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GDP Forecasting for Policy: Evaluating ARIMA, Exponential Smoothing, and XGBoost Models for Fiscal, Monetary, and Welfare Planning

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Abstract: A key economic metric that represents stability, productivity, and national growth is the gross domestic product (GDP). For academic research as well as for decision-makers at various levels, accurate GDP forecasting is crucial. Three distinct time series models are used in this study to anticipate GDP values for 2022–2026: Exponential smoothing (ES), Extreme Gradient Boosting (XGBoost), and AutoRegressive Integrated Moving Average (ARIMA). The study focuses on the GDP of the United States and India during 2000–2021. Forecasts of GDP are used by governments to create fiscal budgets, investments in infrastructure, and social welfare initiatives central banks like the U.S. and Indian Reserve Banks. Forecasts are used by the Federal Reserve to direct inflation control, interest rate decisions, and monetary policy. Such forecasts are incorporated into loan programs, debt management plans, and worldwide economic monitoring by international organizations such as the World Bank and the International Monetary Fund (IMF). GDP projections are used by companies and investors to guide supply chain planning, trade negotiations, and investment risk management. Three models' predictive accuracy is assessed in this study, and ES is found to be the most accurate for short-term GDP projections. This study shows that GDP prediction is not only a technical challenge but also a basis for evidence-based governance, economic stability, and inclusive growth policies in both emerging and mature economies by connecting forecasting accuracy to real-world applications.

Keywords: GDP, USA, India, MAPE, MAD, MSE, ARIMA, XGBoost, ES

1 Introduction

GDP is the foremost economic indicator that determines the value of goods and services produced in a nation during a specified period. It serves as a vital indicator of a country's overall economic performance. GDP reflects economic activity, revealing a nation's economic condition, growth rate, and overall efficiency standards. Precise GDP prediction plays an imperative role in economic planning by enabling policymakers to devise effective fiscal and monetary strategies. It supervises business investment choices, and aids in the evolution of global trade policies. Macroeconomic planning necessitates reliable GDP estimates, as they assist in government budget formation, fixing interest rates, and regulating inflation. Moreover, GDP predictions are expedient for business-related companies, assisting them in making well-informed decisions about market entry and strategic growth.

GDP projections are crucial for policymaking as governments utilize them to plan infrastructure projects and fiscal budgets. Central banks use them to regulate inflation and interest rates, and international bodies make use of them to keep

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an eye on the global economy and manage debt [1]. The existing project assesses the ARIMA, ES, and XGBoost models by means of GDP data from the US and India to meet this criterion. Whilst the United States is an urbane and developed nation that governs the global financial scenario, India is an emergent economy witnessing a flourishing market. Other than benchmarking model performance, the contrast in these two diametrically opposed sets of circumstances provides information that policy makers can utilize it to enhance policies and strategies pertaining to sustainable development, economic planning, and crisis vigilance.

GDP forecasting has significant statistical implications as well as broad socioeconomic ramifications. The development policy is based on accurate forecasts that tell governments where to build infrastructure, how to allocate resources, and what long-term growth rates to aim for [2]. For example, in emerging economies like India, GDP projections serve as a guide for people to invest in health, education, and job creation programs. In this way, growth will result in inclusive development. Projections play a significant role in the process of coordinating labor market policies, welfare programs, and even technological innovation plans in industrialized economies such as the United States. The national GDP estimates are used by the IMF, World Bank, and other international organizations to plan financial aid, monitor the sustainability of debt, and fund initiatives to reduce poverty. Accurate forecasting also enables politicians to anticipate difficult times, provide social safety nets in a timely manner, and lessen inequality during difficult economic times. As a result, predicting GDP is not just a scholarly problem; it is also the cornerstone of economic development planning, which aims to close the gap between economic models and actual performance to combat poverty, provide employment, and achieve sustainable growth.

Forecasts of a sharp decrease in GDP motivated the Atmanirbhar Bharat stimulus program, which addressed the COVID-19 pandemic and prioritized employment protection and the well-being of disadvantaged populations [3][4]. In the United States, GDP forecasts have impacted Federal Reserve monetary policy; rates have been modified to maintain inflation and employment stability in the economy. GDP projections that help reduce unemployment served as the foundation for the development of labor market interventions and stimulus plans during the 2008 financial crisis [4]. At the global scale, the IMF and World Bank involve GDP projections in the lending schemes, debt sustainability, and poverty-reduction models. Proper predictions are also useful in SDG-related development objectives by predicting economic recessions and pre-emptive social safety nets. By so doing, GDP forecasting links economic models with realities of alleviation of poverty, creation of employment and sustainable growth, and thereupon, accuracy in forecasting becomes a cornerstone of viable development policy. In the context of the debt sustainability analysis and the creation of structural adjustment and development credit programs, the IMF and World Bank rely significantly on the GDP projections. Underfunding of welfare or non-recovery borrowing may result from inaccurate GDP forecasting [5]. The United States and India were chosen because they represent two radically different economic situations. India, one of the fastest-growing emerging economies, is distinguished by its dynamic population, structural transformation, and heightened susceptibility to external shocks and volatility. In contrast, the United States possesses the world's largest, most developed economy, which is comparatively stable, has sophisticated financial institutions, and dominates the global financial scene. By comparing these two economies, the study can test forecasting models under both stable, established conditions and highly erratic growth situations. Furthermore, by providing policy-relevant details about how forecasting precision can patronage fiscal planning, budgetary policy, and crisis management in both developed and emerging countries, this also divides the contributions to the method about the flexibility of models in several contexts.

2 Literature Review

Growth planning and economic policy formulation heavily rely on accurate GDP estimates. Whereas the central banks make use of GDP estimates to steer monetary policy, fix interest rates, and regulate inflation, governments use them for planning budget, infrastructure investment, and social welfare outlays. To accomplish debt sustainability assessments, design development loan initiatives, and track advancement towards the Sustainable Development Goals (SDGs), global organizations like the World Bank and IMF fundamentally have faith in GDP projections. The GDP forecasting policy might be especially evident during times of crisis. For instance, fiscal stimulus plans during the 2008 financial crisis were based on output-related contraction projections, and during the COVID-19 pandemic, welfare transfers, job reactions, and supply chain adjustments occurred all over the world in response to contractions forecast by GDP models[6]. These examples show that GDP forecasting is a useful instrument for stabilizing the economy and guiding the long-term growth of the nation, not just an academic exercise. Despite extensive literature on the topic, most of the existing literature concentrates on analyses of GDP in individual countries, or only on traditional models and therefore there is a dearth in knowledge regarding how various methods can perform in various economic contexts.

Using World Bank annual data from 1965 to 2016, the Box-Jenkins approach was used to predict and forecast Egypt's GDP. They determined that ARIMA(1,2,1) was the best model based on the Mean Squared Error (MSE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) criteria after calculating different ARIMA specifications and testing for stationarity. There predictions indicate that Egypt's GDP would continue to rise from 2017 to 2026, verifying the efficacy of ARIMA models in envisaging long-term growth dynamics[7]. Tkacz (2001) investigated the ability of neural network models to utilize leading indicators to forecast GDP growth in Canada. The insights showed that, in contrast to linear and univariate techniques, neural networks produced noticeably fewer forecast errors for the annual growth rate of the real GDP. Their advantage, however, diminished when predicting quarterly GDP growth, as the models were incompetent to beat a naïve no-change baseline. As per Tkacz (2001), the research also suggested that nonlinearities grow more significantly over extended time frames, plausibly reflecting asymmetric impact of monetary policy on the actual economy[8].

To foretell Bangladesh's GDP growth, researchers employed machine learning procedures to evaluate a variety of macroeconomic indicators, incorporating GDP per capita, inflation, government debt, aggregate investment, remittances, and unemployment. Their approach imparted insights into the factors that have the most significant impact on economic performance by emphasizing the complex and nonlinear links between these predictors and GDP growth. The study underlined how machine learning can assist policymakers pinpoint eminent growth factors and establish economic objectives[9].

By Employing the XGBoost technique, researchers developed a predictive model to estimate the U.S. dollar's exchange rate alongside the Indonesian rupiah. The authors employed the Knowledge Discovery in Database (KDD) methodology and time series data from Investing.com to enrich the model via hyperparameter tuning. With testing errors as low as 0.24% RMSE and 0.12% Mean Absolute Percentage Error (MAPE), their findings showcased remarkable predictive accuracy, substantiating the efficacy of XGBoost in financial time series forecasting and uplifting its relevance in investment decision-making scenarios [10].

To estimate India's GDP, Bharathi and Navaprakash (2024) evaluated the ability of the XGBoost and Adaboost algorithms. They discovered that, even though both ensemble techniques have strong predictive capabilities, XGBoost had a considerably higher accuracy rate (94%) compared to Adaboost (89%), utilizing a dataset of twenty samples and statistical analysis in SPSS. Their discoveries highlight the significance of algorithm selection in GDP prediction, where XGBoost distinctly outperforms other algorithms in terms of accuracy [11]. Zheng (2022) posed a contrast in ES and ARIMA's performance in predicting Shanghai's GDP employing 31 years of time series data. Although both models were shown to be applicable, the ES model—specifically, the Holt-Winters no-seasonal model—was thought to be more suitable for long-term policy-driven trends. ES can be regarded as a superior option in these places because the research has shown that approaches that can be used to evaluate GDP forecasts should better reflect sustained structural and policy influences in the context of a fast-growing surface like Shanghai[12].

To predict Jordan's GDP, Al-Khatabee and Jaradat (2023) applied both multivariate linear regression and ES models to sectoral data on the country's GDP from 2008 to 2019. With a R Squared of 0.996, their findings showed that the regression model had an extremely high degree of accuracy, demonstrating the model's efficacy in simulating the link between GDP and the population-related variables. Simultaneously, ES was utilized to provide 2020–2025 predictions, indicating its effectiveness in predicting medium-term economic patterns. The study furthermore emphasized how machine learning regression and traditional time series techniques might function together to aid in Jordan's investment and policy planning [13]. Dritsaki and Dritsaki (2022) forecasted Greece's GDP by employing the modified ES state space model. A maximum likelihood estimator and a model selection criterion based on AIC were used in the study to evaluate additive and multiplicative error structures. The outcomes revealed that the ES model, which considered seasonality and multiplicative errors, provided the most accurate prediction of the data, indicating a drop in GDP in forthcoming quarters with clues of eventual stabilization. Their findings demonstrate the importance of ES state space modeling techniques for policy-sensitive economic shocks and nonlinearities [14].

To estimate the growth of the U.S. GDP, researchers created an ensemble model that combines a Dynamic Factor Model in a Generalized Autoregressive Score (DFM-GAS) structure alongside a Recurrent Neural Network (RNN). Their approach resulted in enhanced one-quarter-ahead projections, especially in the wake of the COVID-19 recovery and the 2008–2009 financial crisis. The association between the model characteristics and business cycle development was also highlighted due to the paper's application of an interpretable machine learning routine with integrated gradients [15].

The use of Google Trends data to forecast GDP growth in both an advanced economy (the United States) and an emerging economy (Brazil) was investigated. Using dynamic factor models using variable selection techniques like LASSO and elastic net, they showed that the combination of Google's research category with conventional economic indicators produced superior forecasts than autoregressive standards. The findings indicated that the profits were more pronounced at the nowcasting and short-horizon levels, and the performance was not different between the two nations. Strangely enough, even subcategories of Google Trends information did not provide additional predictive data compared with the primary categories. The paper highlights the value of incorporating the sources of the big data into the econometric models in order to improve the forecasting of the growth of the GDP [16].

In their investigation of the impact of this independent variable on GDP in the Chinese provinces, they proposed using nocturnal light (NTL) remote sensing data as an exogenous variable to forecast GDP. The authors compared many models, including Linear Regression, ARIMA, AutoRegressive Integrated Moving Average with Exogenous Variables (ARIMAX), and Seasonal AutoRegressive Integrated Moving Average (SARIMA), using GDP data from 1992 to 2016 as well as DMSP/OLS and NPP/VIIRS NTL data. The ARIMAX model that used the NTL data generated the most accurate predictions when evaluated against the GDP for 2017–2019, exhibiting the strong correlation between light intensity and economic activity. It also estimated the growth of GDP by 2030 which revealed imbalanced development patterns among provinces and the necessity to adopt region-specific development policies. This study indicates that remote sensing data can enhance the precision of GDP forecast and address spatial economic imbalance [17].

Yu (2022) recommended an improved neural network based on the Radial Basis Function (RBF), which may be employed to forecast GDP and address the challenges of forecasting extremely intricate nonlinear macroeconomic systems. The model integrates the global species search with rapid convergence and estimation by utilizing the Shuffled Frog Leaping Algorithm (SFLA). Network training, input and output data normalization, and differences of the outcomes with traditional prediction models were all part of the procedure. Through experimental tests for instance the Hermite poly approximation and the Iris classification benchmark, it was shown that the SFLA-optimized RBF network had a lower Root Mean Squared Error (RMSE) and bettered predictive performance. The article highlights the effectiveness of the hybrid neural network-optimization models in the context of economic forecasting, and it can be further expanded to heighten the optimization parameters to improve the efficiency of the computations [18].

Lu (2021) developed a hybrid GDP forecasting model that combines a Backpropagation (BP) neural network with an ARIMA model. First, the linear trend will be extracted using ARIMA. Next, the nonlinear residual force will be forecasted using the BP neural network, and finally, an ultimate forecast will be made based on the combination of the two. This is because, in contrast to other research that focused mostly on weighted model combinations, this study integrates error correcting mechanisms as an integration method. According to experimental validation, the BP neural network's daily prediction error was comparatively low (1.5% compared to ARIMA 2.0). In addition to that, the error-corrected ARIMA-BP model performed better than individual models and conventional combination of weights, which highlights the relevance of mixing linear and nonlinear methods. The paper concludes that the nonlinear mapping of neural networks supplements the time-series capabilities of ARIMA and, thus, the combination of the two frameworks is more precise and resilient in GDP prediction [19].

Using quarterly data of the U.S. GDP from 1976 to 2020, researchers examined the prediction performance of machine learning, linear regression, and autoregressive models. According to their findings, the KNN model would perform best in a one-step ahead forecast since it would capture the self-predictive patterns of GDP. However, when measured over long horizons and incorporating financial and macroeconomic variables, such as the yield curve, linear regression would have the best predictive power. They also noted that linear regression and KNN performed better than standard time series models in the post-COVID-19 period, indicative of the potential application of a dual forecasting approach, that is, KNN to make short-term corrections, and linear regression to design long-term policies [20].

The majority of the studies have only been carried out in one country, have very thin methodological comparisons, or have model-based assessments, as shown in Table 1, despite the fact that statistical-based models (e.g., ARIMA, ES), machine learning (e.g., neural networks, XGBoost), or a combination of these methods have been used to forecast GDP in the past. Experiments comparing statistical and machine learning models between developed and emerging economies and linking forecasting accuracy to policy applications are scarce in the literature. By comparing ARIMA, ES, and XGBoost in India and the US, this article closes that gap and combines methodological rigor with policy relevance. Broadening the socioeconomic application of GDP projections on a national and international level in relation to their use in infrastructure development, monetary policy, fiscal policy, and inclusive development plans is crucial, in addition to methodological comparisons.

3 Methodology

In this study, GDP forecasting was conducted using a univariate approach, where only the historical GDP series is employed as the input variable for ARIMA, ES, and XGBoost models. This deliberate action is used to determine a preliminary predictability metric. By examining solely univariate models, it will be possible to evaluate the relative effectiveness of modern machine learning techniques and conventional statistical methods without the variability and inconsistency that are frequently taken into account when other macroeconomic factors are added. It also makes the country comparative, since GDP is always available and is reliably measured in both India and the United States unlike other indicators like trade balances, unemployment, or fiscal deficits which are defined differently, vary in frequency and reliability. Furthermore, because of its univariate emphasis, the work serves as a springboard for additional research. The general structural causes of economic growth are not provided by univariate models, despite the fact that they provide insightful information on predictive variability. Future iterations of this work will incorporate multivariate models with macroeconomic factors such as interest rates, inflation, and external trade variables. These models are intended to increase the breadth of explanations and the applicability of policy. The more complex, covariate-heavy approaches can then be compared to the rigorous baseline provided by the current study, which can be used to test forecasting models in the future.

Table 1 Comparative Literature Review on GDP Forecasting Models for Selected Countries

Author(s), Year	Country/Region	Method / Model	Data Source	Key Findings
Abonazel & Abd-Elftah (2019) [7]	Egypt	ARIMA (1,2,1)	World Bank (1965–2016)	ARIMA (1,2,1) gave the best fit with the lowest MSE, AIC, and BIC; forecasted a slight increase in GDP from 2017 to 2026.
Tkacz (2001) [8]	Canada	Neural Networks vs Linear/Univariate Models	GDP growth, financial indicators	Neural networks reduced forecast errors for yearly growth; limited advantage for quarterly GDP; unable to beat naïve model.
Hossain et al. (2021) [9]	Bangladesh	Machine Learning (various algorithms)	GDP per capita, inflation, debt, investment, remittances, unemployment	ML models captured nonlinear relations; identified key drivers of GDP growth; offered policy insights.
Islam et al. (2021) [10]	Indonesia	XGBoost (with KDD methodology)	USD/IDR exchange rate (Investing.com)	XGBoost achieved low RMSE (0.235%) and MAPE (0.116%); effective for exchange-rate-based GDP forecasting.
Bharathi & Navaprakash (2024) [11]	India	XGBoost vs Adaboost	20-sample GDP dataset	XGBoost outperformed Adaboost (94% vs 89% accuracy); highlights importance of algorithm selection.
Zheng (2022) [12]	Shanghai, China	ARIMA vs ES (Holt–Winters)	Shanghai GDP (31 years)	ES performed better for long-term trend-driven GDP influenced by policy; ARIMA less effective.
Al-khateeb & Jaradat (2023) [13]	Jordan	Multivariate Linear Regression & Exponential Smoothing	Jordanian statistics (2008–2019)	Regression model achieved $R^2 = 0.9959$; ES provided forecasts up to 2025; both useful for policymakers.
Dritsaki & Dritsaki (2022) [14]	Greece	ETS (ES State-Space)	Quarterly GDP data	Model with multiplicative error and trend performed best; predicted GDP decline in short term.

Our research aims to forecast India's GDP using the XGBoost, ES, and ARIMA models. In addition to collecting data, preprocessing it, implementing and evaluating it, the methodology includes all the phases. To justify the selection of these techniques, we need to look at their effectiveness with respect to time series forecasting

3.1 Descriptive Statistics

India's GDP is growing steadily, with a median value of 1,765.00 billion USD and an average of 1,646.14 billion USD, with considerable variability (standard deviation of 864.95). On the other hand, Table 2 displays a median GDP of 15,300.00 billion USD and a substantially higher average GDP of 15,913.64 billion USD, with greater variability (standard deviation of 3,776.53) across the USA.

Table 2 Descriptive Statistics of GDP (in Billions USD) for India and USA

Country	Mean	Std. Error	Median	Std. Deviation
India	1,646.14	184.41	1,765.00	864.95
USA	15,913.64	805.16	15,300.00	3,776.53

3.2 Dataset preparation and pre-processing

For this study, the dataset focused on India's and US GDP values spanning from 2000 to 2021. The data was gathered from www.kaggle.com and went through several pre-processing stages. These included addressing any missing values, converting non-stationary data and normalizing variables when required. To assess the prediction performance, the dataset was divided into two parts i.e. training data from 2000 to 2016 and test data from 2017 to 2021. The R software was chosen as the primary tool for this research due to its all-embracing capabilities in statistical computing, time series analysis and data visualization.

3.3 Model Selection and Justification

Three predictive models have been chosen for examination:

1. **XGBoost:** XGBoost is a powerful machine learning model that is most popularly known for its ability to uncover complex patterns within data. It makes use of collection of decision trees that are meticulously configured via regularization techniques. These decision trees make the model highly effective in detecting multifaceted, non-linear relationships while also enriching its predictive performance and offers robustness against overfitting. It acts as an excellent choice for time series forecasting that consist of complex patterns and multi-dimensional data.
2. **ES:** ES is a conventional statistical approach that gives decreasing weights to previous observations, which makes it proficient at handling recent patterns or seasonal fluctuations. Moreover, methods like Holt's linear trend and Holt-Winters' seasonal approach are beneficial while modeling stable economic indicators with foreseeable trends like GDP. This technique offers accurate forecasts when it comes to data that incorporates stable and structural patterns.
3. **ARIMA:**: An essential technique in time series prediction, ARIMA employs weighted moving averages, differencing, and the analysis of past data. It entails three main factors: Auto Regressive (AR), Integrated (I), and Moving Average (MA), which collaborate to detect and predict patterns in time series data. These models were opted to enable a contrast between machine learning methods and traditional statistical techniques.

3.4 Stationarity Testing for Augmented-Dickey-Fuller (ADF)

A vital trait of time series analysis, specifically concerning statistical modelling and forecasting, is stationarity. A time series is deemed weakly stationary if its mean, variance, and autocovariance structure remain invariable over time. To make certain that the estimated parameters keep hold of their significance over time, various econometric and prediction models, including the ARIMA model, presume stationarity. Trends, seasonality, and unit root attributes are typical traits of non-stationary data that can bring about incorrect regression deductions and predictions. Inaccurate outcomes may occur if the model mistakes trends and variations for long-term patterns when non-stationarity exists. To fit the ARIMA model, differencing will be applied to remove non-stationarity from India's GDP data, transforming it into a stationary series. The ADF test evaluates if the data exhibits stationarity. The data is considered non-stationary when the p-value from the test exceeds 0.05, in which scenario differencing should be applied. Differencing is a method employed to remove trends and stabilize the average by deducting the earlier observation from the present one.

3.5 Finding the Parameters of the ARIMA Model with ACF and PACF Analysis

To help determine the order of the AR and MA components of the ARIMA model, the AutoCorrelation Function (ACF) measures the correlation between a time series and its lagged values, capturing both direct and indirect dependencies, while the Partial AutoCorrelation Function (PACF) isolates the direct effect of a given lag, controlling for the intermediate lags. The ACF plot was analysed to determine the lag at which autocorrelations significantly diminish, which provided information about the appropriate MA(q) order, while the PACF plot was evaluated to determine the lag structure of the AR(p) component by determining the point at which partial autocorrelations drop to insignificant levels. These diagnostics were employed to identify the finest values for p and q to construct an ARIMA model for predicting GDP.

3.6 Forecasting GDP

Post choice of the most appropriate ARIMA model, historical GDP values were fed into the model to generate predictions for the years 2017-2021. The model was trained on past data from 2000-2016 to identify long term trends,

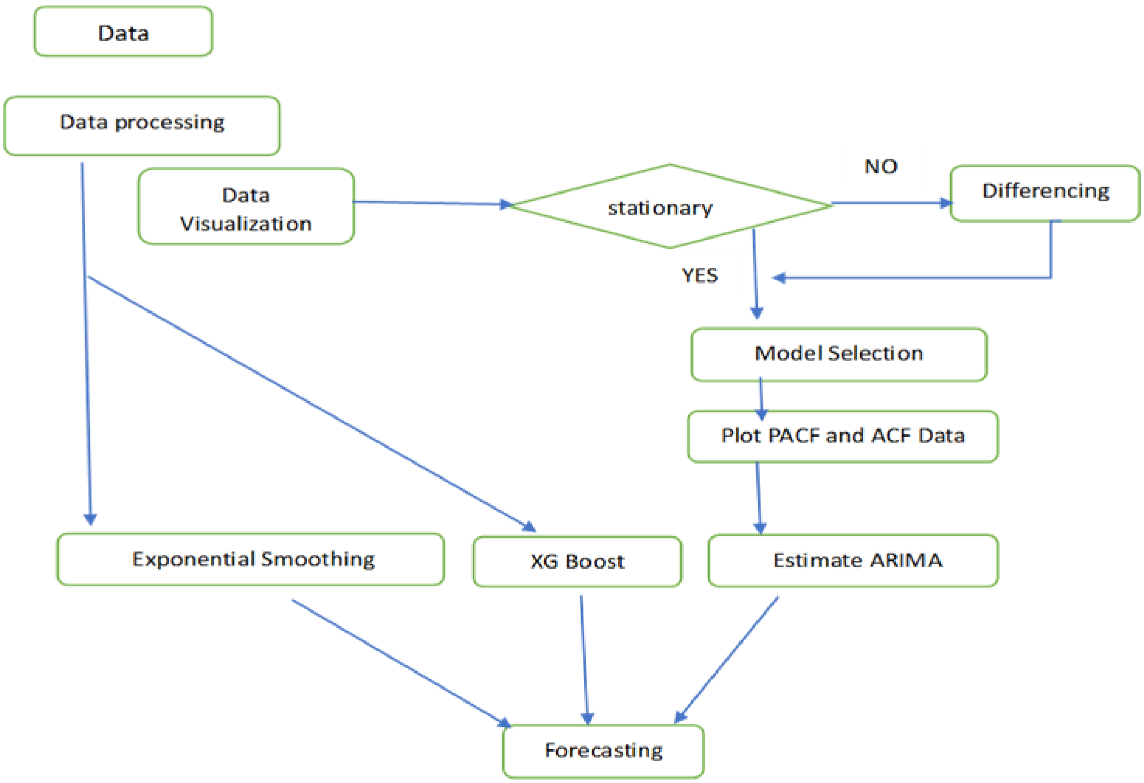

Fig. 1 Flow chart

cyclical patterns and underlying economic changes. Using the fitted model, the forecasts for GDP were generated, in view of historical economic trends illustrated by the examination of ACF and PACF plots. A comparison was drawn between actual and predicted GDP values to appraise the accuracy of the predictions. Likewise, error metrics such as Mean Absolute Deviation (MAD), MSE, MAPE were computed to assess the forecast performance of the model. The Box-Jenkins methodology, a methodical approach for recognizing, estimating, and diagnosing time series models, inspired the flowchart used in this study is illustrated in Figure 1. The Box-Jenkins approach, traditionally applied with ARIMA models, put emphases on key steps such as verifying stationarity through differencing, determining the model with ACF and PACF plots, estimating parameters, and evaluating the model's validity [21][22]. The approaches applied in this research go beyond of conventional statistical modeling to incorporate ES and existing machine learning techniques such as XGBoost.

4 Results and Analysis

This research aims on concluding the most effective technique for predicting GDP growth in India and the USA: ARIMA, ES and XGBoost. The study's findings support data-driven decision making for future forecasts and offer essential insights into the strengths and weaknesses of statistical and machine learning models corresponding to economic forecasting.

4.1 Assessment of the ES Model for Forecasting India and USA's GDP

The procedure began by splitting the data into two fragments: the training data from 2000 to 2016 and the test data spanning from 2017 to 2021. Based on the training data, values of test data were predicted to assess the precision of ES in predicting GDP of both the nations. In comparison of the predicted and actual GDP values, the predictive performance of the model was evaluated. The findings in Table 3 reveal that although the ES model worked effectively in highlighting the overall pattern of India's economic expansion, there were some deviations of expected values from actual GDP values. The actual GDP in 2017, for instance, was $2.62 trillion, while the forecasted GDP was slightly lower at $2.41 trillion. Similarly, the model's 2018 GDP estimate of $2.53 trillion varied marginally from the real GDP of $2.76 trillion. The trend prevailed with a forecast of $2.66 trillion while the observed GDP was $2.85 trillion in 2019. Owing to the COVID-19 pandemic and other correlated factors, India's GDP fell to $2.67 trillion in 2020, however the model predicted an upward trend from 2019 and forecasted GDP as $2.78 trillion instead. The model forecasted a GDP of $2.90 trillion by 2021, taking into account the previous year GDP. But the actual GDP jumped significantly to $3.20 trillion post COVID-19 recovery. Altogether, the ES model represented the general trend accurately but underrated economic fluctuations, stressing the need for modifications when external shocks affect GDP growth.

Table 3 India and USA GDPs (2017–2021) using ES (in trillions of US Dollars)

Year	India Predicted	India Actual	USA Predicted	USA Actual
2017	2.41	2.62	19.26	19.50
2018	2.53	2.76	19.83	20.50
2019	2.66	2.85	20.39	21.40
2020	2.78	2.67	20.95	21.10
2021	2.90	3.20	21.51	23.30

The findings in Table 3 highlighted that there was variation between expected and real GDP values, although ES model accurately showed the general trend in GDP growth. The actual GDP in 2017 was $19.50 trillion, compared to the model's $19.26 trillion prediction. Likewise, the 2018 GDP estimate was $19.83 trillion, which was marginally less than the $20.50 trillion real GDP. The trend persisted in 2019, when the observed GDP was $21.40 trillion, while the predicted GDP was $20.39 trillion. On the same line as India, the COVID-19 pandemic-induced economic shrinkage caused a decline in the USA GDP in 2020 to $21.10 trillion whereas, the model predicted a growth to reach $20.95 trillion. Following the recovery from the pandemic, the actual GDP rose to $23.30 trillion by 2021, but the estimated amount stayed lower than it at $21.51 trillion. Analysing the results of accuracy of ES in predicting GDP of the two countries, we get familiar with the benefits and drawbacks of using this model for economic forecasting. While the model works well in identifying long term trends, it falls short when it comes to taking into account, the abrupt and unpredictable economic shocks like financial crisis or worldwide pandemics since it is based upon the idea that the historical patterns prevail in future as well.

4.2 Findings from XG Boost' s GDP Forecast for India and USA

The second model we used to estimate the GDP of the USA and India was the XGBoost model. Evaluating the forecasts of India's GDP from 2017 to 2021 using the XGBoost model serves as crucial information to demonstrate the effectiveness of the model for future predictions. To recognize any potential limitations or areas of improvement in model's capacity for forecasting GDP, a comparative table of predicted and actual GDP values was studied. The actual values were seen to follow an upward trend, ultimately attaining $3.20 trillion in 2021 but the XGBoost model consistently predicted a GDP of $2.29 trillion for all the five years of test data. This divergence indicates that the model was unable to factor in the underlying economic forces driving GDP growth over time. There are multiple causes of such low variation in predictions. First, there is a chance that the model overfitted to the training data (2000-2016), successfully identifying the historical trends but faced challenges while projecting outside the observed time period. Secondly, the essential macroeconomic indicators that are critical to GDP fluctuation, like inflation rates, trade balances, policy changes and external economic shocks, seem to be missing from the model.

From Table 4, it can be observed that the XGBoost model did not account for the economy's natural growth and fluctuations, steadily estimating a GDP of $18.70 trillion for the period from 2017 to 2021. The actual GDP numbers, on the contrary, show a persistent upward trend: $19.50 trillion in 2017, $20.50 trillion in 2018, $21.40 trillion in 2019, $21.10 trillion in 2020, and $23.30 trillion in 2021. This disparity reflects that the model underestimated GDP growth by failing to take into consideration the changing economic mechanisms. We are faced with a notable weakness in the XGBoost model: its inability to factor in structural and economic disturbances. The COVID-19 pandemic serves as a good example here which diminished the USA GDP to $21.10 trillion. However, the model could not capture the drop and instead, continued to predict $18.70 trillion for USA GDP. These findings show that although XGBoost understands past trends well, it has trouble in accommodating unpredictable changes in the economy. One of the main causes of this limitation is that XGBoost is less sensitive to external economic shocks like pandemics, policy changes, and global

Table 4 India and USA GDPs (2017–2021) using XGBoost (in trillions of US Dollars)

Year	India Predicted	India Actual	USA Predicted	USA Actual
2017	2.29	2.62	18.70	19.50
2018	2.29	2.76	18.70	20.50
2019	2.29	2.85	18.70	21.40
2020	2.29	2.67	18.70	21.10
2021	2.29	3.20	18.70	23.30

financial crises because it mainly depends on historical data patterns. Future studies should concentrate on improving feature selection by integrating macroeconomic factors that have a direct impact on GDP growth in order to boost XG Boost's forecasting performance.

4.3 Time Series Modeling for India and USA's GDP Prediction Using ARIMA

A popular statistical method for time series forecasting, especially with regard to financial and economic data like GDP, stock prices, and inflation, is the ARIMA model. It is crucial to confirm that the time series is stationary that is, that the mean, variance, and autocorrelation structure hold steady over time before implementing ARIMA. Statistical tests like the ADF test are commonly used to confirm this. Trends and seasonality are eliminated using differencing techniques if stationarity requirements are not satisfied.

4.3.1 Assessing Stationarity with the ADF Test for India's GDP

Non-stationary time series can produce forecasts that are not reliable, ensuring stationarity is an essential precondition for ARIMA modelling. Using 5% significance level, ADF test was deployed to check for stationarity of India's GDP data. A p-value of 0.03 and a Dickey-Fuller test statistic of -3.8624 was obtained. As the p-value was less than the 0.05 cutoff, it was validated that the GDP series was stationary and the null hypothesis of a unit root was rejected. This finding established that the series could be used in its current form without any transformations or differencing. The original dataset was initially subjected to ADF test to assess stationarity but the test results pointed to non-stationarity through the presence of a unit root. So, as a next step, first-order differencing(d=1) was performed by calculating the difference between consecutive GDP observations to remove trends and stabilize the mean. The ADF test was re-executed, resulting in a test statistic of -3.8624 and a significantly lower p-value. Thus, it was confirmed that the transformed GDP series is appropriate for statistical modeling.

4.3.2 ACF and PACF plots for India's GDP

The ACF plot for India's GDP is shown in Figure 2 that depicts the correlation between GDP values and past observations over a number of time lags. The high strength of trend in the data can be seen on the basis of the ACF values in the plot, represented by vertical bars declining steadily over time. Given how heavily GDP values rely on their historical values, this implies that the time series is non-stationary. The necessity of transformation methods like differencing to attain stationarity is further supported by the existence of statistically significant autocorrelations outside of the confidence intervals, which are shown by the blue dashed lines. With an autocorrelation coefficient of roughly 0.85 at lag 1, Figure 2 shows a significant positive correlation between the GDP of the current year and that of the previous year. The autocorrelation progressively decreases with increasing lag, reaching 0.4 at lag 5 and getting close to zero near lag 10. Even at higher lags, some values, however, continue to be marginally significant, suggesting a slow rather than an abrupt decay. Before using time series modelling techniques like ARIMA, this pattern indicates that India's GDP data follows a consistent long-term trend, requiring differencing to eliminate non-stationary effects. Provided PACF plot in Figure 2 shows a notable peak at lag 1, which is followed by a steep drop with no more notable peaks outside of the confidence interval. India's GDP is strongly impacted by its recent past value, but not significantly by further lagged values, according to this pattern, which is suggestive of an AR (1) process. A cutoff in PACF after lag 1 in the context of ARIMA modelling corresponds to a possible AR (1) model, indicating that GDP values can be reliably predicted by a first-order autoregressive process. This interpretation is consistent with GDP's economic nature, which holds that historical values significantly influence current trends.

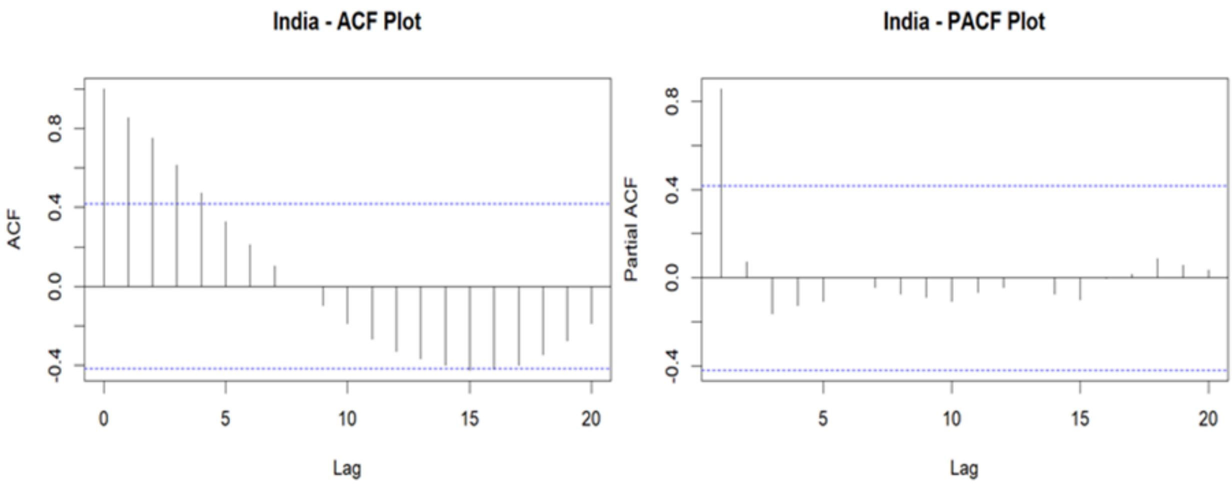

Fig. 2 ACF and PACF plots for India's GDP

4.3.3 ARIMA model selection for India

The ACF and PACF plots were examined to identify the best ARIMA model for predicting India's GDP. This was done by identifying the relevant AR and MA components. Since the ACF plot was characterised by a gradual decay, it was clear that the data was non-stationary. First order differencing(d=1) was used to convert it into stationary data. Post differencing, the significant spike at lag 1 indicated a moving average component. At the same time, the PACF plot with a sharp cutoff after lag1 led to the usage of AR (1) process. Altogether, ADF test results verifying stationarity post first-order differencing and patterns in ACF and PACF plots served as the reason for choosing ARIMA (1,1,0) model.

•**d (Differencing Order):** indicates how many times the series must be differenced in order to become stationary.($d = 1$)
•**p (Autoregressive Order - AR):** indicates how many lag values were used in the regression model.($p = 1$)
•**q (Moving Average Order - MA):** indicates how many lags forecast errors are incorporated into the model. ($q = 0$)

Using ARIMA model, India's GDP for the years 2017-2021 was forecasted and the predictive accuracy was analysed by measuring the difference in actual and predicted GDP figures. The observations highlight that the model underestimated for all the years. Figure 3 shows that there is a considerable difference between the model's forecasted GDP value, $2.38 trillion and the real GDP value, $2.62 trillion. Following the same trend, the model produced lower values than the true GDP values in 2018 ($2.76 trillion actual vs. $2.44 trillion predicted) and in 2019 ($2.85 trillion actual vs. $2.48 trillion predicted). The year 2020, marked by an economic disruption due to COVID-19 pandemic, witnessed GDP declining to $2.67 trillion. But the model could not effectively reflect the magnitude of the economic shock in its prediction of $2.50 trillion, bringing into light, its inability to factor in abrupt shocks. In addition to this, its shortcoming is also reflected in its incapacity of capturing swift economic recovering, like here in 2021, when the actual GDP rose to $3.20 trillion while the model only forecasted $2.52 trillion. In Table 5 and Figure 3, estimates of India's GDP from 2017-2021 along with

Table 5 India GDP (2017–2021) using ARIMA (in trillions of US Dollars)

Year	Predicted	Actual Values
2017	2.38	2.62
2018	2.44	2.76
2019	2.48	2.85
2020	2.50	2.67
2021	2.52	3.20

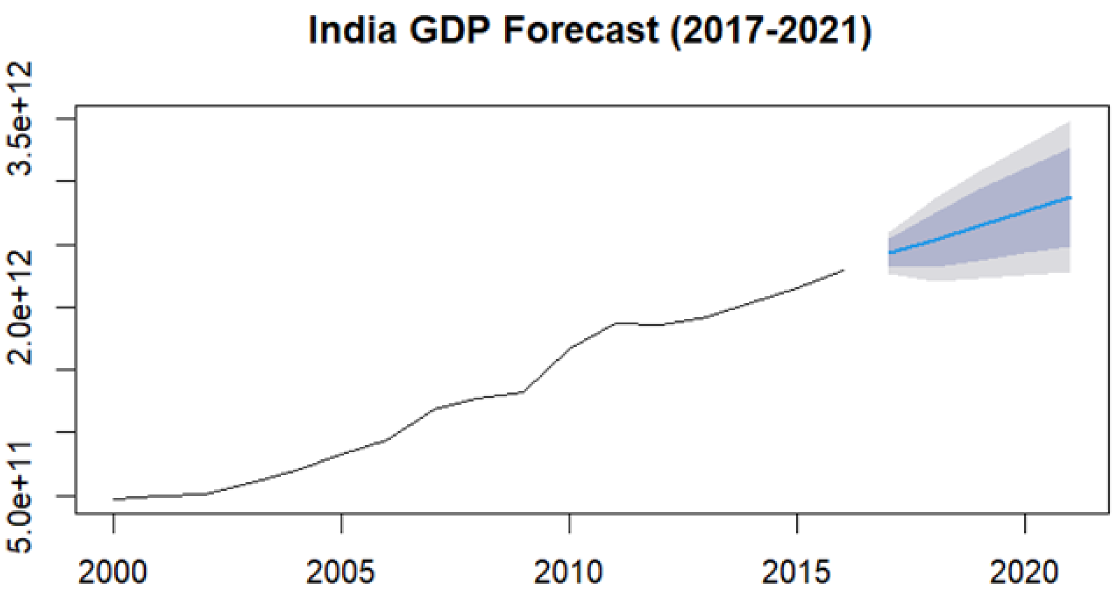

Fig. 3 India's Forecast for the years 2017-2021

the historical data have been plotted using ARIMA model which are approximately \$2.38 trillion in 2017, \$2.44 trillion in 2018, \$2.48 trillion in 2019, \$2.50 trillion in 2020, and \$2.52 trillion in 2021. There are deviations between the estimated and actual values, the biggest discrepancy being in 2021 when the GDP grew noticeably to \$3.20 trillion but the model underpredicted it as \$2.52 trillion.

4.3.4 Assessing Stationarity with the ADF Test for USA's GDP

With a significance level of 0.05, the ADF test was conducted to examine the stationarity of GDP data from the United States. The test statistic came out to be -2.5256 while the p-value was 0.3721. Since the p-value exceeded the 0.05 significance level, the null hypothesis of a unit root could not be rejected. This indicated that the U.S GDP series was non-stationary in the initial form. To ensure that the series was made stationary and consequently, suitable for ARIMA modelling, the method of differencing was adopted. On performing first-order differencing(d=1) between successive GDP values, stationarity was attained, eliminating trends and obtaining steady mean. On re-running the ADF test, an improved statistic of -2.5256 and a notably lower p-value was generated. These insights formed the statistical foundation for verifying that the differenced GDP satisfied the stationarity assumption of ARIMA modelling.

4.3.5 ACF and PACF plots for USA's GDP

The monotonic reduction in autocorrelation over successive time lags pointed towards presence of a trend component in the data. A significant positive correlation between the GDP of the current year and that of the prior year is shown by the autocorrelation, which is noticeably high at lag 1 (about 0.85). The autocorrelation values decrease with increasing lag, reaching approximately 0.4 at lag 5 and getting close to zero by lag 10 to 15. Non-stationarity is suggested by this slow decline rather than a sudden cutoff, which emphasizes the necessity of transformation to stabilize the mean.

With a significant positive partial autocorrelation at lag 1 (nearly 0.85), the PACF shows a sharp decline after lag 1 in Figure 4. For higher lags, the PACF rapidly drops near zero. An AR process of order 1 is characterized by this cutoff at lag 1, indicating that GDP is largely dependent on its recent past value rather than on a number of earlier values. Higher-order autoregressive terms are not required because there are no significant correlations after lag 1. The necessity of first-order differencing (d = 1) to eliminate the trend and guarantee stationarity is further supported by comparing the PACF with the ACF plot, which showed a gradual decay.

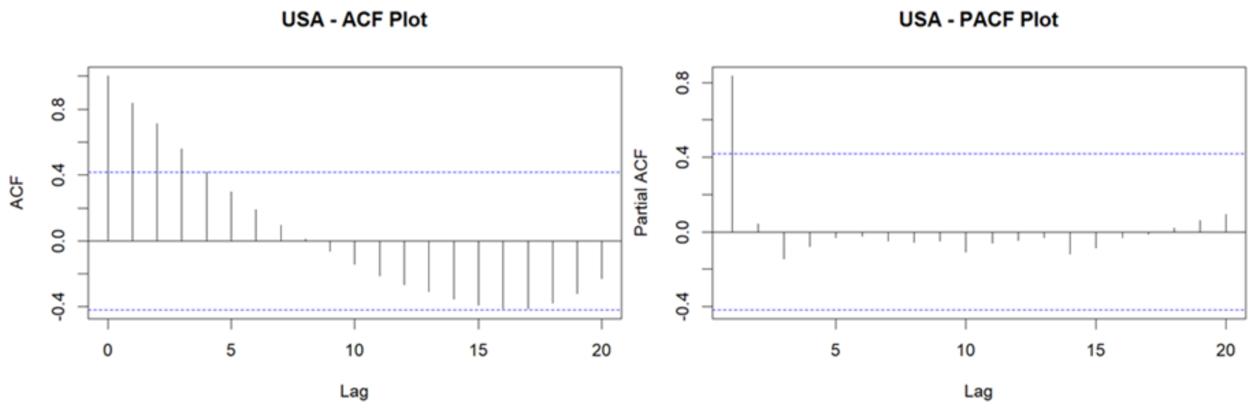

Fig. 4 ACF and PACF Plot for USA's GDP

4.3.6 ARIMA model selection for USA

To decide the ARIMA model best-suited for predicting USA GDP, the corresponding ACF and PACF plots were studied. Determining the appropriate AR and MA components was necessary for this. Steady decline in ACF plot suggested non-stationarity in the data which was resolved using first-order differencing therefore, d was chosen as 1. After differencing, a notable peak at lag 1 and a slow decrease in the values following lag 1 was observed. This highlighted existence of a MA (1) component. Concurrently, the PACF plot was marked by a sharp cutoff after lag 1, indicating AR (1) process. Thus, ARIMA (1,1,0) model was identified as the ideal model. Using ARIMA model, forecasts for USA's GDP for the years 2017-2021 were produced as illustrated in figure 6. The accuracy of the model was assessed by comparing the predicted values with the observed GDP values. In the year 2017, there was an underestimation by the model, its prediction being \$19.12 trillion, while the actual GDP varied slightly and stood at \$19.50 trillion. The trend of underprediction persisted in 2018 and 2019 when the model projected GDP values of \$19.48 trillion in 2018 and \$19.77 trillion in 2019, respectively, whereas the actual values were significantly larger at \$20.50 trillion and \$21.40 trillion respectively as shown in Table 6. The disparity rose substantially in 2020 where the predicted GDP was \$20.02 trillion while the actual GDP was \$21.10 trillion. The economic effects of the COVID-19 pandemic, which interfered with normal growth patterns, are to blame for this discrepancy. The biggest discrepancy occurred in 2021, when the actual GDP jumped to \$23.30 trillion while the ARIMA model predicted a GDP of \$20.23 trillion, underscoring the model's inability to predict abrupt economic recoveries.

Table 6 USA GDP (2017–2021) using ARIMA (in trillions of US Dollars)

Year	Predicted	Actual Values
2017	19.12	19.50
2018	19.48	20.50
2019	19.77	21.40
2020	20.02	21.10
2021	20.24	23.30

4.4 Error Matrix

Three key error metrics MAD, MAPE, and MSE, were utilized to evaluate the models are shown in Table 7. The ES model recorded the lowest MAPE for both India (7.26%) and the USA (3.52%) among the three models analysed: ES, XGBoost,

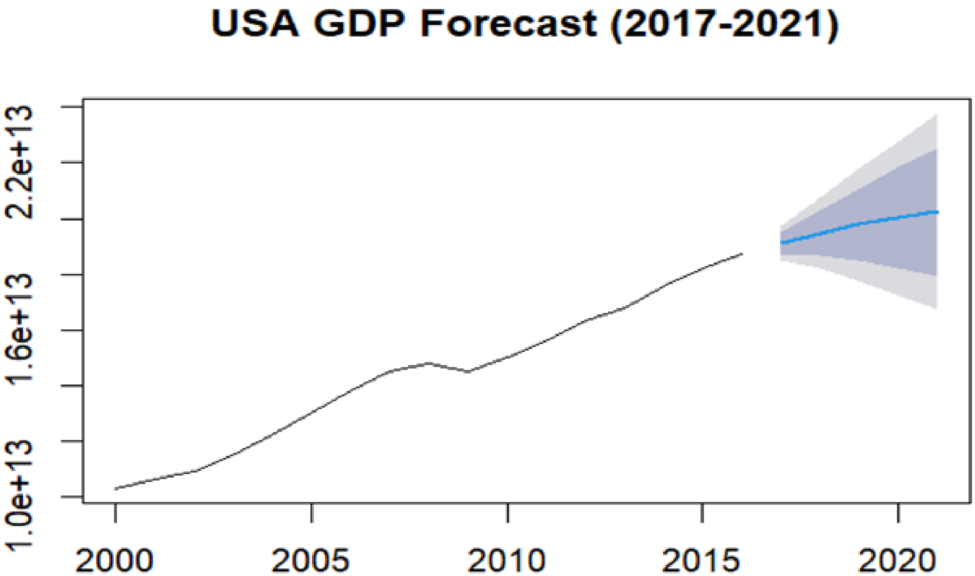

Fig. 5 USA GDP (2017-2021) using ARIMA (in trillions of US Dollars)

Table 7 Error Metrics for India and USA

2*Models	India			USA		
	MAD	**MAPE**	**MSE**	**MAD**	**MAPE**	**MSE**
ES	\$206.9 billion	7.26%	4.65×10^{22}	\$771 billion	3.52%	9.48×10^{23}
XGBoost	\$0.0693 billion	9.10%	0.0055	\$0.3201 billion	19.13%	0.1288
ARIMA	\$3562 billion	12.28%	1.5826	\$14337 billion	6.56%	2.8760

and ARIMA. This implies that in both the instances, ES generated the most accurate predictions with the smallest relative percentage error. ARIMA's forecasts for India had the highest MAPE at 12.277%, indicating that its accuracy was lower in comparison to ES and XGBoost. Correspondingly, XGBoost was the least precise model regarding relative error for the USA, showing the highest MAPE (19.1343%).

4.4.1 Using ES to Project India and USA's GDP for 2022–2026

The exploration of forecasting the model's comparative performance discovered that ES excelled to be the best in predicting GDP with the minimum of relative error, generating the lowest MAPE for India and USA at 7.26% and 3.52% correspondingly. ES was employed to foresee the GDP of India and the USA from the period 2022-2026 as shown in Figure 6, because of its outstanding accuracy and precision as related to other two approaches in minimizing forecasting errors. Estimates indicate \$3.16 trillion in 2022, \$3.29 trillion in 2023, \$3.41 trillion in 2024, \$3.54 trillion in 2025, and \$3.67 trillion in 2026, presented in Table 8. Figure 6 shows a rapid growth in India's GDP. This rising trend aligns with the past trends which signifies continuous economic development. Although, these outcomes rely on macroeconomic stability and the real GDP findings could be affected by external factors in instance as unforeseen economic disturbances, change in policy or worldwide financial unpredictability.

Because of its proven accuracy in reducing forecasting errors, the ES model was used to predict the USA's GDP for the years 2022–2026. The model is a reliable tool for predicting GDP because it smooth's short-term fluctuations while accurately capturing economic trends. With GDP estimates of \$23.57 trillion in 2022, \$24.13 trillion in 2023, \$24.69 trillion in 2024, \$25.26 trillion in 2025, and \$25.82 trillion in 2026, the projected figures show a steady upward trend in the U.S. economy, as shown in Table 8. This steady growth trajectory points to ongoing economic expansion for these

Table 8 India and USA's GDP Forecast for the Years 2022–2026 (in trillions of US Dollars)

Year	India's GDP Forecast	USA's GDP Forecast
2022	3.16	23.57
2023	3.29	24.13
2024	3.42	24.70
2025	3.55	25.26
2026	3.67	25.82

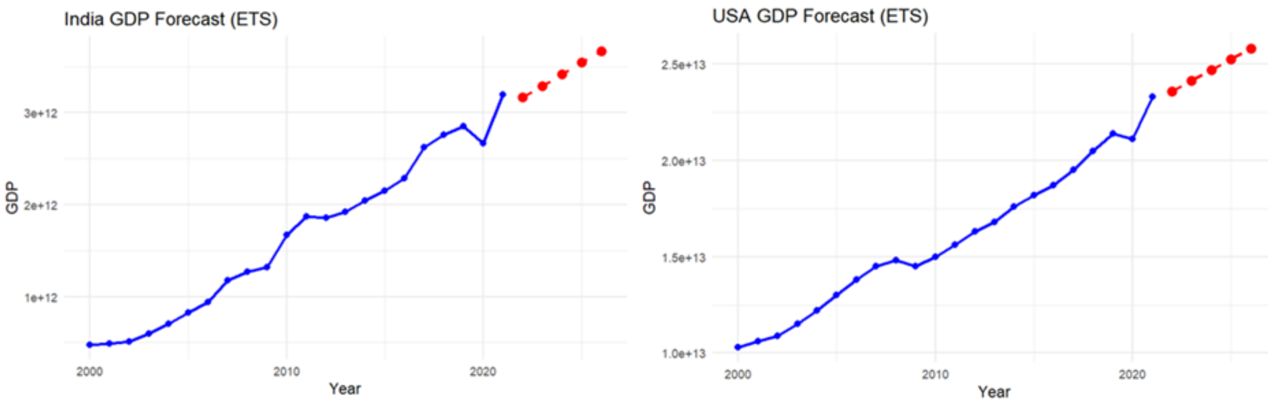

Fig. 6 Forecast Using ES for the years 2022-2026

years as shown in Figure 6. These forecasts, however, are predicated on the idea of steady economic conditions and do not take into consideration possible disturbances like policy changes, inflationary pressures, or geopolitical events.

5 Discussion

ES, ARIMA, and XGBoost, these three models were employed in this study to foresee the GDP of the USA and India for the years 2022–2026. ES showed the highest predictive accuracy, as indicated by the lowest MAPE values for both countries out of all the three models. The outcomes emphasize the significance of GDP forecasting for allocation of resources, financial development, and policy planning. These models help financiers, institutions and policymakers by providing crucial insights through decision-making by recommending a progressive assessment of economic development. The ability to predict future GDP trends aids in the development of policies that support inclusive and long-term growth for two economically significant nations, India and the United States. Due to its capability to detect recent fluctuations in level and momentum impacts in the GDP series, ES performs outperforms others. These assets are particularly pivotal in developing nations like India, where the growth tendencies encompass fiscal spending, a surge in consumption, and a speedier cycle of investments. Although growth in the US is more foreseeable, ES may still acclimate to cyclical factors such as policy alterations or worldwide disruptions.

This study provides significant essential inferences related to academic research in forthcoming years and in real-life scenarios. Policymakers can make use of precise GDP estimates for infrastructure investments, financial planning and employment schemes, fiscal institutions can utilize them to alter interest rates, make outline for financial and economic policies and evaluate private sector firms. In consultation and investment sectors, reliable GDP predictions can offer essential macroeconomic frameworks for strategic planning and decision-making.

The comprehension of the core assumptions of the model is necessary when utilizing ES to foresee future macroeconomic indicators like GDP, which could influence forecast's reliability and accuracy. The model's fundamental presumptions: stability and continuation of historical patterns and trends, accordingly the framework of the past data such as seasonality and trend will persist into the future. This may be fallacious in the event of rapid structural disruptions or unforeseen economic conditions, could affect the reliability of the forecast outcomes.

To foster robust and sustainable GDP growth in the USA and India, policymakers must implement targeted strategies across the essential economic sectors. To leverage its demographic edge, India must concentrate on providing universal access to quality education and vocational training, on the other hand, the USA needs to work upon improving the workforce skills in Artificial Intelligence and renewable energy sectors. Formation of infrastructure is crucial for economic advancement and growth. For the industrial and rural development, India must upgrade its energy, transportation, and digital infrastructure. The USA ought to invest in renewable energy and upgrade obsolete systems. By encouragement of R&D and innovation via financial incentives and collaboration between public and private parties can enhance competition among high-value industries. Both nations need to adopt clean technologies and digital governance models as a part of active transformation to green and digital economies.

During the times of economic disruption as in case of COVID-19 pandemic, which severely impacted the economies of both India and USA, was unforeseen by historical data, the predictions turned out to be vague and untrue. Thereby, when the model overlooks unexpected turning points or non-linear dynamics in economic development, this supposition might generate wrong results. In addition, selection of smoothing parameters influences prediction accuracy which results in deterioration of performance. Beyond technical forecasts, the results have important socioeconomic policy implications. With precise GDP forecasts, governments can anticipate economic downturns that could exacerbate unemployment and poverty. These forecasts support social safety nets and inclusive development programs in India, even as they have an impact on labor market interventions, welfare adjustments, and fiscal transfers in the US. Forecast-based planning thus becomes an essential instrument for preserving balanced growth and reducing inequality.

6 Limitations and Future Scope

It is important to recognize a number of limitations even if this study shows how much better the ES model is than ARIMA and XGBoost. The primary drawback stems from the univariate assumption, which used only historical GDP data to anticipate GDP. Although this method makes model comparison easier, it limits the results' explanatory power because macroeconomic factors that affect GDP dynamics include inflation, interest rates, currency rates, trade balance, and government spending. The model's capacity to represent structural shifts, policy shocks, and interconnections between economic sectors is hampered by the exclusion of key variables. Additionally, historical patterns are assumed to continue into the future in the models, which may not be the case at times of abrupt disruptions like financial crises, pandemics, or significant changes in policy. As a result, these models' forecast accuracy could decrease in unstable or non-linear economic environments.

Future studies should focus on creating multivariate and hybrid forecasting frameworks in order to get around these limitations. Interpretability and accuracy may be improved by include macroeconomic data and policy variables. Both linear and nonlinear relationships can be modeled by combining machine learning techniques (such as neural networks, random forests, or XGBoost) with conventional time series techniques (such as ARIMA or ES). In addition, adding high-frequency or alternative data sources such as satellite imaging, Google Trends, or sentiment indexes may further improve response to real-time economic movements. Future research can offer deeper insights for fiscal planning, policymaking, and crisis management in both developed and emerging economies by extending the analysis beyond univariate GDP series and including a variety of data sources.

7 Suggestions

India and USA necessarily implement resolute and adaptable economic plans or policies to sustain and make the GDP growth better. India's top priorities must include advancement in investment of public and private infrastructure, accelerating business contracts, promoting innovation and entrepreneurship by means of regulatory changes, also to support startups. A skilful and efficient labour force that is the requirement of a rapidly progressing economy can be formed by enhancing the quality of education and professional training. Alternatively, in USA policies that modernize infrastructure, promotion in technical development, and increasing access to wisely priced healthcare and education can led to enhancement in long-term growth and productivity. Additionally, a robust and rigid economic foundation can be set up by regulating inflation, safeguarding macroeconomic stability and by ensuring a complete development agenda by focusing on welfare plans and programs. In addition to being a statistical exercise, GDP forecasting is an essential tool for policymaking. Governments, central banks, and welfare organizations can plan measures that support economic stability and inclusive growth with the help of accurate forecasts. Forecasts' policy relevance may be comprehended in three primary areas:

Fiscal Planning: Governments can predict income flows and modify fiscal budgets, taxation policies, infrastructure projects, and welfare allocations in accordance with accurate GDP estimates. Such as, government bodies might lessen deficits if growth is robust or raise expenses or subsidies if a GDP slowdown is anticipated [23].

Monetary Policy: GDP forecasts act as preliminary warning indicators for central banks, enabling them to modify monetary policy tools like interest rates, inflation targeting, and liquidity control. The central bank may implement stricter policies if estimates imply overheating and reduce rates to stimulate growth if a recession is anticipated [24].

Social Welfare: Precise predictions further reinforce social welfare policies by guiding social safety nets, subsidies, and job initiatives during downturns. For example, estimates of GDP falloff during COVID-19 directly affected welfare assistance and aid packages for underprivileged groups [25].

Conclusion

Compared to ARIMA and XGBoost, ES proved to be the most reliable model for predicting GDP from 2022–2026, showing the fewest prediction errors. Accurate GDP estimates are important for academic modeling, but they also serve as the foundation for evidence-based governance. on practice, accurate forecasts facilitate fiscal planning since they enable governments to create realistic budgets, allocate resources, and concentrate investments on infrastructure and development. They direct monetary policy by giving central banks information on growth cycle prediction, interest rate adjustment, inflation and employment stability. More significantly, social welfare policies are based on GDP projections, which allow decision-makers to anticipate recessions and promptly enact measures like job provisions, subsidies, or safety nets to protect vulnerable groups. Effective GDP forecasting is a crucial tool for preserving stability, reducing inequality, and fostering long-term inclusive growth in both emerging and developed economies, as this study shows by presenting forecasting accuracy as an indicator of fiscal, monetary, and welfare policies.

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