



Uzair Essa Kori¹, Sumreen Fatima², Sumera Saad³, Ammara Tayyab⁴ & Khushboo Ishaq⁵

¹Pakistan Bureau of Statistics, Islamabad Email: uzair@pbs.gov.pk

²Department of Community Health Sciences, Aga Khan university, Karachi Pakistan

Email: sumreen.fatima@aku.edu

³Department of Mathematics and Statistics, Institute of Business Management, Karachi Pakistan.

Email: sumera.saad@iobm.edu.pk

⁴Forman Christian College (A Chartered University), Lahore Pakistan Email: ammaratayyab@fccollege.edu.pk

⁵Department of Statistics, University of Sindh Jamshoro, Pakistan Email: khushboo-2k21@scholars.usindh.edu.pk

KEYWORDS	ABSTRACT
Economic growth; GDP; Forecasting; Time series; Neural networks	Gross domestic product (GDP) growth is an important indicator of macroeconomic performance and provides essential information for economic planning, resource allocation, and policy formulation. Accurate forecasting of economic growth is therefore crucial, particularly for developing economies such as Pakistan, where economic conditions can be influenced by substantial structural and macroeconomic changes. This study comparatively evaluates alternative forecasting approaches for Pakistan's real GDP growth and generates forecasts for the period 2023–2032. Annual real GDP growth data covering 1960–2022 are used to develop and evaluate five forecasting approaches: Autoregressive Integrated Moving Average (ARIMA), double exponential smoothing, multilayer perceptron (MLP), neural network autoregressive (NNAR), and a hybrid forecasting model. The models are assessed comparatively to identify their ability to capture the underlying temporal patterns in Pakistan's economic growth and provide reliable long-term forecasts. The empirical results indicate that the multilayer perceptron (MLP) model provides the most accurate forecasting performance among the evaluated approaches. The findings demonstrate the potential of nonlinear neural-network-based methods to capture complex patterns in Pakistan's historical GDP growth that may not be adequately represented by conventional statistical and exponential smoothing techniques. The resulting forecasts for 2023–2032 provide an empirical basis for assessing the prospective trajectory of Pakistan's economic growth. Overall, the study contributes to the forecasting literature by providing a comparative assessment of conventional, exponential smoothing, neural network, and hybrid approaches using a long historical series of Pakistan's real GDP growth. The findings may assist researchers, economic planners, and policymakers in selecting appropriate forecasting techniques and developing evidence-based strategies for medium- to long-term economic planning.
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Corresponding Author	Sumera Saad & Ammara Tayyab
Email:	sumera.saad@iobm.edu.pk , ammaratayyab@fccollege.edu.pk
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Introduction

GDP measures the total economic output of a nation over a specific time period, including all goods and services produced there. It makes no difference whether the people are local citizens or work for foreign-owned businesses. The government counts their output as GDP if they are within the nation's borders. Understanding Pakistan's economy, a rapidly rising country with a population of over 220 million, begins with measuring and analyzing GDP. For both policymakers and the government, GDP forecasting is crucial, and precise anticipated figures aid in the development of better plans. Government policymakers commonly use GDP forecasting to raise the standard of living for citizens, address unemployment and poverty issues, and other issues that can be readily resolved with the aid of better policies.

Earlier studies forecasted economic time series using a variety of strategies. Univariate forecasting, often known as the Autoregressive Integrated Moving Average (ARIMA) model created by Box and Jenkins in 1976, is one of the methods. This method is well-liked since it has demonstrated the capacity to forecast events with accuracy when all the requirements for its application are met. The ARIMA model was used by Kenny et al. (1998) in one of their studies to forecast inflation in Ireland. In the study, a workable methodology for calculating important parameters, such as the integrated degree, the number of autoregressive terms, and the number of moving average terms necessary for precise inflation forecasting, was presented. This study serves as an example of how ARIMA modelling can be used to forecast Irish inflation. The Autoregressive Integrated Moving Average (ARIMA) model has been widely used in research projects to forecast a variety of economic indicators. Dongdong (2010) examined Chinese monthly CPI data and discovered that an ARIMA (12, 1, 12) model produced reliable forecasts, indicating that it might be used to inform monetary policy decisions. Using an ARIMA model, Kiriakidis and Kargas (2013) accurately anticipated the Greek GDP recession. The consumer price index in Bandar Lampung was predicted using ARIMA (1, 1, 0) by Kharimah et al. (2015), indicating that the CPI will rise in the future. Using an ARIMA (1, 1, 1) model, Dritsaki (2015) predicted the real GDP of Greece and noted consistent growth. Yang and colleagues (2016) used ARIMA (2, 2, 2) to forecast China's Gross Domestic Product (GDP). Wabomba et al. (2016) correctly predicted the annual returns of Kenyan GDP using ARIMA models. ARIMA was used by Uwimana et al. (2018) to forecast GDP growth in African economies until 2030. Agrawal (2018) employed ARIMA to anticipate India's real GDP, and the long-term outcomes were consistent. The ARIMA (1, 2, 1) model was finally found to be suitable for predicting the Egyptian GDP until 2026 by Abonazel and Abd-Elftah (2019).

In a 2007 study, Samimi, Shirazi, and Fazlollahtabar used artificial neural networks and the exponential smoothing technique to forecast Iran's GDP. They used these techniques to anticipate the GDP for the years 2004 and 2005 using quarterly data from 1998 to 2003. Their study's findings demonstrated that using neural networks to forecast GDP produced better results than using other techniques.

Dong and Zhu (2014) made an effort in their 2014 study to predict the per capita GDP for eight regions within China's Yunnan Province. They utilized the exponential smoothing method and the corrected exponential smoothing method to forecast the variable under investigation. The outcomes demonstrated the superior performance of the modified exponential smoothing model (MESM). Recent studies have advanced hybrid decomposition, deep learning, causal estimation, and machine-learning-based forecasting for complex environmental and time-series applications (Qureshi et al., 2025; Abbasi et al., 2026; Noor et al., 2026). These approaches have also been applied to causal and climate-related forecasting problems (Ahmad et al., 2026; Abbas et al., 2026). In order to forecast the indices of economic growth in Turkey, Oral (2019) compared the available exponential smoothing algorithms in order to identify the best approach. According to the study's findings, the best method for predicting the seasonal patterns shown in Turkey's economic development indices is the Holt Winters smoothing exponential model. Recent studies have demonstrated the increasing application of time-series and machine-learning methods to Pakistan-specific economic, social, and environmental problems (Rashid et al., 2025; Muqaddas & Tulain, 2026; Sofia et al., 2026). In contrast to conventional economic forecasting models, machine learning methods place a higher priority on accurate prediction without predefined assumptions or judgements. Due to their improved predictive skills and technical developments, they provide more flexibility and have been widely embraced across numerous domains. Plakandaras et al. (2015) provided an example of how machine learning technologies outperformed conventional econometric models in terms of projecting US property prices. Studies on inflation forecasting carried out by Medeiros et al. (2019) and Inoue and Kilian (2008) provide evidence that these models have also proven their efficacy in low-frequency data sets. Their capacity to generate accurate projections has contributed to their expanding use in a variety of industries, including forecasting of traffic patterns and property prices.

Artificial neural networks (ANNs) are frequently employed as effective forecasting models in a variety of sectors, including economics, business, finance, energy, and hydrology. They are accepted as reliable and frequently used methods for prediction problems. Analysing the relationships between input and output variables forms the basis of ANN models, which makes them appropriate for examining seasonal time series data. Researchers have expressed a lot of interest in using ANNs to forecast occurrences in several fields. Studies in fields like economics, finance, and hydrology have drawn attention to this statistical method, demonstrating how well it can identify intricate patterns and make precise forecasts. By collecting latent characteristics of the population, input variables in forecasting models play a critical role in producing precise forecasts. The neural network approach's capacity to simulate nonlinear interactions without prior knowledge of their nature enables accurate function approximation and is one of its primary advantages. This sets it apart from methods like ARIMA and linear regression, which depend on linearity and might not be appropriate for all types of real-world data. Similar outcomes can be obtained using neural networks as opposed to more conventional methods like (seasonal) ARIMA models. Ali et al. (2026) examined regime shifts and seasonal forecasting of monthly temperature in Karachi, highlighting the importance of accounting for changing temporal patterns in climate series. Additionally, neural networks are capable of handling the forecasting of multivariate time

series, where causal and cointegration investigations are crucial for modelling and prediction purposes.

The hybrid ANN-ARIMA model has three main iterations in the literature. The models run an ARIMA model on a set of time series data before comparing the anticipated data to the actual data and taking into account any errors. Zhang (2003) suggests using an additive Autoregressive Integrated Moving Average-Artificial Neural Network (ARIMA-ANN) model to include a non-linear component. The Wolf sunspot data, Canadian lynx data, and exchange rate data between the British pound and the US dollar are the three unique datasets that this model is used to analyse. Within the ANN framework, several simulations and methodologies are used to look over and evaluate these datasets.

It is crucial to recover these properties from the data in order to capture both the linear autocorrelation structure and non-linear component inherent in time series data. A suggested strategy, as suggested in the Khashei (2012) study, is using the ARIMA linear model residuals to derive knowledge about the non-linearity. Then, for modelling purposes, this data can be put into an Artificial Neural Network (ANN). The same datasets—the Wolf sunspot data, the Canadian lynx data, and the exchange rate data between the British pound and the US dollar—are used to test the generalised hybrid ARIMA-ANN model that is introduced in the article.

Methodology

The data consists of GDP along with per capita income and growth annual change from 1960 to 2022 which are available on the website of Macrotrends (<https://www.macrotrends.net/countries/PAK/pakistan/gdp-gross-domestic-product>).

Methods

Autoregressive Integrated Moving Average

The statistical technique known as ARIMA (Autoregressive Integrated Moving Average) is frequently used for forecasting and time series analysis. To identify the underlying patterns and trends in data, it combines moving average (MA), differencing (I), and autoregressive (AR) components. This makes it possible for researchers to make precise predictions and get insightful knowledge about the behaviour and course of the time series data they are studying. The general autoregressive integrated moving average (ARIMA) process is of the form

$$W_t = \alpha_1 W_{t-1} + \dots + \alpha_p W_{t-p} + Z_t + \dots + \beta_q Z_{t-q}$$

Where $\alpha_1, \dots, \alpha_p$ and $\beta_0, \dots, \beta_q$ are the coefficients of auto regressive (AR) and moving average (MA) process respectively.

The above equation can be written as

$$\phi(B)(1-B)^d X_t = \theta(B)Z_t$$

Double Exponential Smoothing

It is possible to manage time series data with trends using double exponential smoothing, an extension of the standard exponential smoothing method. When the data shows both a trend and a level component, it is especially powerful. Two smoothing factors are used in the procedure, one for capturing the level and the other for capturing the trend. It can create forecasts that include both short-term fluctuations and long-term trends by using a weighted average of previous observations, level, and trend estimations. The general form of double exponential smoothing is of the form

$$\beta_t = \beta(s_t - s_{t-1}) + (1 - \beta)b_{t-1}$$

Where s_t, s_{t-1} are smoothed statistic and previous smoothed statistic respectively. α is the smoothing factor of data which lies between 0 and 1.

Multilayer Perceptron (MLP)

A fundamental and popular artificial neural network model in the fields of machine learning and pattern recognition is the multilayer perceptron (MLP). It is made up of numerous layers of interconnected nodes, also referred to as synthetic neurons or perceptrons. In an MLP, each neuron gets input from the layer before it and uses a nonlinear activation function to produce an output. An input layer, one or more hidden layers, and an output layer are the standard layers that make up a system. By modifying the weights and biases of the connections between neurons through a process called backpropagation, MLPs may learn complex patterns and correlations in data. The general form of MLP model is given as

$$a = \phi \left(\sum_j w_j x_j + b \right)$$

Where X_j are the inputs to the unit, w_j are the weights, b is the bias, ϕ is the nonlinear activation function, and a is the unit's activation.

Neural Network AutoRegressive (NNAR)

The Neural Network AutoRegressive (NNAR) model is a state-of-the-art method for time series analysis and machine learning. In order to capture complicated temporal connections and generate precise predictions, the NNAR model combines the strength of neural networks with the autoregressive framework. Its adaptability and capacity for dealing with non-linear correlations make it a crucial instrument in the field of time series analysis, allowing researchers to gather insightful knowledge and make defensible decisions based on precise forecasts. A NNAR model uses an activation function and a linear combination function. These formations' functions are defined as.

$$net_j = \sum_i w_{ij}y_{ij}$$

$$f(y) = \frac{1}{1 + e^{-y}}$$

Hybrid model

The hybrid model, which combines Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANN), is a novel strategy that makes use of the advantages of both approaches to improve time series forecasting. While ANN can handle complicated nonlinear interactions and capture nuanced patterns, ARIMA captures the linear dependencies and autoregressive character of the data. In this hybrid model, initial predictions are made using the ARIMA model, and the ANN is subsequently fed with the residuals between the expected and actual values. By learning and modelling the nonlinear relationships inside the residuals, the ANN significantly improves the predictions. The hybrid model attempts to increase the accuracy and resilience of time series forecasting by combining the advantages of ARIMA and ANN.

Results and Analysis

Analysis and forecasting is performed using RStudio, jupyter notebook and minitab software.

ARIMA

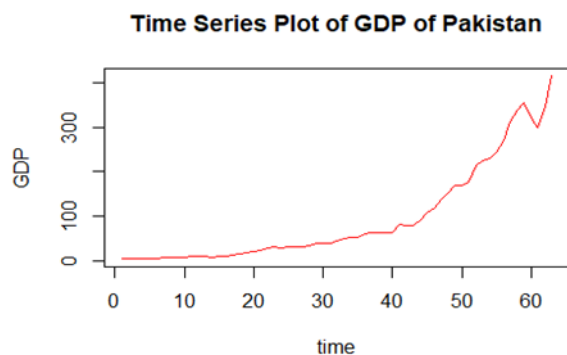


Figure 1: Time series plot of GDP

Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF), and Augmented Dickey-Fuller (ADF) unit root test graphs were used to evaluate the stationarity qualities of the data. The autocorrelation and partial autocorrelation patterns in the data were examined using the ACF and PACF graphs. The ADF test was also used to see if the data showed a unit root, which would indicate non-stationarity. A first-order integration (difference) method was proposed to convert the series into a stationary form in order to overcome non-stationarity.

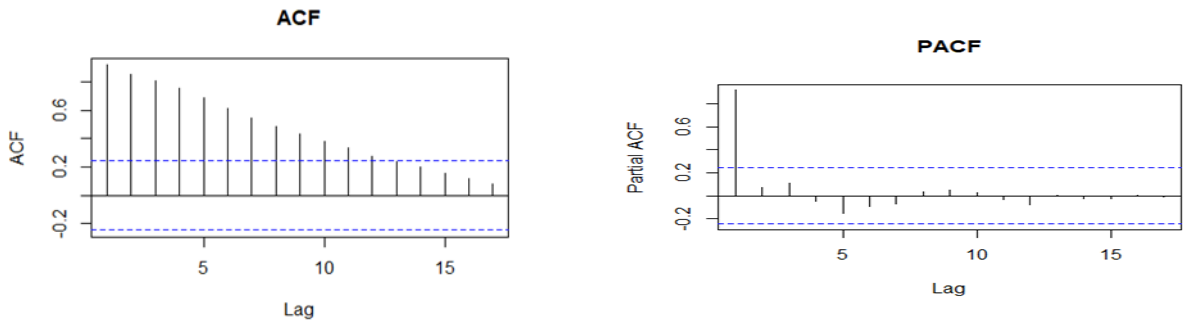


Figure 2: ACF and PACF plots of time series

Table 1: Augmented Dicky Fuller Unit test

Variable	Observed ADF test	Lag order	1 st difference ADF test	Lag order	2 nd difference ADF test	Lag order
GDP	1.6367	3	-4.9602	3	-9.0442	3

The outcome indicates that the data is non-stationary because the p value is higher than the 0.05 level of significance that was specified.

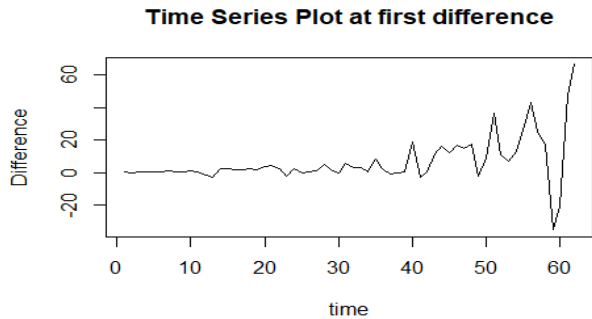


Figure 3: Time series plot at 1st difference

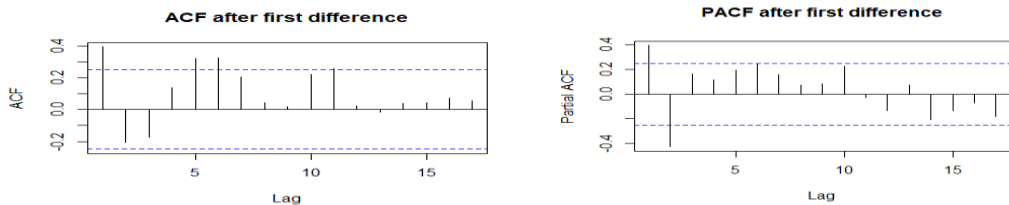


Figure 4: ACF and PACF plots at first difference

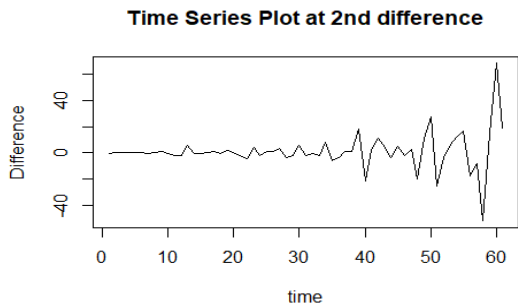


Figure 5: Time series plot at 2nd difference

Graph of second difference of the original GDP shows the stationary of the data.

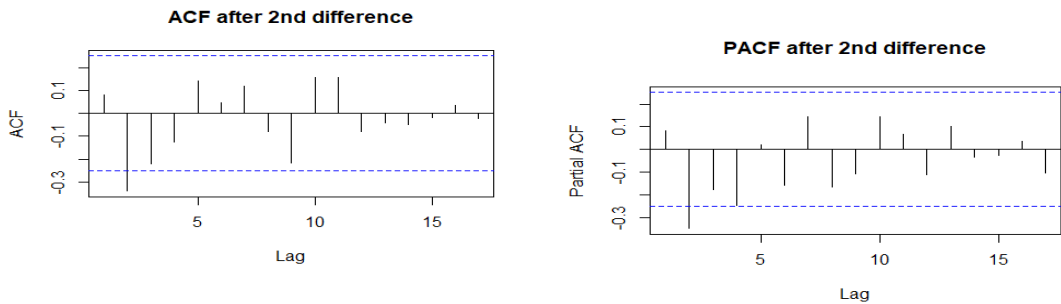


Figure 6: ACF and PACF plots of 2nd difference

Table 2: All possible ARIMA models

ARIMA model	AIC
(2,2,2)*	459.8448
(1,2,1)	496.9115
(1,2,2)	481.5422
(2,2,1)	466.6087

After examining all of these potential models, we contend that the ARIMA (2, 2, 2) model, whose AIC is lowest, is the optimal model for predicting.

Table 3: ARIMA (2, 2, 2) model estimates

ARIMA model (2, 2, 2)		
Type	Coefficient	SE(Coef)
AR1	0.9929	0.1172
AR2	-0.8494	0.0857
MA1	-1.6353	0.1597
MA2	0.7847	0.1482

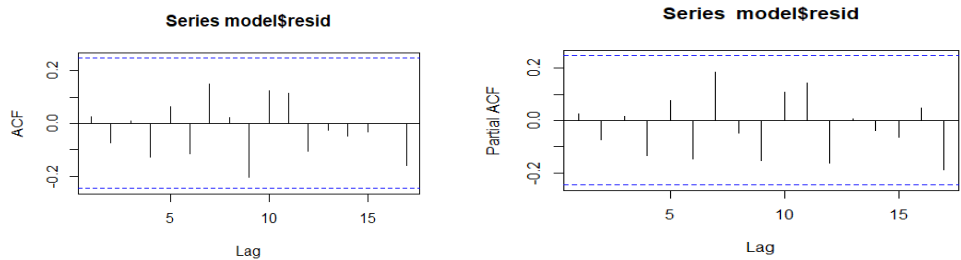


Figure 7: ACF and PACF plots of residuals

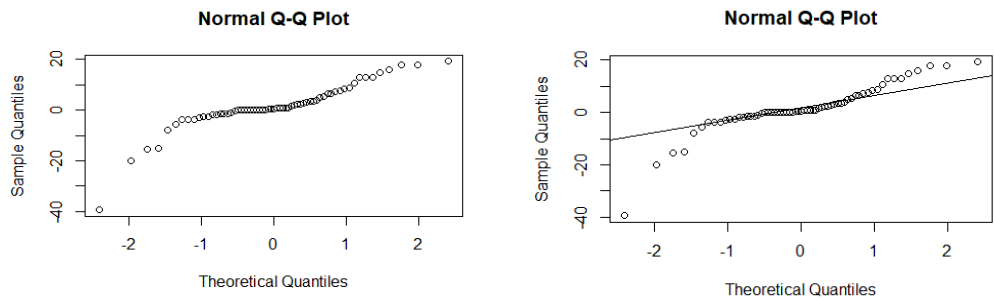


Figure 8: Residuals normal probability plots

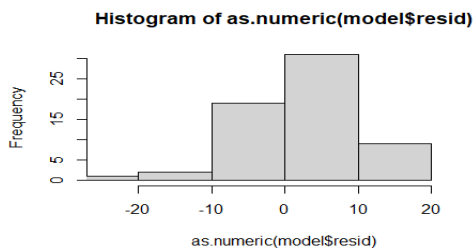


Figure 9: Histogram of residuals

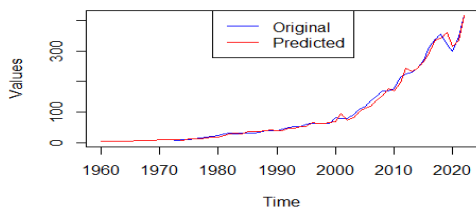


Figure 10: Original vs predicted time series plot

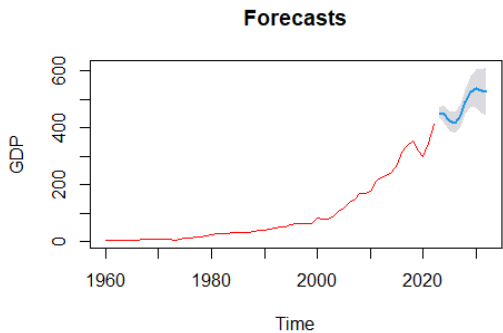


Figure 11: Time Series plot of Forecast GDP for the year 2023 – 2032

Table 4: Forecast for the year 2023 to 2032 at 95% limits.

Years	Forecast	Lower	Upper
2023	453.8394	435.2076	472.4713
2024	449.3195	417.9032	480.7357
2025	425.1375	388.4894	461.7857
2026	418.3584	380.4690	456.2477
2027	445.5578	406.6883	484.4273
2028	491.7124	448.7163	534.7084
2029	527.8269	474.4650	581.1889
2030	537.8735	471.6156	604.1314
2031	530.5655	453.9613	607.1696
2032	528.1677	444.4013	611.9342

Double Exponential Smoothing

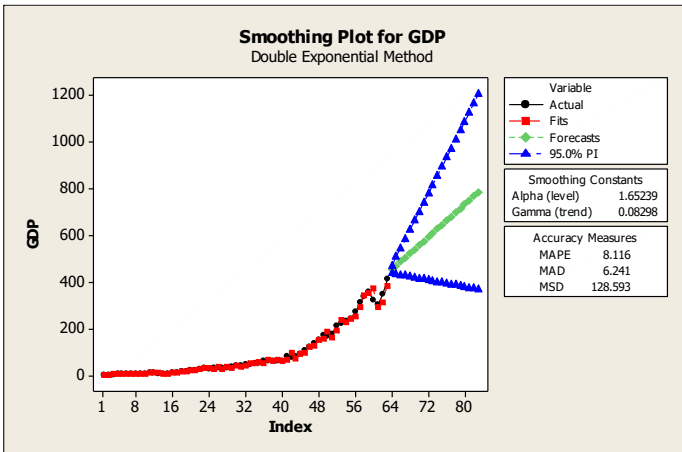


Figure 12: Time Series plot of forecast GDP for the year 2023 – 2032

Table 5: Forecast for the year 2023 to 2032 at 95% limits.

Years	Forecast	Lower	Upper
2023	452.146	436.855	467.44
2024	469.643	433.290	506.00
2025	487.140	429.625	544.66
2026	504.638	425.941	583.33
2027	522.135	422.250	622.02
2028	539.632	418.556	660.71
2029	557.129	414.860	699.40
2030	574.627	411.162	738.09
2031	592.124	407.464	776.78
2032	609.621	403.766	815.48

Multilayer Perceptron (MLP)

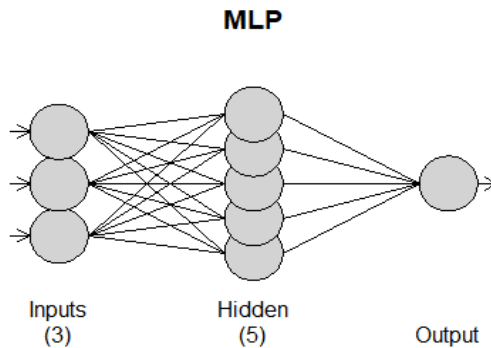


Figure 13: Structure of the multilayer perceptron (MLP) modeling technique.

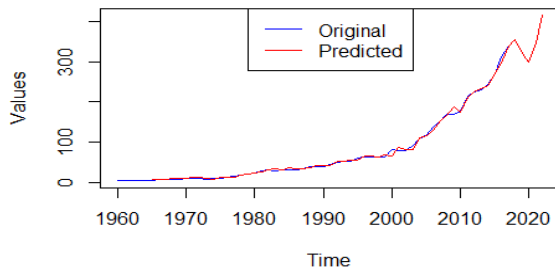


Figure 14: Original vs predicted time series plot

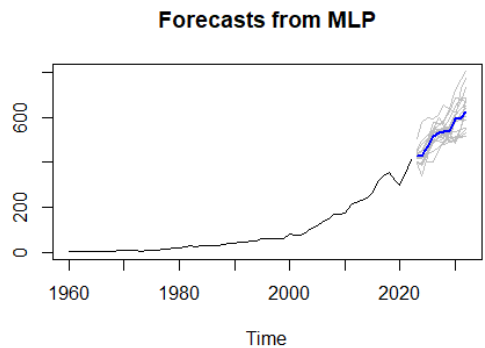


Figure 15: Forecasts from MLP for the year 2023 to 2032

Table 6: Forecast for the year 2023 to 2032.

Years	Forecast
2023	428.0039
2024	430.1770
2025	467.1455
2026	515.7365
2027	529.6469
2028	538.4071
2029	537.3743
2030	590.1146
2031	598.5942
2032	622.1735

Neural Network AutoRegressive (NNAR)

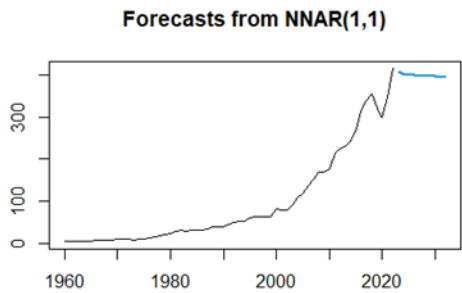


Figure 16: Forecasts from NNAR for the year 2023 to 2032

Table 7: Forecast for the year 2023 to 2032.

Years	Forecast
2023	407.8966
2024	403.5239
2025	400.7283
2026	398.9166
2027	397.7323
2028	396.9538
2029	396.4402
2030	396.1005
2031	395.8755
2032	395.7264

Hybrid model

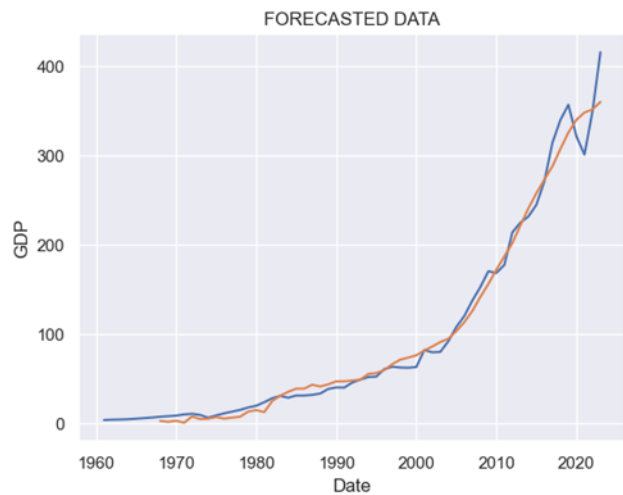


Figure 17: Forecasted data using Hybrid model

Accuracy measures

Numerous researchers used various accuracy measures and statistical tests to evaluate the effectiveness of prediction models in the literature. However, in this study, we first employ three accuracy mean errors, such as the root mean square error (RMSE), the mean absolute error (MAE), and the mean absolute error percentage (MAPE), for the suggested evaluation of all sixteen combination models. The following are the mathematical equations for these mean errors:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_i - \hat{x}_i)^2}{n}}$$

$$MAE = \frac{\sum_{i=1}^n |\hat{x} - x_i|}{n}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{x_i - \hat{x}_i}{x_i} \right|$$

Table 8: Model Comparison

Model	RMSE	MAE	MAPE
ARIMA	9.042239	5.602782	7.825347
Double Exponential Smoothing	11.340001	6.241	8.116
Multilayer Perceptron (MLP)	5.076443	3.043556	10.33367
Neural Network AutoRegressive (NNAR)	12.45796	6.479029	8.417001
Hybrid model	16.11520	8.457237	---

Conclusion

In conclusion, this study intended to create projections for the years 2023 to 2032 in order to offer useful insights into Pakistan's real GDP growth. Based on data spanning from 1960 to 2022, many forecasting models, including Autoregressive Integrated Moving Average (ARIMA), double exponential smoothing, multilayer perceptron (MLP), and a hybrid model, were used. RStudio, Jupyter Notebook, and Minitab tools were used in this research project for analysis and forecasting. The multilayer perceptron (MLP) within the artificial neural network framework was found to best model through comparative study. The evaluation of root mean square error (RMSE) and mean absolute error (MAE) among the many models taken into consideration served as the basis for choosing the best-fitted model. The outcomes show that machine learning techniques perform better than conventional forecasting techniques. When compared to traditional methods, the use of machine learning algorithms produced more precise predictions, proving their better performance. This result underlines the significance and value of incorporating machine learning into forecasting. Machine learning enhances decision-making across a variety of sectors by utilising cutting-edge computational approaches and the power of data-driven algorithms. The results of this study help to improve forecasting procedures and demonstrate how machine learning has the ability to produce predictions that are more accurate in practical situations. Future research could further explore advanced molecular featurization and attention-based representation learning to improve the modeling of complex climate properties (Ali, 2026; Ali & Mohlenkamp, 2026; Ali & Bano, 2026).

Author Contributions

UEK: Conceptualization, methodology, data curation, formal analysis, and software. S.F.: Data collection, investigation, statistical analysis, and visualization. S.S.: Supervision, study design, validation, and project administration. A.T.: Literature review, interpretation of results, and

manuscript writing. K.I. Manuscript review and editing, validation, and overall coordination. All authors contributed equally to the study, critically reviewed the manuscript, and approved the final version.

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