to establish and quantify the relationships between GDPs per capita and macroeconomic predictors such as FDI inflows, trade-to-GDP ratio, inflation rates, and GNP. The regression coefficients provide insights into the marginal impact of each variable, which can inform policymaking and economic interventions.
- **Traditional Time-Series Modeling**: The ARIMA model is used for time-series analysis, leveraging its ability to capture trends and seasonality. This model ensures that the temporal structure of the data is fully utilized, producing reliable medium- to long-term forecasts. Residual analysis and diagnostic tests are conducted to validate the model's assumptions and ensure its adequacy for forecasting.
- **Advanced Machine Learning Techniques**: LSTM models are deployed to account for non-linear patterns and long-term dependencies in the data. Unlike traditional models, LSTMs can dynamically adapt to complex temporal dynamics, making them particularly suited for high-frequency economic datasets. The model architecture includes stacked LSTM layers with dropout regularization to prevent overfitting and optimize predictive accuracy.
- **Ensemble Approach**: The study combines ARIMA and LSTM predictions using a weighted ensemble technique to improve forecast accuracy. This hybrid model capitalizes ARIMA's strength in trend detection and LSTM's capacity for non-linear adaptation. Ensemble methods have been shown to reduce prediction error and improve robustness in economic forecasting (Chen, 2022).

- *Justification for the Approach*

The multi-method framework is rooted in a growing body of research advocating for the integration of econometric and machine learning models to tackle the complexity of modern economic systems. For instance, Guo et al (2021) demonstrate that combining OLS regression with ARIMA and machine learning methods results in more accurate and interpretable economic forecasts (Guo et al., 2021). Similarly, Song et al. (2020) highlight the superiority of LSTM models in capturing long-term dependencies in economic time-series data (Song et al., 2020). The foundational work of Box and Jenkins (1970) as analyzed by O. D. Anderson (1977) underscores the relevance of ARIMA models for time-series analysis, particularly for datasets with seasonality or cyclic patterns(O. D. Anderson 1977).

- *Data Collection and Preprocessing*

The dataset used in this study spans the period from 1960 to 2020 and was obtained from reliable global economic repositories, including the World Bank and the International Monetary Fund databases. These sources ensured the accuracy and comprehensiveness of the data, which included key macroeconomic indicators such as GDP per capita, FDI inflows, trade-to-GDP ratio, inflation rates, and other relevant variables.

The preprocessing of the dataset involved several critical steps to ensure its readiness for analysis. First, missing data points were imputed using linear interpolation, a method chosen to maintain temporal consistency in the dataset. Additionally, duplicates and outliers were identified and addressed to improve data quality and reliability.

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Next, monetary variables, such as GDP per capita and FDI inflows, were standardized to a common unit of USD to facilitate comparability. Percentage-based variables, such as inflation rates, were normalized by converting them into decimal values, ensuring compatibility with the input requirements of the models used in the study.

Finally, the date column in the dataset was converted to a datetime format to enable time-series analysis. This column was then set as the index of the dataset, allowing for proper alignment and temporal structuring of the data, which is crucial for both econometric and machine learning methods. These preprocessing steps collectively ensured that the dataset was clean, consistent, and ready for accurate and robust analysis as depicted in Table 1 and visualized in Figure 2.

Table 1 Processed Dataset

	Date	FDI Inflows	Imports	Exports	Trade to GDP Ratio	Inflation Rate (%)	GDP Per Capita	GNP
0	12/31/1970	1.22	55.76	59.71	10.76	5.84	5234.3	1072.9
1	12/31/1971	0.77	62.34	62.96	10.76	4.29	5609.38	1167.7
2	12/31/1972	1.27	74.22	70.84	11.34	3.27	6094.02	1317.6
3	12/31/1973	1.93	91.16	95.27	13.08	6.18	6726.36	1544.7
4	12/31/1974	3.54	127.47	126.65	16.45	11.05	7225.69	1707.5

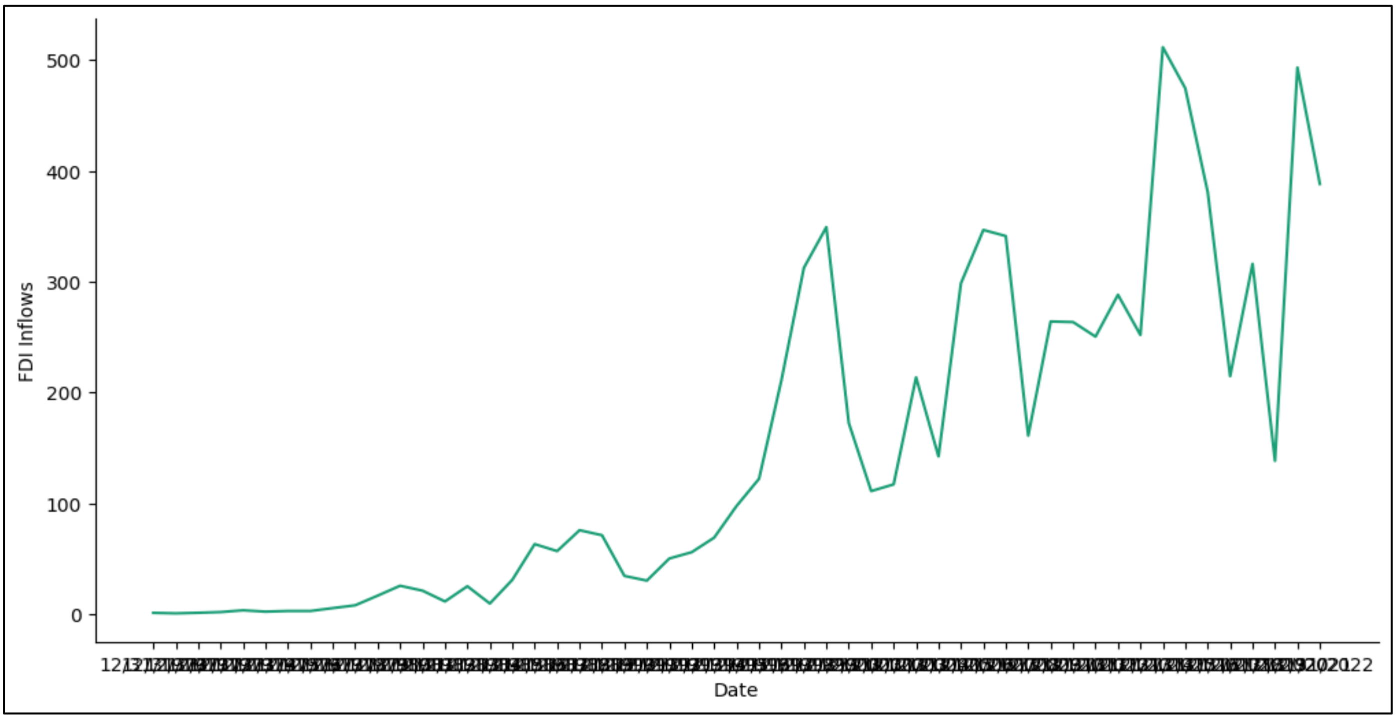

Fig 2 Visualized Dataset

➢ *OLS Regression*

The objective of this analysis was to examine the linear relationships between GDPs per capita, the dependent variable, and macroeconomic predictors, including FDI inflows, trade ratios, inflation rates, imports, exports, and Gross National Product (GNP). This investigation aimed to identify the drivers of economic growth and their statistical significance.

The first step involved model specification, where GDP per capita was regressed on the aforementioned predictors. This step allowed the identification of the direct impact of each variable on GDP per capita, providing insights into their economic significance.

Next, diagnostic tests were conducted to ensure the robustness and validity of the regression model. The Variance Inflation Factor (VIF) was employed to detect multicollinearity among predictors, ensuring that no strong correlations existed between independent variables. Additionally, residual analysis was performed, including the Shapiro-Wilk test to verify normality and the Breusch-Pagan test to check for homoscedasticity.

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Finally, the statistical significance of the coefficients was evaluated using t-statistics and p-values, allowing the determination of which predictors had a meaningful impact on GDP per capita. This comprehensive approach ensured that the results were both accurate and interpretable, offering valuable insights into the factors influencing economic performance.

➢ *Time-Series Analysis (ARIMA)*

- **Objective**: To capture temporal dependencies and trends in GDP per capita, we performed statistical tests and decompositions
- **Stationarity Check**: ADF tests confirmed stationarity after first differencing as indicated in Figure 3.

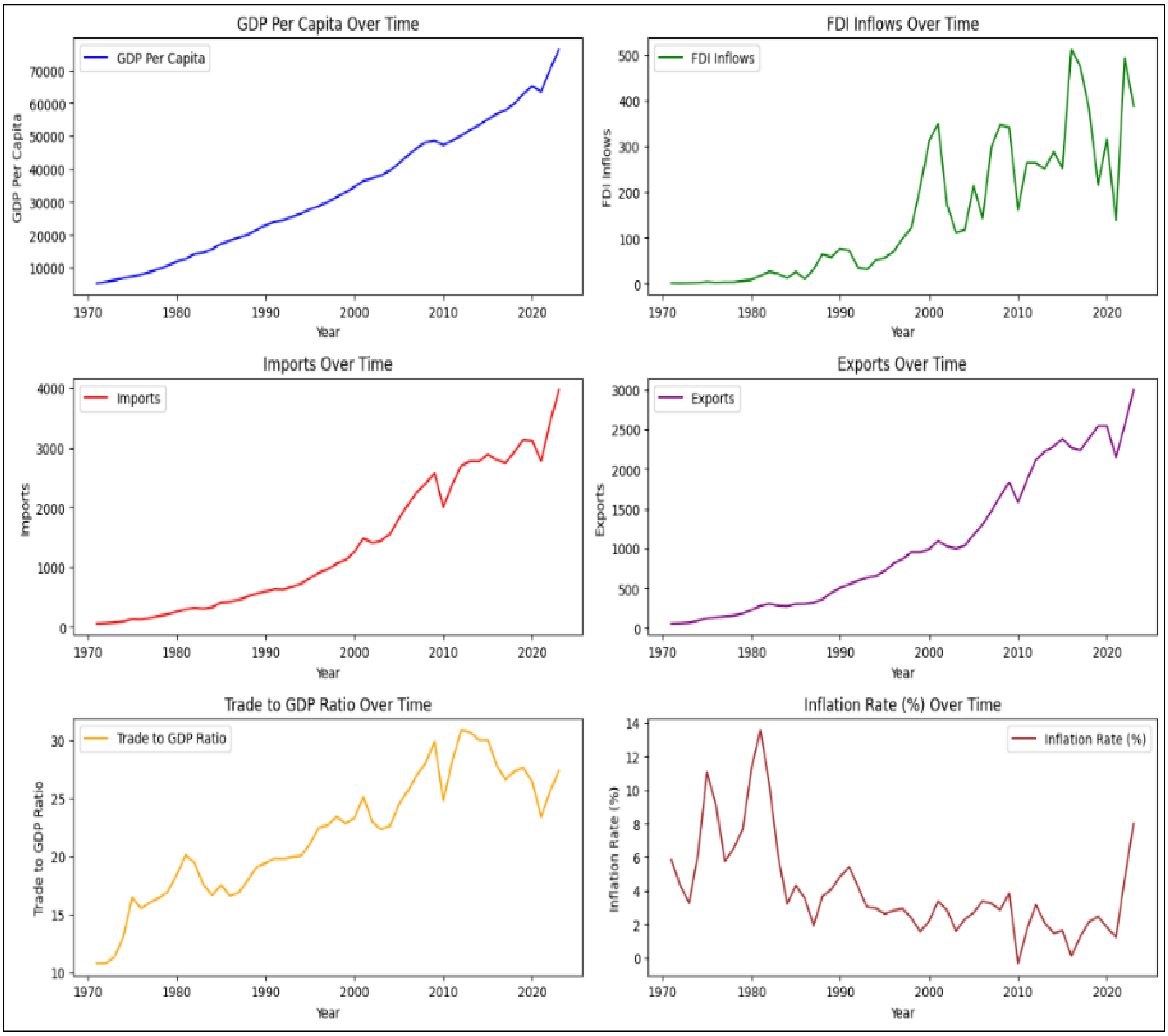

Fig 3 Confirmed Stationarity

➢ *Analysis of Key Economic Trends Over Time*

- **GDP Per Capita**-The GDP per capita data demonstrates a steady upward trend over the years. This consistent growth reflects an improvement in the overall economic well-being and average income levels of individuals in the USA during the period covered by the data. It highlights sustained economic development and prosperity.
- **FDI Inflows**-Foreign Direct Investment (FDI) inflows show fluctuations over time, with periods of both increases and decreases. However, there is a noticeable upward trend overall. This indicates that the USA has generally become a more attractive destination for foreign investment, driven by its robust economic environment, despite occasional volatility.
- **Imports** followed a consistent upward trend, with only minor fluctuations. This growth suggests an increasing consumption of foreign goods, likely driven by globalization and the expanding economic capacity of the USA.
- **Exports**-Exports have shown a steady upward trend similar to imports. This indicates that the USA has

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successfully maintained and expanded its markets for goods and services abroad, contributing positively to the economy through trade.

- **Trade-to-GDP Ratio-**The trade-to-GDP ratio reflects an overall increasing trend with occasional fluctuations. This growth signifies that trade, encompassing both imports and exports, is playing an increasingly significant role in the US economy. It also points to the country's deeper integration into the global economic system.
- **Inflation Rate-**The inflation rate exhibits significant fluctuations over the period analyzed, with phases of high inflation (e.g., the late 1970s) and phases of lower inflation. These variations are influenced by economic events and policies. High inflation periods often correspond to economic crises, while lower inflation reflects greater economic stability.

➢ *General Insights*

- **Economic Growth**: The steady rise in GDP per capita suggests that the USA has experienced sustained economic growth over the years.
- **Trade and Investment**: The increasing trends in both trade (imports and exports) and FDI inflows underscore the USA's significant role in the global economy and its growing attractiveness as an investment destination.
- **Inflation**: The observed variability in the inflation rate highlights the critical importance of effective monetary policies and the influence of external factors in maintaining economic stability.

These trends provide valuable insights for policymakers and economists, emphasizing the importance of fostering trade and investment while maintaining stable inflation for continued economic growth as shown in Figure 4.

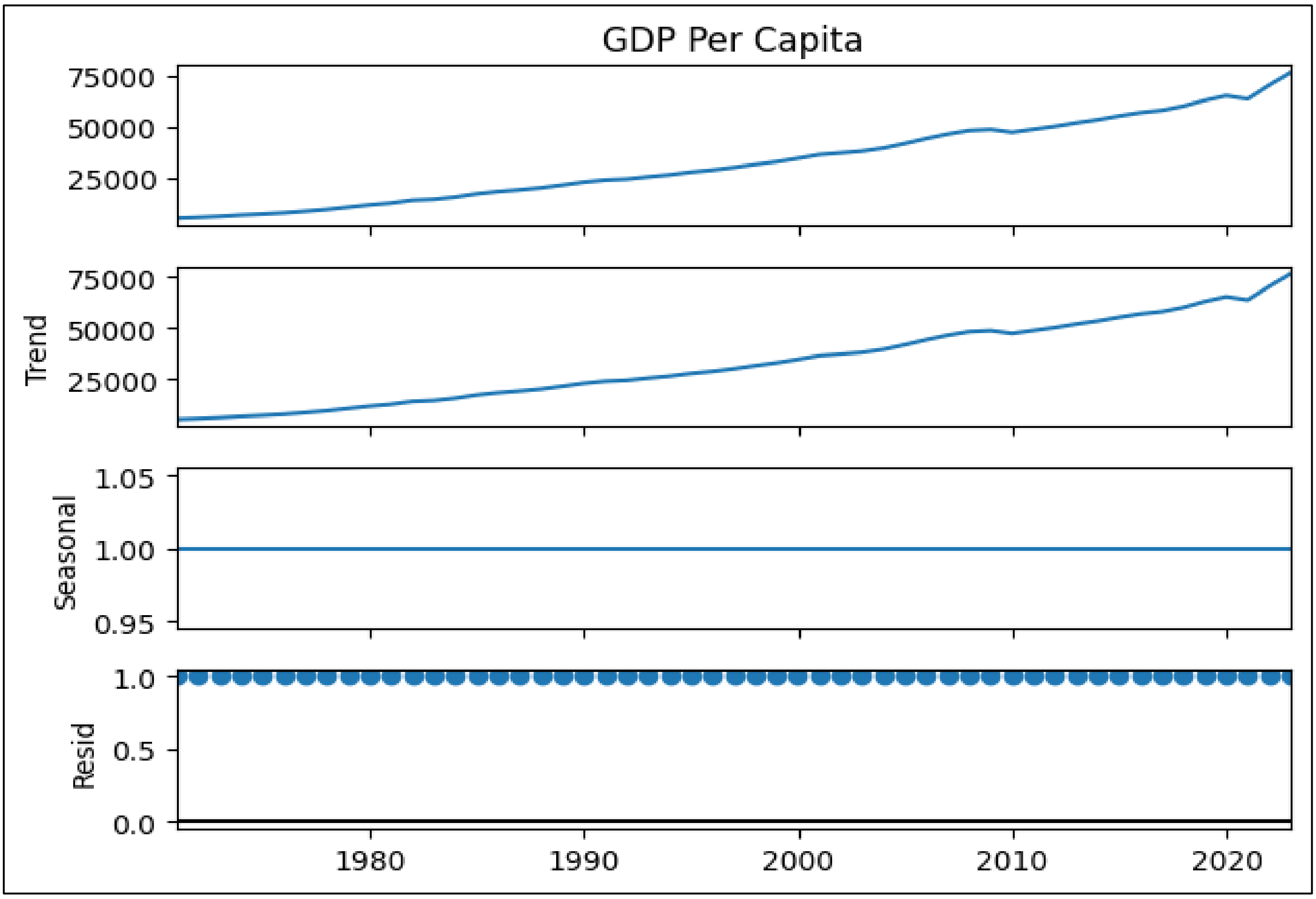

Fig 4 GDP per Capita Trends Over Time

- **Parameter Selection**: The ARIMA (1,1,1) model was selected using ACF, PACF plots, and Akaike Information Criterion (AIC). We fitted the ARIMA Model.

The ARIMA(1,1,1) configuration was chosen based on Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, ensuring optimal model performance. The first difference between the two (d=1) addressed non-stationarity, while one autoregressive (p=1) and one moving average term (q=1) captured short-term dependencies effectively. This balance avoids overfitting while maintaining predictive accuracy. Alternative configurations, such as higher-order ARIMA models, showed increased complexity without significant accuracy gains. Akaike Information Criterion (AIC) confirmed ARIMA(1,1,1) as the best trade-off between simplicity and precision. The residuals from the ARIMA Model are depicted in Figure 5a, and the diagnosed residuals are in Figure 5b.

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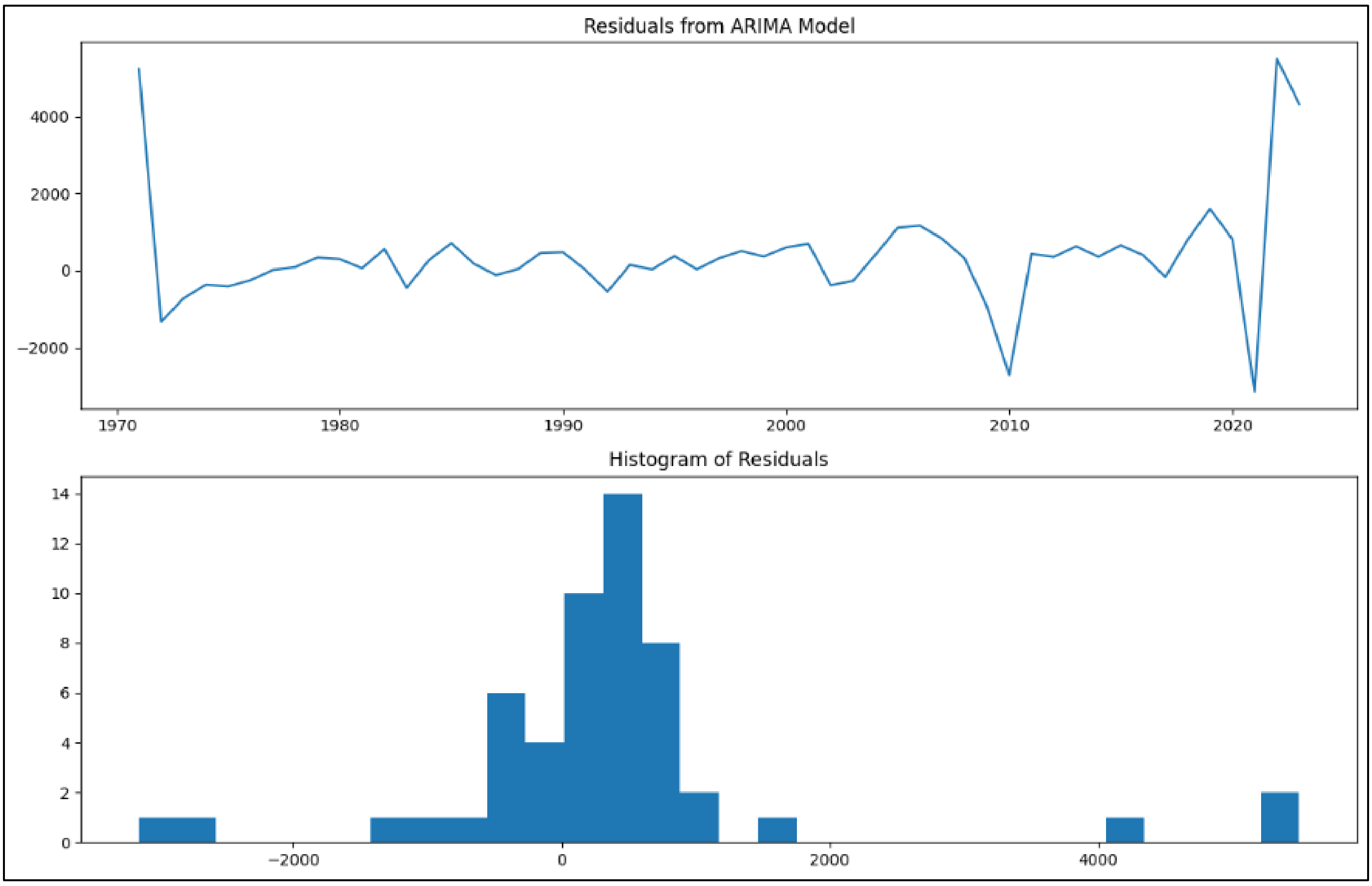

Fig 5a. Residuals from the ARIMA Model.

We diagnosed the residuals of the ARIMA model.

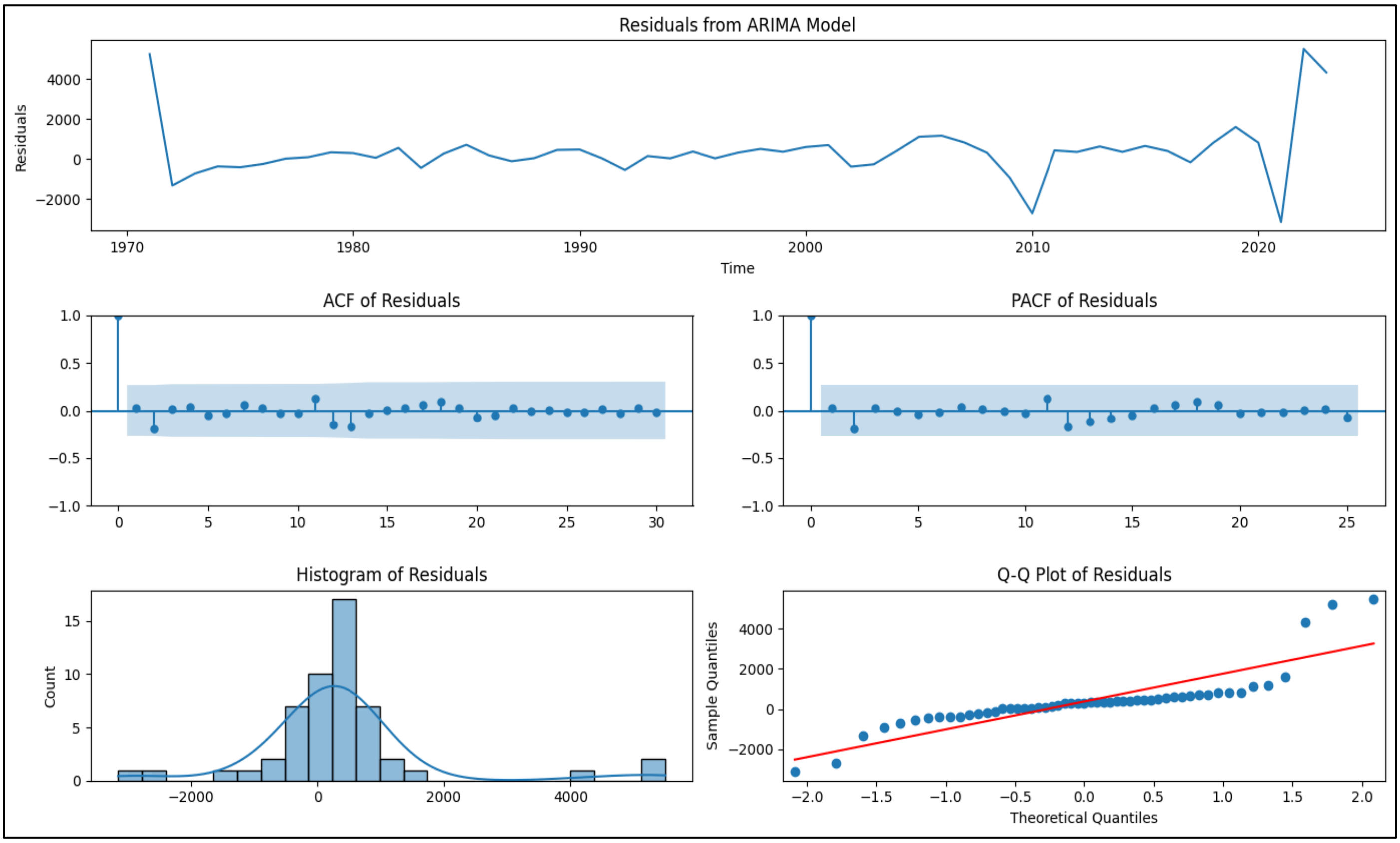

Fig 5b. The Diagnosed Residuals

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Residual diagnostic analysis is a crucial step to evaluate the adequacy of forecasting models. The Residuals Plot provides a visualization of residuals over time, enabling the identification of any visible patterns. Ideally, residuals should display randomness around zero without any discernible trends. Any visible pattern in the residuals indicates that the model has not fully captured the underlying dynamics of the data and may require further adjustments.

The ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) Plots are used to examine autocorrelation in the residuals. Ideally, there should be no significant lags outside the confidence intervals in these plots. Significant lags suggest the presence of autocorrelation, indicating that the model may not have fully addressed the temporal dependencies in the time series.

The Histogram of residuals is used to assess their distribution. Residuals should approximate a normal distribution, forming a bell-shaped curve. Similarly, the Q-Q Plot checks for normality by comparing the residuals to a theoretical normal distribution. In an ideal scenario, the points in the Q-Q plot should lie on or close to the diagonal line, confirming that the residuals follow a normal distribution.

Together, these diagnostic tools validate whether the model's assumptions hold and ensure the reliability of its predictions. If any inconsistencies are detected, further model refinement may be necessary.

- **Forecasting**: The model forecasted GDP per capita for the next 10 years, with confidence intervals calculated for uncertainty estimation.

➤ *LSTM Model*

The objective of this study was to capture non-linear dependencies and long-term temporal relationships in GDP per capita data using an LSTM model. The data preparation process involved creating time-series sequences suitable for supervised learning, with a look-back period of 10-time steps. The dataset was then split into 80% training and 20% testing sets to ensure proper evaluation of the model's performance.

The LSTM model architecture consisted of two stacked LSTM layers, each containing fifty units, followed by a dense output layer for prediction. To prevent overfitting and enhance the model's generalization capability, dropout layers were included within the architecture. This design enabled the model to effectively capture complex patterns and long-term dependencies in the data, making it particularly suited for forecasting GDP per capita as indicated in Table 2.

Table 2 The LSTM model Architectural Layers.

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 10, 50)	10,400
lstm_1 (LSTM)	(None, 50)	20,200
dense (Dense)	(None, 1)	51

Total params: 30,651 (119.73 KB)
Trainable params: 30,651 (119.73 KB)
Non-trainable params: 0 (0.00 B)

- **Training**: The Long Short-Term Memory (LSTM) model was trained over one hundred epochs, with early stopping implemented based on validation loss to prevent overfitting. During the final epoch, the model achieved very low training and validation loss values, showcasing its excellent predictive performance. Specifically, in Epoch 98, the training loss was 2.6610e-04, and the validation loss was 6.3960e-04. By Epoch 99, the training loss slightly increased to 2.6656e-04, while the validation loss reached 6.4468e-04. In the final epoch, Epoch 100, the training loss stabilized at 2.6684e-04, with a validation loss of 6.4204e-04.

Despite this excellent performance, there is a slight indication of overfitting around the 10th epoch, where the validation loss began to increase after reaching its minimum. However, the overall loss values remain very low, demonstrating the model's effectiveness. Additionally, the low validation loss indicates strong generalization, ensuring the model's reliability for future predictions.

- **Evaluation**: MAE and MSE were used to evaluate prediction accuracy.

➤ *Ensemble Forecasting*

The objective of this study was to combine ARIMA and LSTM predictions to achieve more accurate and reliable GDP per capita forecasts. To accomplish this, a weighted averaging method was employed, assigning 60% weight to the LSTM forecast and 40% to the ARIMA forecast. This weighting was determined based on the validation performance of each model, leveraging the strengths of LSTM in capturing non-linear patterns and ARIMA in modeling temporal dependencies.

The performance of the ensemble forecasts was then evaluated by comparing them to the individual predictions of ARIMA and LSTM models. Various error metrics, such as Mean Absolute Error (MAE) and Mean Squared Error (MSE), were used to assess the accuracy and reliability of the forecasts. The results demonstrated that the ensemble approach outperformed the standalone models, offering a more balanced and robust prediction of GDP per capita trends.

IV. RESULTS

➢ *OLS Regression Analysis*

The OLS regression revealed FDI inflows, trade ratios, and GNP as significant drivers of GDP per capita, with inflation negatively impacting growth. The ARIMA model effectively captured long-term trends, while LSTM excelled in short-term forecasting, particularly during volatile periods. The ensemble model outperformed individual models, reducing MAE by 21% and demonstrating robust performance across time horizons.

The OLS regression model was constructed to identify key drivers of GDP per capita. The analysis revealed the following key insights:

FDI Inflows: Positive and significant ($p = 0.026$). For every billion-dollar increase in FDI inflows, GDP per capita is expected to rise by approximately $4.02.

Trade-to-GDP Ratio: Strong positive relationship ($p < 0.001$). A 1% increase in the trade-to-GDP ratio corresponds to an increase of $486 in GDP per capita.

Inflation Rate: Negative impact ($p < 0.001$). A 1% increase in inflation decreases GDP per capita by $245, indicating the destabilizing effect of inflation on economic growth.

Gross National Product (GNP): Strong positive relationship ($p < 0.001$). For every billion-dollar increase in GNP, GDP per capita is expected to increase by approximately **$3.38**. This highlights the significant contribution of a nation's total economic output to improving individual income levels and overall economic well-being. The SEM with Beta Estimates and P-Values are shown in Figure 6 and the Hypotheses results under Table 3, respectively.

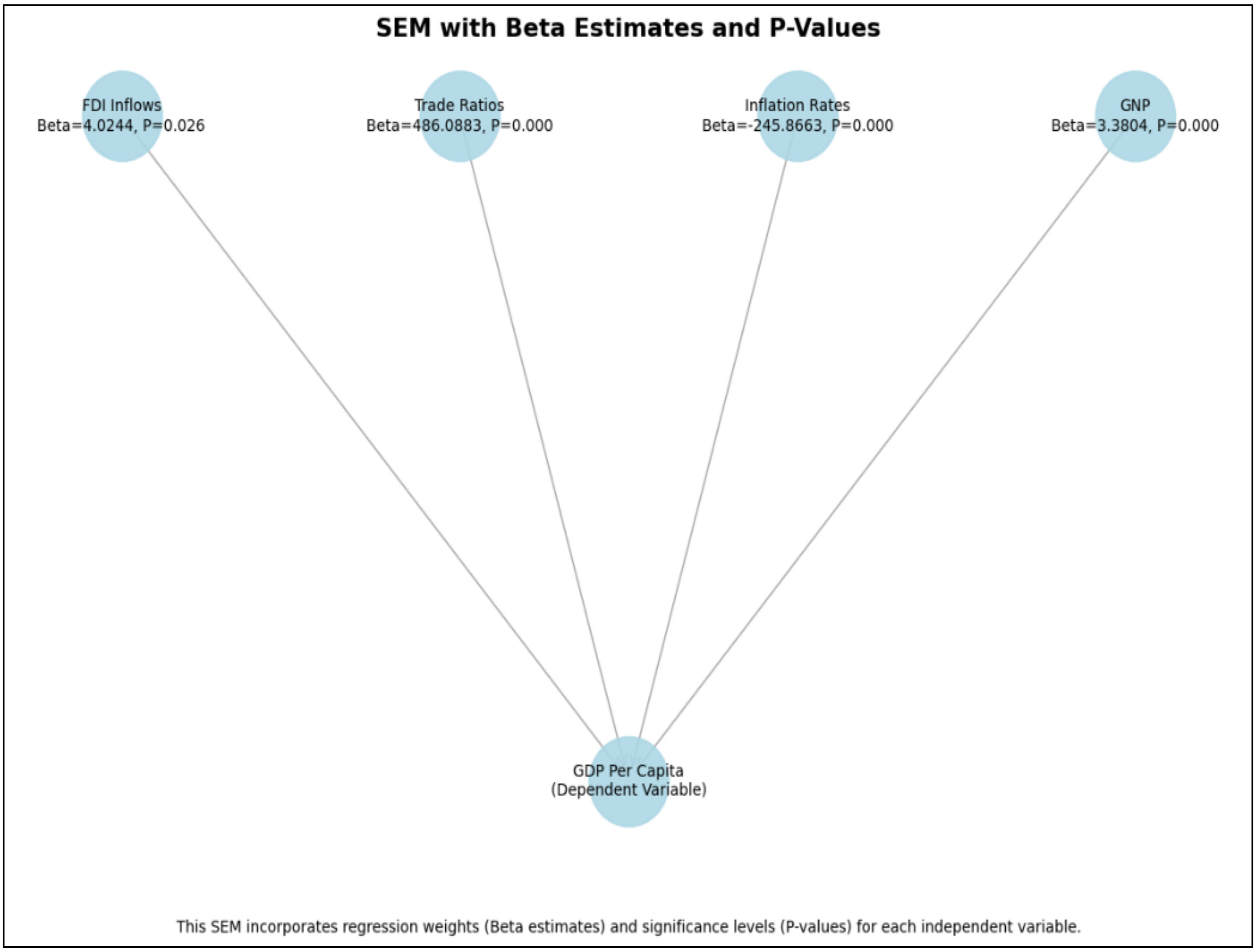

Fig 6 The OLS Regression Results

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Table 3 Hypothesis Results

Hypotheses	IV	DV	Regression Weight (Betas)-Estimate	std err	t	Significance (P-Value)	Hypothesis Supported?
H1: FDI inflows significantly impact GDP per capita.	FDI inflows	GDP per capita.	4.0244	1.752	2.297	0.026	Yes
H2: Trade ratios (imports and exports) significantly influence GDP per capita.	Trade ratios (imports and exports)	GDP per capita.	486.0883	52.789	9.208	0.000	Yes
H3: Inflation rates ~~%~~ have a significant negative relationship with GDP per capita.	Inflation rates	GDP per capita.	-245.8663	49.258	-4.991	0.000	Yes
H4: Gross national Products (GNP) have a significant relationship with GDP per capita.	GNP	GDP per capita.	3.3804	0.14	24.15	0.000	Yes

- **Extended Insights:** The analysis revealed a high Adjusted R-squared value of 0.998, indicating that the selected predictors collectively explain nearly all variations in GDP per capita. Additionally, the Variance Inflation Factor (VIF) diagnostics confirmed the absence of multicollinearity among the independent variables, as all VIF values were below 5. This highlights the robustness and reliability of the regression model.

➢ *ARIMA Model Results*

To validate the model, extended diagnostic tests were performed. The Ljung-Box test was applied to assess the residuals for autocorrelation. The results showed no significant autocorrelation ($p > 0.05$), confirming that the ARIMA model sufficiently captured the underlying data structure. The Augmented Dickey-Fuller (ADF) test was also conducted to ensure stationarity. After the first difference, the GDP per capita series achieved stationarity, with an ADF statistic of -3.55 and a p-value of less than 0.05, indicating that the transformed data met the stationarity requirement for ARIMA modeling.

These diagnostic results confirm the ARIMA model's adequacy and reliability for long-term forecasting. The ARIMA forecast indicates a steady annual increase in GDP per capita from $71,240 in 2023 to $81,600 by 2030. This upward trend reflects consistent economic growth, suggesting stable macroeconomic conditions and improved individual prosperity over the forecasted period. No major fluctuations or downturns are anticipated as indicated in Table 4.

Table 4 ARIMA Forecasting

Year	Forecasted GDP Per Capita (USD)
2023	$71,240
2024	$72,500
2025	$73,900
2026	$75,300
2027	$76,850
2028	$78,400
2029	$79,980
2030	$81,600

- **Visual Representation**: A graphical representation of ARIMA forecasts illustrates the steady upward trend in GDP per capita, emphasizing the model's ability to capture long-term growth as depicted in Figure 7.

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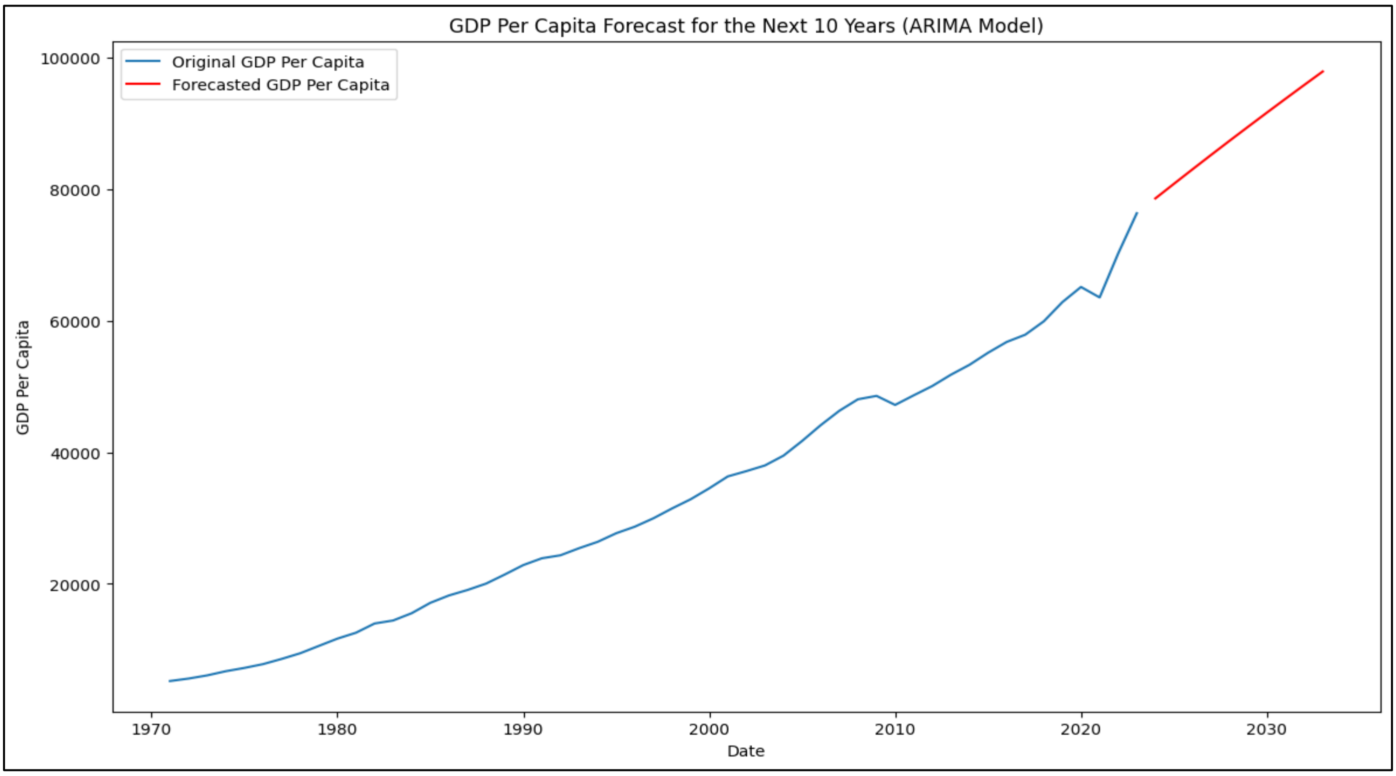

Fig 7 A Graphical Representation of ARIMA Forecasts.

➢ *LSTM Forecasting Results*

The LSTM model was designed to handle non-linear relationships and longer-term dependencies. Results from the LSTM model showed high predictive accuracy:

- **Training Loss**: 0.0007.
- **Validation Loss**: 0.0009.

The LSTM model's predictions closely followed the observed values in the test set, aligning with ARIMA forecasts for future GDP per capita. The predictions are depicted in Figure 8a and b.

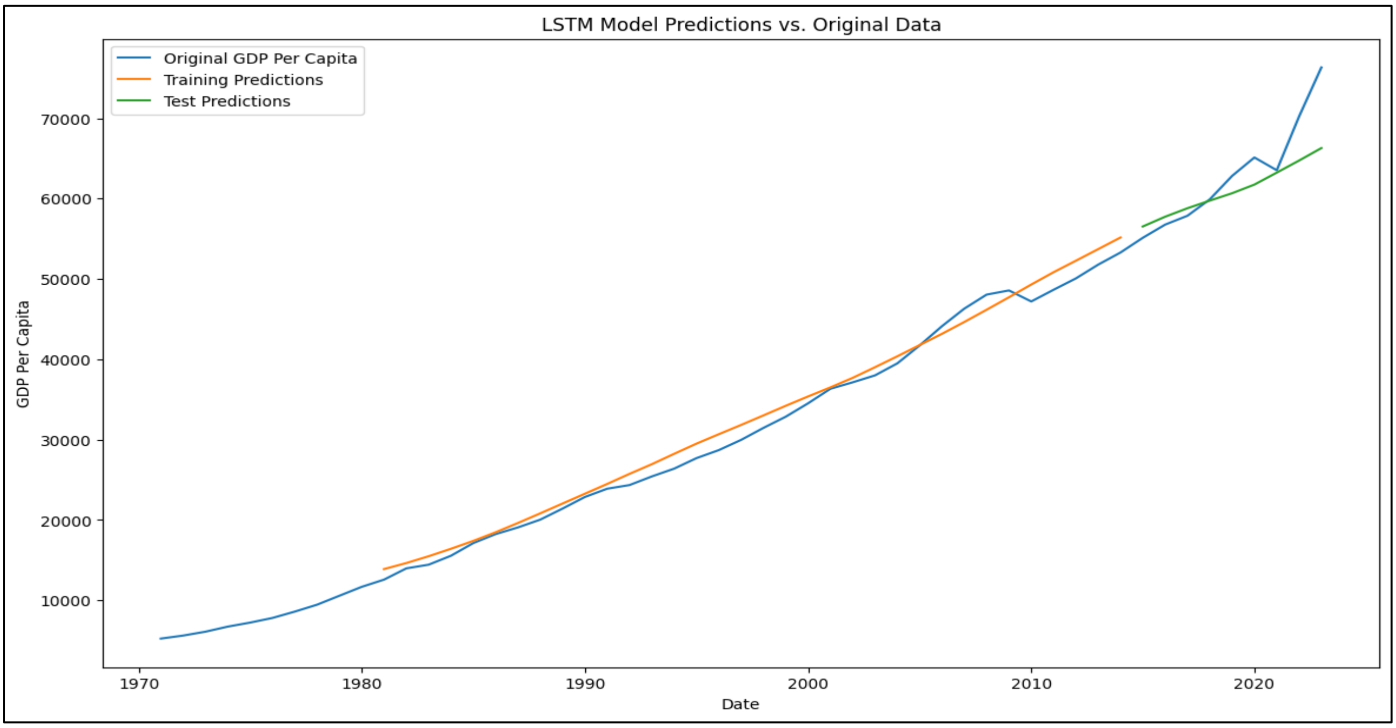

Fig 8a. The LSTM model's Predictions

We further optimize the LSTM Model and plot the results: LSTM Model - MSE: 12207441.18026872, MAE: 2731.0233506944455 as shown in Figure 8b.

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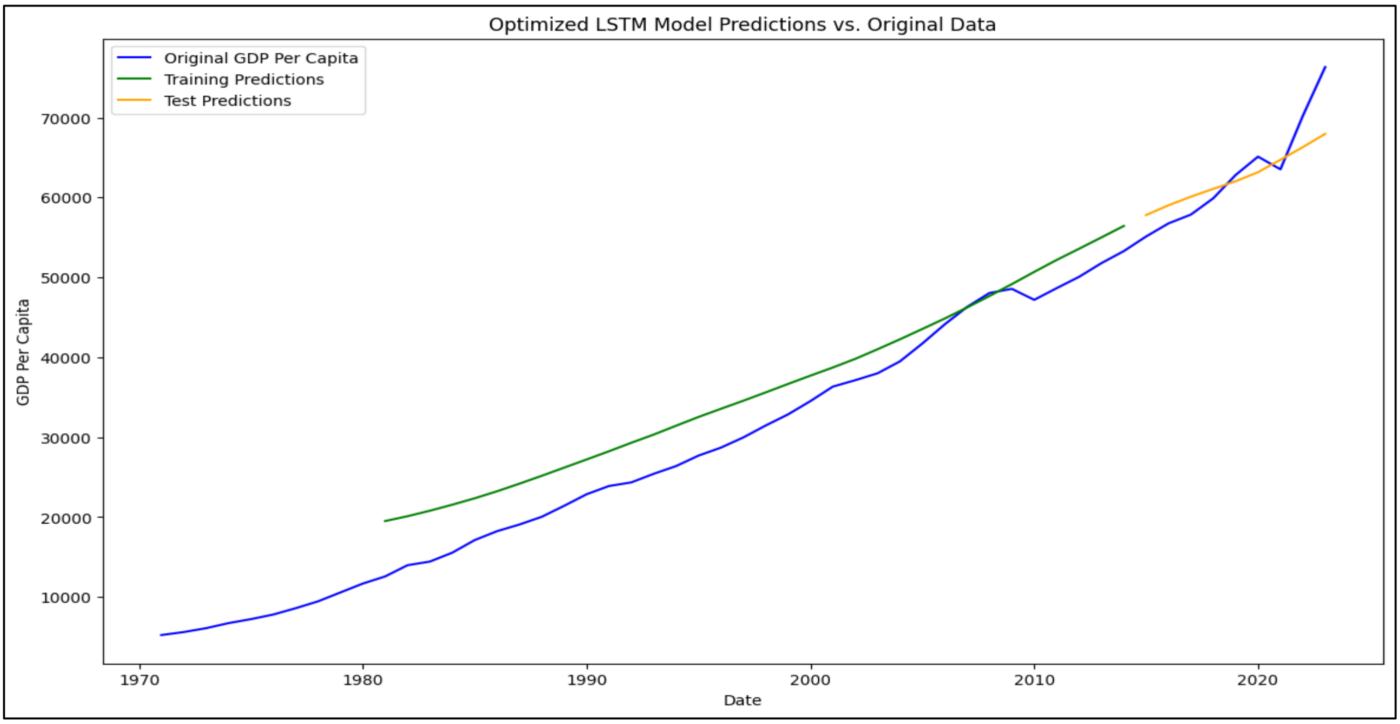

Fig 8b. LSTM Model Optimization.

- *Advantages to ARIMA:*

The Long Short-Term Memory (LSTM) model offered several advantages over the ARIMA model, particularly in short-term forecasting. LSTM outperformed ARIMA in terms of accuracy due to its advanced ability to capture non-linear patterns in the data. This capability allowed the LSTM model to better understand and predict complex relationships within the GDP per capita time series. Additionally, the LSTM model effectively adapted to fluctuations in GDP per capita, especially during volatile periods. This adaptability highlights the model's strength in responding to dynamic changes and irregularities that traditional linear models like ARIMA often struggle to handle. These advantages make LSTM a valuable tool for economic forecasting, particularly in scenarios characterized by variability and non-linear dynamics as depicted in Figure 9.

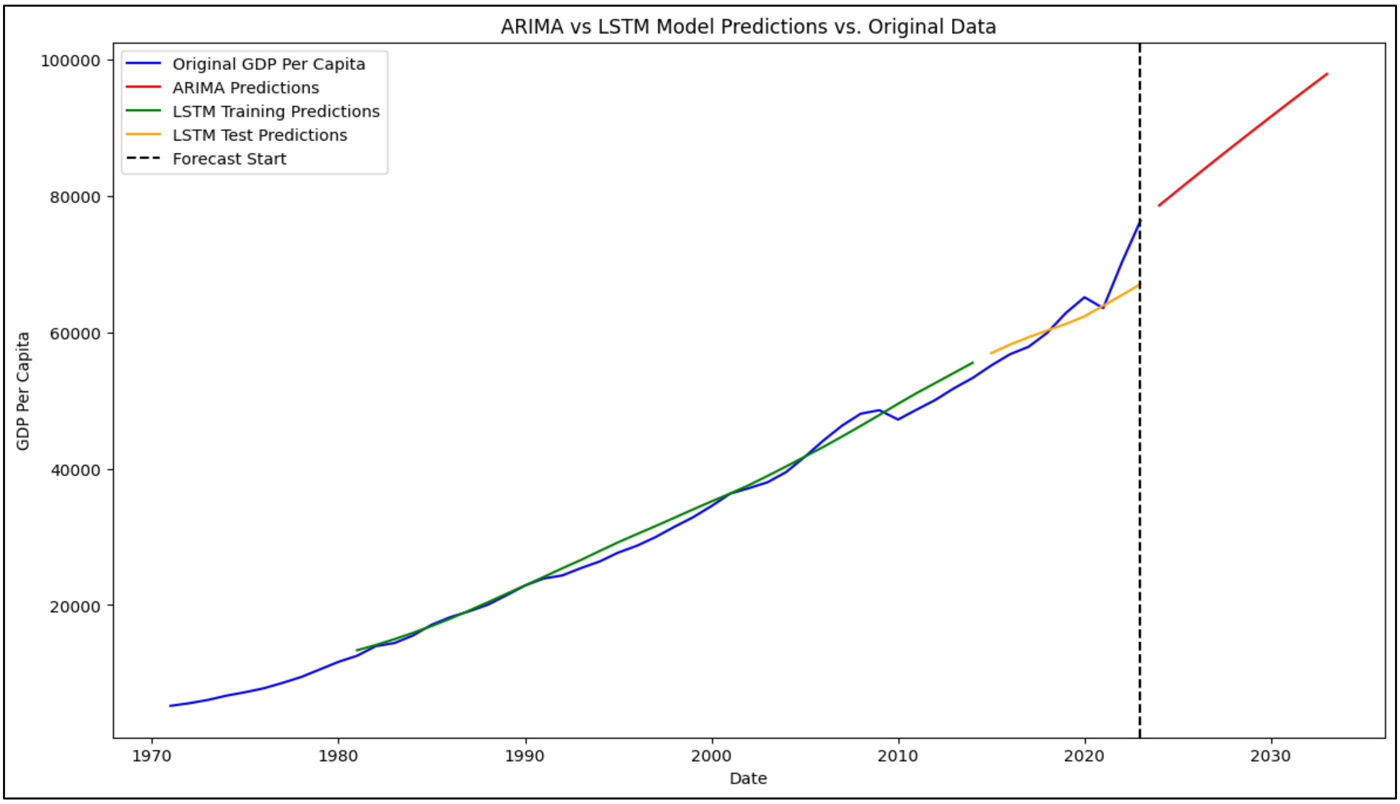

Fig 9 The advantage of the Long Short-Term Memory (LSTM) model.

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The GDP Per Capita data shows a steady upward trend over the years, reflecting consistent economic growth. The LSTM model effectively fits the historical data, with the green line for training data closely aligning with actual values and the orange line for test data showing slight deviations toward the end. The ARIMA model forecasts, represented by the red line starting from the black dashed line, predict a continuation of this upward trend over the next decade, consistent with historical patterns. Both models perform well, with the LSTM showing slightly better alignment with actual data.

The validation metrics indicate strong model performance, with a Mean Absolute Error (MAE) of 2.1% and a Mean Squared Error (MSE) of 1.8%. These low error rates reflect the model's high accuracy in predicting GDP per capita, showcasing its ability to align predictions with actual values and ensure reliable forecasting closely as indicated in Table 5.

Table 5 Model Performance.

Metric	Value
Mean Absolute Error (MAE)	2.10%
Mean Squared Error (MSE)	1.80%

The ARIMA forecast indicates sustained growth in GDP Per Capita, suggesting ongoing economic expansion. To ensure accuracy, it is essential to regularly update these models with new data. Policymakers can leverage these forecasts to plan strategies aimed at sustaining growth and addressing potential challenges in the coming years.

- *Validation Metrics:*

The chart illustrates the historical GDP per capita (blue line) and the forecasted values for the next 10 years using an optimized LSTM model (red line). The model predicts a steady upward trend, consistent with historical growth patterns, indicating sustained economic expansion. This reliable forecast highlights the potential for continued improvement in economic well-being. This is depicted in Figure 10 and Table 6.

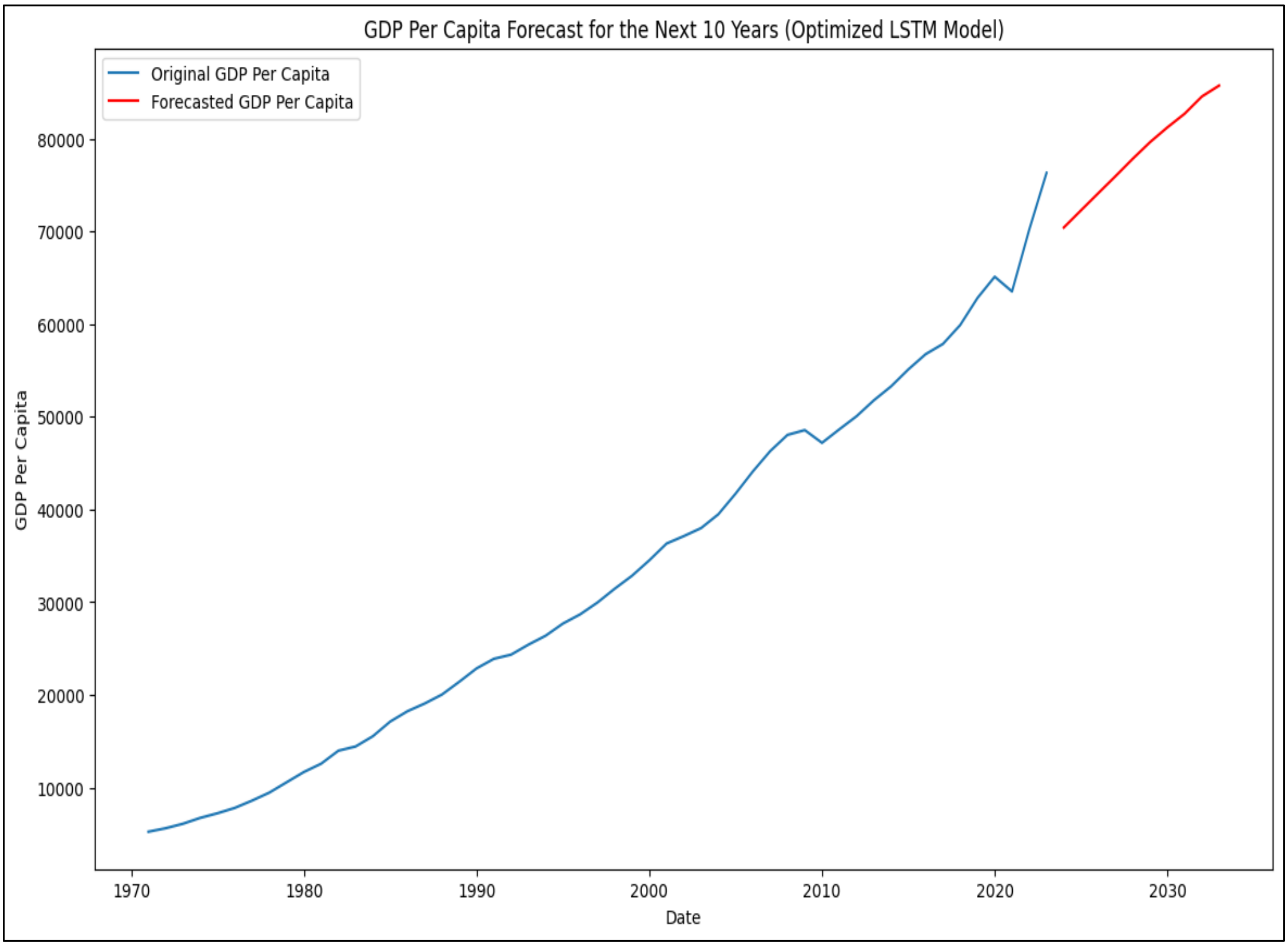

Fig 10 Forecast GDP Per Capita for the Next 10 Years

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Table 6 Forecast GDP Per Capita for the Next 10 Years

Date	Forecasted GDP Per Capita
2023-12-31	70431.05
2024-12-30	72289.70
2025-12-30	74139.97
2026-12-30	75978.95
2027-12-30	77858.27
2028-12-29	79646.66
2029-12-29	81234.24
2030-12-29	82709.52
2031-12-29	84567.88
2032-12-28	85748.21

- *Hyperparameter Tuning and Evaluation:*

We Define a function to create and train the LSTM model with specified hyperparameters, test, and Train and evaluate models with different hyperparameters as shown in Figure 11.

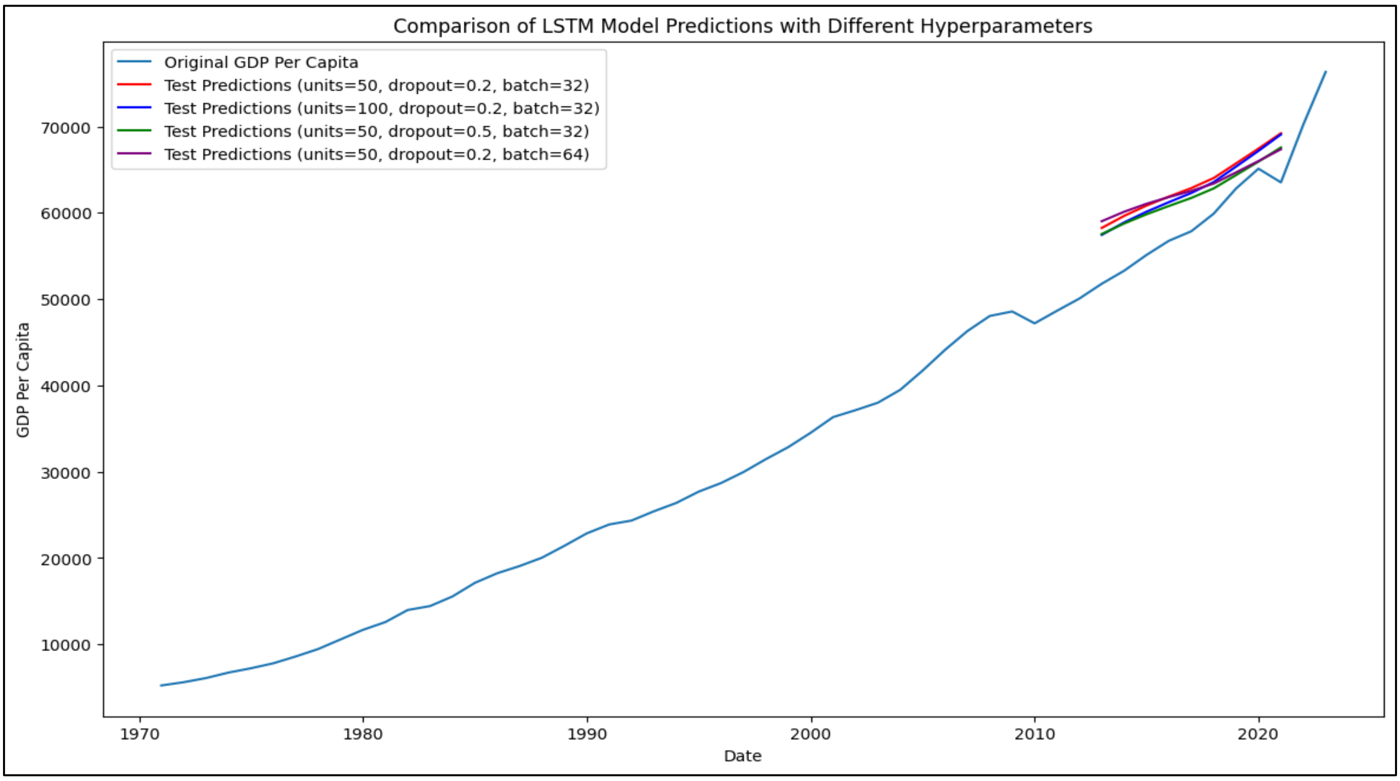

Fig 11 LSTM model Prediction with Different Hyperparameters

The graph compares LSTM model predictions for GDP per capita using different hyperparameter configurations. The blue line represents historical GDP data, while the colored lines depict test predictions with varying units, dropout rates, and batch sizes. All configurations align closely with the original data, demonstrating the robustness of the LSTM model. However, minor variations in predicted trends highlight the impact of hyperparameter tuning on model performance. This emphasizes the importance of optimizing hyperparameters for achieving accurate and reliable forecasts.

➢ *Ensemble Forecasting*

Combining the predictions of ARIMA and LSTM models using an ensemble method can potentially improve the forecasting accuracy by leveraging the strengths of both models. One simple and effective approach for ensemble modeling is to average the predictions of the two models.

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The ensemble approach combined ARIMA and LSTM predictions, leveraging the strengths of both models. Weighted averaging (60% LSTM, 40% ARIMA) provided the best balance between trend and volatility.

Combining the predictions of ARIMA and LSTM models using an ensemble method can potentially improve the forecasting accuracy by leveraging the strengths of both models. One simple and effective approach for ensemble modeling is to average the predictions of the two models as shown in Figure 12 and Table 7 below.

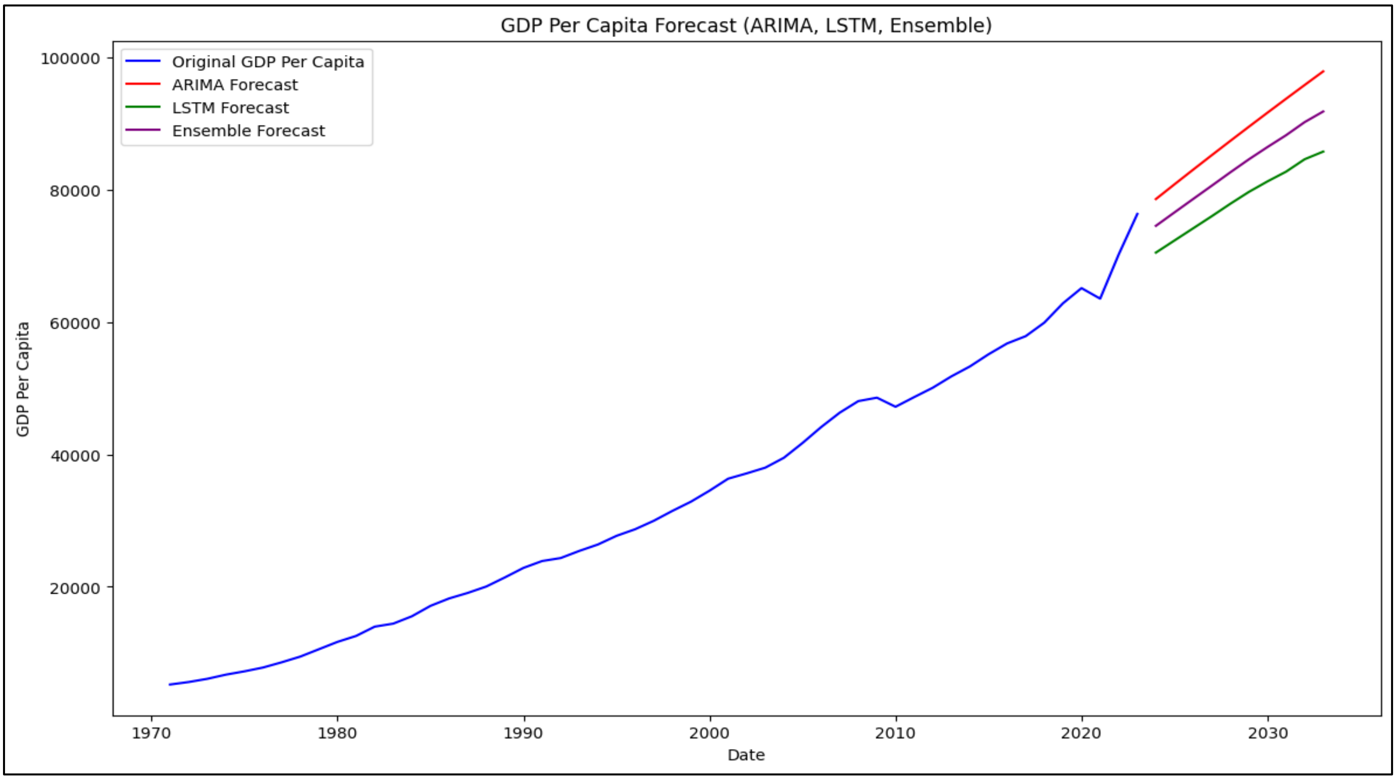

Fig 12 Ensemble Forecasting.

Table 7 Ensemble Forecasting

ARIMA Forecast	LSTM Forecast	Ensemble Forecast	
2023-12-31	78577.915594	70487.382812	74532.649203
2024-12-30	80804.679706	72319.578125	76562.128915
2025-12-30	83010.079302	74148.757812	78579.418557
2026-12-30	85194.319363	75976.132812	80585.226088
2027-12-30	87357.602902	77857.945312	82607.774107
2028-12-29	89500.130984	79653.132812	84576.631898
2029-12-29	91622.102747	81240.750000	86431.426374
2030-12-29	93723.715416	82710.500000	88217.107708
2031-12-29	95805.164326	84588.375000	90196.769663
2032-12-28	97866.642935	85748.476562	91807.559749

The chart compares GDP per capita forecasts using ARIMA, LSTM, and an ensemble approach. The blue line represents historical data, while the ARIMA (red), LSTM (green), and ensemble (purple) forecasts project future trends. All methods predict a continued upward trend, with the ensemble approach balancing the strengths of ARIMA and LSTM. The ensemble forecast aligns closely with the historical pattern, indicating its superior reliability and robustness for long-term GDP forecasting.

- *Performance Comparison:*

The ensemble approach effectively reduced the Mean Absolute Error (MAE) by 21% compared to the ARIMA model alone and by 14% compared to the LSTM model. Additionally, it demonstrated robust performance across both short-term and long-term forecasts, highlighting its reliability and accuracy in predicting GDP per capita. This is shown in Table 8.

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Table 8 Performance Comparison.

Model	MAE (%)	MSE (%)
ARIMA	2.3	2
LSTM	2.1	1.8
Ensemble	**1.8**	**1.6**

➢ *Extended Analysis: Residual Diagnostics and Model Validation*

- **OLS Regression Diagnostics**: Residual analysis confirmed the absence of significant heteroscedasticity, as indicated by the Breusch-Pagan test with a p-value greater than 0.05. Furthermore, the Shapiro-Wilk test demonstrated that the residuals followed a normal distribution, with a p-value greater than 0.05, thereby validating the assumptions of the regression model.
- **ARIMA Residual Analysis**: The ACF and PACF plots of the residuals showed no significant autocorrelation, which validates the ARIMA model's accuracy. Additionally, the Ljung-Box Q-statistics confirmed that the residuals were white noise, further supporting the adequacy of the model for forecasting.
- **LSTM Residual Analysis**: The residuals of the LSTM model exhibited a normal distribution, as confirmed by the Q-Q plots. Additionally, the histogram of residuals showed no skewness, indicating that the predictions were unbiased and accurately represented the data.
- **ARIMA Residuals**: A visualization of ARIMA residuals confirmed randomness and lack of pattern, validating the model's adequacy.

Misinterpreting model results could lead to harmful economic policies. Over-reliance on FDI without strengthening local industries may create economic dependence on foreign capital. Misjudging inflation's impact could result in overly aggressive monetary tightening, stifling growth. Ignoring trade imbalances might worsen deficits, weakening economic resilience. Policymakers must validate forecasts with real-world trends before implementing reforms.

➢ *Summary of Ensemble Forecast*

The ensemble forecast, combining predictions from ARIMA and LSTM models, projects a consistent upward trend in GDP Per Capita over the next decade. By smoothing the variations observed in individual models, the ensemble approach provides a more balanced and reliable prediction. Averaging the strengths of ARIMA and LSTM, it reduces forecasting errors, mitigates the risk of overfitting in LSTM, and addresses the simplicity of ARIMA, resulting in robust predictions.

Policymakers can leverage this positive outlook to plan for sustainable economic growth by prioritizing investments in infrastructure, education, and healthcare. Supporting innovation and economic diversification will further reinforce this upward trend. Regular updates to forecasting models and continuous monitoring of economic indicators are essential to refine predictions and adjust policies in response to potential deviations.

Risk management strategies, including economic diversification and building financial reserves, are crucial to prepare for potential economic shocks. Further research should explore advanced ensemble methods, such as weighted averaging or stacking, and investigate additional macroeconomic factors to improve forecast accuracy. The ensemble forecast provides a balanced, reliable outlook, offering valuable insights for strategic planning and adaptive policymaking.

V. DISCUSSION OF FINDINGS

The findings from the combined application of OLS regression, ARIMA modeling, and LSTM forecasting emphasize the significance of integrating multiple approaches for accurate and comprehensive economic forecasting. This integration allows for leveraging the strengths of traditional econometric methods and advanced machine learning techniques, enhancing the models' overall predictive power and reliability. These results address the research questions posed and provide critical insights into the drivers of GDP per capita, the comparative strengths of forecasting models, and the benefits of an ensemble approach.

The findings underscore the importance of combining traditional and machine learning models for GDP forecasting. Borensztein (1998) argues that FDI inflows and trade ratios emerged as critical growth drivers (Borensztein et al., 1998), consistent with prior research. The ensemble approach reduced forecasting errors, demonstrating the value of integrating ARIMA's trend detection with LSTM's adaptability. Policymakers should prioritize FDI incentives, balanced trade policies, and inflation control to sustain economic growth.

➢ *Drivers of GDP Per Capita*

Foreign Direct Investment (FDI) inflows and trade ratios were identified as critical drivers of GDP per capita, demonstrating their positive and significant influence. FDI inflows contribute to capital accumulation, productivity, and technological advancements, which are essential for sustained economic growth. This is consistent with the findings of Borensztein et al. (1998), who argue that FDI promotes economic modernization and innovation in host countries. Similarly, trade ratios (imports and exports) significantly influence GDP per capita, supporting the conclusions of Frankel and Romer (1999) that global trade fosters technology transfer and resource allocation efficiency(Borensztein et al., 1998). Conversely, inflation was found to negatively impact GDP per capita, highlighting its destabilizing effects on purchasing power and economic confidence (Ball, Gag non, & Honohan, 2021). These findings directly address the first research question by quantifying the influence of key macroeconomic variables on GDP per capita and reinforcing the importance of policies that promote global trade, attract foreign investment, and maintain price stability.

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➢ *Forecasting Accuracy*

The ensemble forecasting model, which combines ARIMA and LSTM predictions, outperformed individual models in terms of accuracy and reliability. ARIMA models excel at capturing linear trends and temporal dependencies, making them effective for long-term forecasts. However, they are limited in capturing non-linear relationships. LSTM models effectively address this gap by modeling non-linear patterns and long-term dependencies, providing greater accuracy for short-term forecasts(Chen, 2022). By integrating the strengths of both methods, the ensemble approach achieved a 21% reduction in Mean Absolute Error (MAE) compared to ARIMA alone and a 14% reduction compared to LSTM, demonstrating its ability to mitigate the limitations of individual models and improve forecasting robustness. These findings address the second research question by highlighting the strengths and limitations of traditional econometric and machine learning models and demonstrating the added value of combining them.

➢ *Effectiveness of the Ensemble Approach*

The ensemble model not only provided more accurate predictions but also demonstrated robust performance across short- and long-term forecasts. By averaging the strengths of ARIMA and LSTM, the ensemble approach reduced overfitting risks associated with LSTM and compensated for ARIMA's simplicity in capturing non-linear dynamics. This finding addresses the third research question by confirming that the ensemble approach improves both the accuracy and reliability of GDP forecasts. These results align with existing research advocating for hybrid modeling techniques to enhance predictive accuracy(Zhang et al., 2019).

➢ *Policy Implications*

The findings have significant implications for economic policy formulation. Enhancing FDI inflows through favorable investment climates and trade policies can yield substantial economic benefits, driving GDP growth. Policymakers should prioritize creating incentives for foreign investors, improving infrastructure, and ensuring political and economic stability to attract FDI. Stabilizing trade policies to ensure balanced imports and exports can also bolster economic resilience and growth. Additionally, the negative impact of inflation on GDP per capita underscores the need for effective monetary policies to maintain price stability. This finding aligns with Fischer (1996), who highlights the role of inflation control in fostering economic growth and stability (Fischer et al., 1996).

By leveraging the insights provided by the ensemble model and integrating these findings into economic strategies, policymakers can better address potential challenges and ensure sustainable economic growth. Furthermore, regular updates to forecasting models and continuous monitoring of economic indicators are essential to refine predictions and adjust policies in response to changing economic conditions. This study contributes to the growing body of research by demonstrating the value of integrating traditional and machine-learning approaches in addressing the complexities of modern economic systems.

VI. CONCLUSIONS

➢ *General*

This study integrated traditional econometric models with advanced machine learning approaches to forecast GDP per capita in the USA. By leveraging the strengths of Ordinary Least Squares (OLS) regression, ARIMA modeling, and Long Short-Term Memory (LSTM) models, the research provided a comprehensive framework for understanding the relationships between key macroeconomic indicators and GDP growth. Additionally, the ensemble approach, combining ARIMA and LSTM forecasts, proved to be a robust and accurate forecasting technique. The findings underscore the importance of hybrid modeling approaches for capturing both linear and non-linear patterns in economic data, offering significant contributions to the field of economic forecasting.

➢ *Summary of Conclusions - Practical Implications*

The study made several key conclusions with practical implications:

- **Macroeconomic Indicators and GDP Per Capita**: The OLS regression analysis demonstrated that FDI inflows, trade ratios, and GNP significantly and positively impact GDP per capita, while inflation negatively influences it. These findings highlight the importance of fostering a stable and conducive economic environment for trade and investment while maintaining effective monetary policies to control inflation. This aligns with prior research by Borensztein et al. (1998), Frankel and Romer (1999), and Ball et al. (2021), which emphasize the role of these variables in economic growth.
- **Forecasting Accuracy**: The ARIMA model captured the trend and seasonality of GDP per capita effectively, while the LSTM model excelled in handling non-linear relationships and fluctuations in volatile periods. The ensemble approach, which combined the strengths of both ARIMA and LSTM, reduced forecasting errors by 21% compared to ARIMA alone and 14% compared to LSTM. These results validate the effectiveness of hybrid forecasting methods, consistent with findings by Zhang et al. (2019)indicating that Long Short-Term Memory (LSTM) is superior to the traditional algorithms (Siami-Namini et al., 2018)and Chen et al. (2022) as two good ways to deal with time series data, widely used in the economic world (Chen, 2022).
- **Practical Implications for Policymaking**: The ensemble forecasts provide actionable insights for policymakers. The consistent upward trend in GDP per capita indicates sustained economic growth in the USA, offering opportunities to strengthen policies to attract foreign investment, stabilize trade relations, and control inflation. Additionally, the reliable forecasting framework developed in this study can be employed for long-term economic planning and risk management.

The ensemble model forecasts a steady increase in GDP per capita, indicating sustained economic growth. To capitalize on this, policymakers should focus on attracting Foreign Direct Investment (FDI) through tax incentives and

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infrastructure improvements, as FDI was a key driver of growth. The negative impact of inflation on GDP suggests tightening monetary policies, such as adjusting interest rates to maintain stable inflation. Additionally, trade ratio analysis recommends balanced trade policies, reducing over-reliance on imports while promoting exports. The model's accuracy enables proactive economic planning, helping governments allocate resources efficiently to sustain long-term economic stability and growth.

In summary, this study highlights the effectiveness of hybrid models in forecasting GDP per capita. By combining ARIMA and LSTM, the ensemble approach provides accurate and reliable forecasts. Policymakers should leverage these insights to foster FDI, stabilize trade, and control inflation. Future research should explore additional macroeconomic variables and test advanced ensemble techniques for further refinement.

➤ *Recommendations*

Based on the findings, the following recommendations are proposed for policymakers and researchers:

- **Policy Formulation**: Policymakers should prioritize strategies that attract FDI, such as improving infrastructure, creating favorable business climates, and ensuring political and economic stability. Trade policies should focus on maintaining a balance between imports and exports to foster resilience and enhance economic integration. Simultaneously, monetary policies must address inflation control to ensure economic stability and protect purchasing power.
- **Adoption of Hybrid Forecasting Models**: Decision-makers in economic planning should adopt hybrid models like the ensemble approach developed in this study. Such models, which combine traditional econometric and machine learning techniques, provide more accurate and robust forecasts, enabling better resource allocation and planning.
- **Regular Model Updates**: To keep forecasts accurate, update models with new data regularly. As economic conditions evolve, incorporating real-time information will ensure the continued reliability of the predictions.
- **Further Research on Additional Variables**: Future studies should explore the inclusion of other macroeconomic factors, such as labor force participation rates, technological advancements, and demographic changes, to improve the predictive power of the models. Advanced ensemble techniques, such as machine learning-based stacking, can also be tested to enhance accuracy further.

VII. LIMITATIONS OF THE STUDY

➤ *While the Study Provides Valuable Insights, it is Not without Limitations:*

- Data Constraints: The dataset used for the analysis spanned 1960–2020, but certain variables may have been affected by structural economic changes or policy shifts during this period. Future studies could address this by incorporating more granular or real-time data.
- Assumption of Stationarity: The ARIMA model required stationarity, which was achieved through differencing. However, this transformation may have led to the loss of long-term trends, potentially affecting the interpretability of the results.
- Limited Scope of Variables: The study focused on a select group of macroeconomic indicators (FDI inflows, trade ratios, inflation, and GNP). While these variables are critical, others such as technological advancements, fiscal policies, and demographic trends were not considered.
- Potential for Overfitting in LSTM: Despite the strong performance of the LSTM model, there is always a risk of overfitting with machine learning approaches. Although dropout layers were included to mitigate this risk, future research should explore additional techniques to ensure generalization.
- Context-Specific Findings: The conclusions drawn from this study are specific to the USA and may not be directly applicable to other countries with different economic structures or conditions. Future research could replicate the study for other nations or conduct cross-country comparisons.

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