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Research Article

A comparative analysis and prediction of the economic growth of Pakistan using machine learning models

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Abstract: This article investigates a comparative analysis of machine learning models for Pakistan's Gross Domestic Product (GDP), an important indicator of the nation's economic development. GDP is crucial to assess well-versed decisions. Since machine learning techniques are more sophisticated, much interest has been developed in predicting GDP to handle complex data patterns and enhance prediction accuracy. In this study, we evaluated the performance of a variety of machine learning algorithms like Auto-Regressive Integrated Moving Average (ARIMA), double exponential smoothing, Multilayer Perceptron (MLP), Neural Network Auto-Regressive (NNAR), and hybrid machine learning models on data from 1960 to 2022. The MLP used in Artificial Neural Networks (ANNs) outperforms based on the outcomes. This comparative analysis provides insights into the most suitable model for accurate prediction of Pakistani GDP for the years 2023 to 2032. This article provides a detailed analysis of various machine learning models used to predict Pakistan's GDP accurately. GDP prediction is an essential indicator of a nation's economic development and is crucial in making informed decisions. With the advancements in machine learning techniques, there has been a growing interest in predicting GDP due to their efficiency in handling complex data patterns and improving prediction accuracy.

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1. Introduction

Gross Domestic Product (GDP) measures the total economic output of a nation over a specific time period, including all goods and services produced there. Whether the people are local citizens or work for foreign-owned businesses makes no difference. 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 analysing GDP. For policymakers and the government, GDP forecasting is crucial, and precise anticipated figures aid in developing better plans. Government policymakers commonly use GDP forecasting to raise citizens' living standards, address unemployment and poverty issues, and other issues that can be readily resolved with better policies (Maccarrone *et al.*, 2021).

Earlier studies forecasted economic time series using a variety of strategies. The univariate forecasting model was shaped by Box and Jenkins in 1976 and named the Auto-Regressive Integrated Moving Average (ARIMA). This method is well-liked since it has demonstrated the capacity to accurately forecast events 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. The study presented a workable methodology for calculating important parameters, such as the degree of integration, auto-regressive terms in number, and the moving average terms in numbers as necessary for precise inflation forecasting. This study serves as an example of how ARIMA modelling can be used to forecast Irish inflation. The ARIMA model has been widely practised in research projects to predict the diversity of economic indicators.

Artificial Neural Networks (ANNs) are frequently employed as effective forecasting models in various sectors, including economics, business, finance, energy, and hydrology. They are accepted as reliable and frequently used methods for prediction problems. Analysing the relationships among input and output variables forms the origin of the ANN model, making them appropriate for examining seasonal time series data. Researchers have expressed much 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 population characteristics, 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 ARIMA and linear regression methods, which depend on linearity and might not be appropriate for all real-world data types. Similar outcomes can be obtained using neural networks as opposed to more conventional methods like (seasonal) ARIMA models. Additionally, neural networks can handle multivariate time series forecasting, where causal and co-integration investigations are crucial for modelling and prediction purposes (Uddin & Tanzim, 2021).

2. Literature review

To forecast the indices of economic growth in Turkey, Oral (2019) compared the available exponential smoothing algorithms to identify the best approach. According to the study's findings, the Holt-Winters smoothing exponential model is the best method for predicting the seasonal patterns shown in Turkey's economic development indices. 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. Kiriakidis and Kargas (2013) accurately anticipated the Greek GDP recession using an ARIMA model. 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 *et al.* (2016) utilised (2, 2, 2) model of ARIMA to forecast China's GDP. Wabomba *et al.* (2016) correctly predicted the yearly profits 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 model of (1,2,1) of ARIMA was finally found to be appropriate for predicting the Egyptian GDP until 2026 by Abonazel and Abd-Elftah (2019).

Samimi *et al.* (2005) used artificial neural networks and the exponential smoothing technique to forecast Iran's GDP. They used these techniques to anticipate the GDP for 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) conducted a study to predict the per capita GDP for eight regions in China's Yunnan Province. They used the exponential smoothing method and the corrected exponential smoothing method to forecast the variable. The results showed that the Modified Exponential Smoothing Model (MESM) performed better than the other methods.

Contrary to the conventional model of economic forecasting, machine learning methods have placed a higher priority on accurate prediction without predefined assumptions or judgments. 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. Previous research on price rise estimations that were 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 various industries, including forecasting traffic patterns and property prices. Alonso and Carbó (2021) presented different machine-learning models that have been tested for their effectiveness in predicting credit defaults. Bhardwaj *et al.* (2022) focused on forecasting the annual GDP per capita of 33 OECD countries, using both traditional and deep learning models. Meanwhile, Srinivasan *et al.* (2023) used advanced machine learning algorithms to predict the Indian GDP and found that the polynomial regression model was more accurate than the linear regression model. These studies demonstrate the importance of utilising advanced machine learning models for economic forecasting. In summary, these findings provide valuable insights into the efficacy of machine learning algorithms in predicting Indian GDP.

The hybrid ANN-ARIMA model has three main iterations in the literature. The ARIMA model is used to analyse time series data by comparing anticipated data to actual data and considering any errors. Zhang (2003) suggests using an ARIMA-ANN model comprising an additive-considering-integrated Moving Average (MA) and ANN to incorporate a non-linear component. This model is applied to three unique datasets - the Wolf sunspot data, Canadian lynx data, and exchange rate data between the British pound and the US dollar. Various simulations and methodologies are used to analyse and evaluate these datasets within the ANN framework.

3. Methods

The data consists of GDP, per capita income, and the annual growth change from 1960 to 2022, which are available on the Macro Trends website.

3.1. Auto-Regressive Integrated Moving Average (ARIMA)

The statistical method ARIMA is a widely used method for time series analysis and forecasting. It combines three components: Moving Average (MA), Differencing (I), and Auto-Regressive (AR), to identify patterns and trends in the data. This helps researchers make accurate predictions and gain insightful knowledge about the behaviour and course of the time series data they are studying. The ARIMA process is represented by Equation (1).

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

Where $\alpha_1, \dots, \alpha_p$ and $\beta_0, \dots, \beta_q$ are the coefficients of Auto-Regressive (AR) and Moving Average (MA) processes, respectively.

The above Equation (1) can be written as,

$$\phi(B)(1-B)^d X_t = \theta(B) Z_t \tag{2}$$

3.2. 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. It is especially powerful when the data shows both a trend and a level component.

The procedure uses two smoothing factors, one for capturing the level and the other for capturing the trend. It can create forecasts that include fluctuations mutually in short and long-term trends by using a weighted standard of earlier levels of observations and trend estimations. The general form of double exponential smoothing is given by Equation (3).

$$\beta_t = \beta(s_t - s_{t-1}) + (1-\beta) b_{t-1} \tag{3}$$

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

3.3. Multilayer Perceptron

The Multilayer Perceptron (MLP) is a fundamental and popular artificial neural network model in machine learning and pattern recognition. It is made up of numerous layers of interconnected nodes, which is also referred to as synthetic neurons or perceptions. In an MLP, each neuron gets input from the layer before it and uses a nonlinear activation function to create a production.

A standard system comprises an input layer, one or more hidden layers, and an output layer. MLPs can learn complex patterns and correlations in data by adjusting the weights and biases of the connections between neurons through a process called back-propagation. Equation (4) gives the general form of an MLP model.

$$a = \phi\left(\sum_j w_j x_j + b\right) \tag{4}$$

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.

3.4. Neural Network Auto-Regressive

The Neural Network Auto-Regressive (NNAR) model is a state-of-the-art method for time series analysis and machine learning. To capture complicated temporal connections and generate precise predictions, the NNAR model combines the strength of neural networks with the auto-regressive framework. Its adaptability and capacity for dealing with non-linear correlations make it a crucial instrument in the field of time series analysis, thereby allowing researchers to gather insightful knowledge and make sound, defensible decisions based on precise forecasts.

The NNAR model uses an activation function and a linear combination function. These formations' functions are defined as follows.

$$net_j = \sum_i w_{ij} y_{ij} \tag{5}$$

$$f(y) = \frac{1}{1+e^{-y}} \tag{6}$$

3.5. Hybrid model

The hybrid model, which combines ARIMA and ANN, is a novel strategy that uses the advantages of both approaches to improve time series forecasting. While ANN can handle complicated nonlinear interactions and capture nuanced patterns, ARIMA captures the data's linear dependencies and auto-regressive character.

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. The ANN significantly improves the predictions by learning and modelling the nonlinear relationships inside the residuals. The hybrid model attempts to increase the accuracy and resilience of time series forecasting by combining the advantages of ARIMA and ANN.

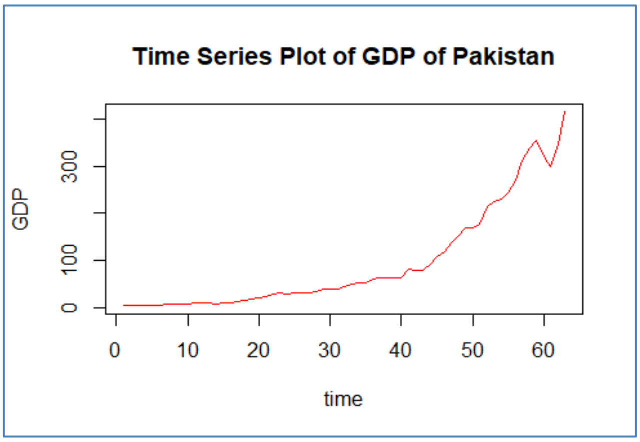
4. Results and analysis

Analysis and forecasting are performed using statistical software of R series and with the help of Jupiter Notebook, which is used to predict any phenomena.

4.1. ARIMA models

Figure 1 illustrates the component origin test with an Autocorrelation Function (ACF), a Partial Autocorrelation Function (PACF), and an Augmented Dickey-fuller (ADF).

Figure 1: Time series plot of GDP



Figures 2 and 3 display the specific graphs used to evaluate any data's stationary qualities. The ACF and PACF graphs examined the patterns for autocorrelation and partial autocorrelation. The ADF test was also used to see if the data showed a unit root, indicating non-stationary. An integration of the first order (disparity) method was projected to convert the sequence into a still form to overcome non-stationary.

Figure 2: Time series plot of ACF

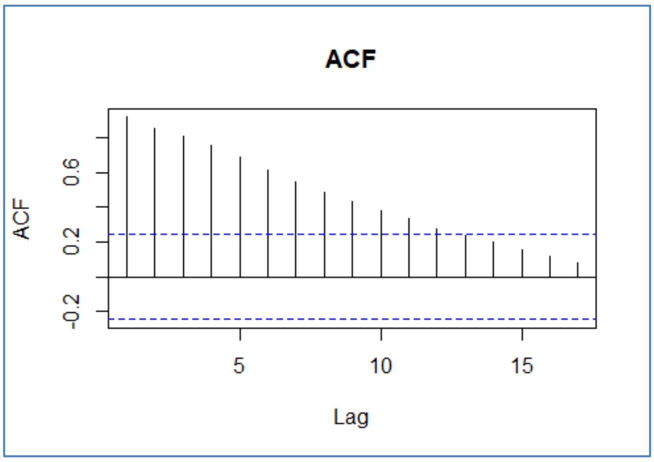


Figure 3: Time series plot of PACF

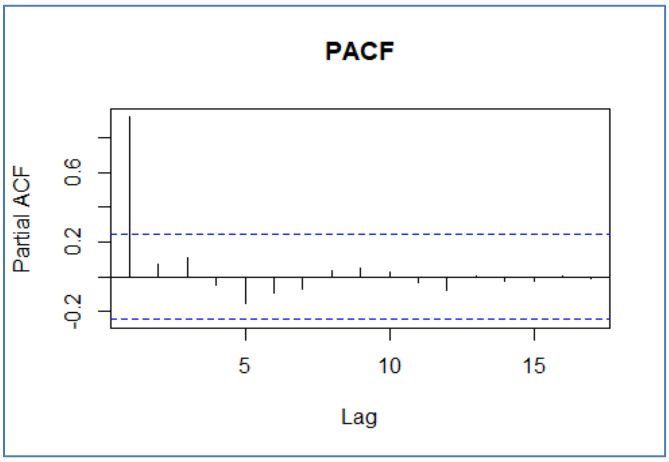


Table-1 shows the outcome, which tries to indicate that the entered data is non-stationary.

Table-1: Test of Dicky Fuller augmented unit

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

Figure 4 shows that the given p-value is higher than the specified value of 0.05 level of significance at the first difference.

Figure 4: First difference of time series plot

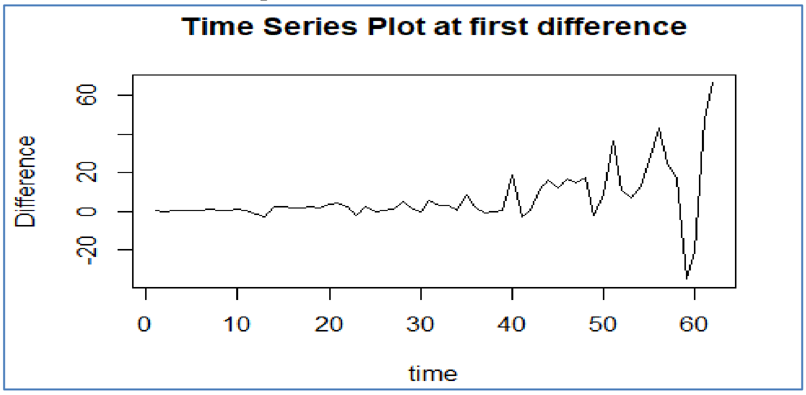


Figure 5 displays the second difference graph for the original GDP, which demonstrates inactive data.

Figure 5: Time series plot at 2nd difference

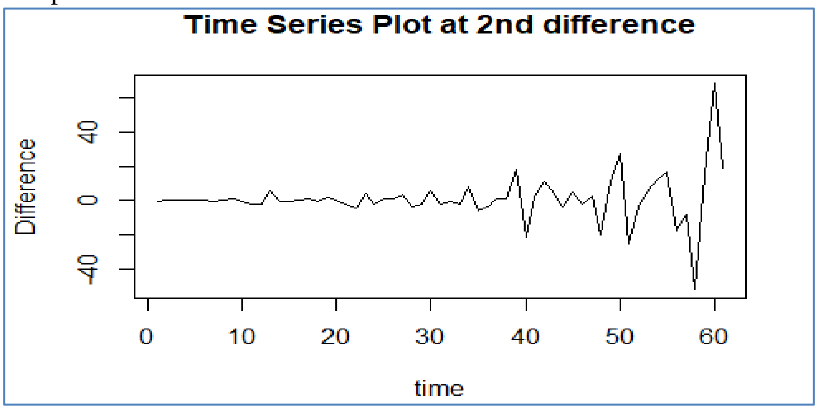


Table-2 shows all possible ARIMA models; after examining all of these potential models, it contends that the (2,2,2) model of ARIMA, whose Akaike Information Criterion (AIC) is lowest, is the optimal model to predict.

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

The data in Table-3 shows the ARIMA model estimate for (2,2,2). After examining the data, it shows that this model is the lowest among all given models. Figure 6 shows the normal probability graph with a maximum of 25 frequencies.

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

Type	Coefficient	S.E(Co-eff)
AR1	0.9929	0.1172
AR2	-0.8494	0.0857
MA1	-1.6353	0.1597
MA2	0.7847	0.1482

Figure 6(a & b): Residuals normal probability plots

Fig. 6(a)

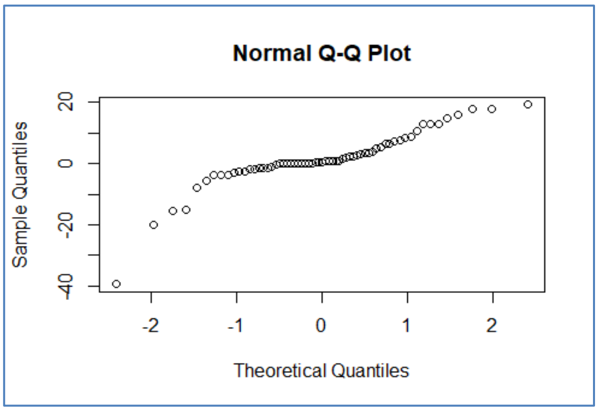


Fig. 6(b)

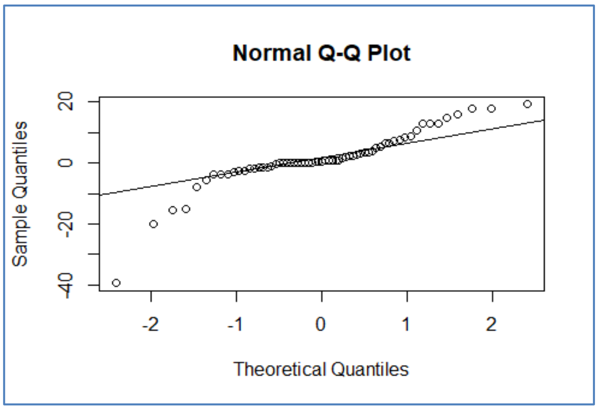
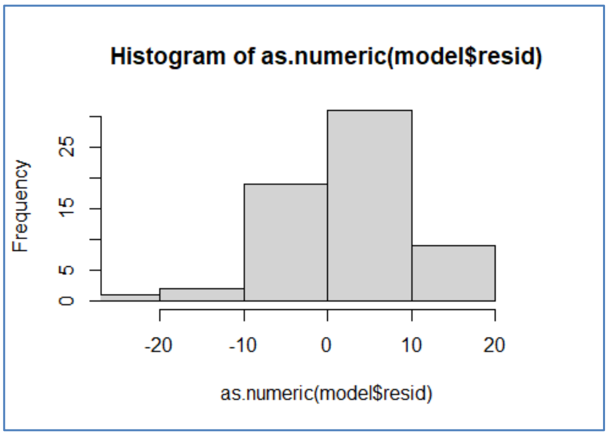


Figure 7: Histogram of residuals



Analysis of the Table-4 shows that the GDP is raised during the predicted years 2023 to 2032. The 2030 year predicted the highest GDP compared to other years.

Table-4: Estimate from 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

4.2. Double exponential smoothing

Figure 8 shows the double prediction of GDP for the specific period of 2023 up to 2032. Table-5 shows parallel to double prediction. As mentioned in Figure 8, the maximum prediction is reported for the year 2032, which is comparatively much better than the years from 2023 to 2031. It is an ideal future prediction for any GDP.

Figure 8: Time series plot of forecast GDP for the year 2023–2032

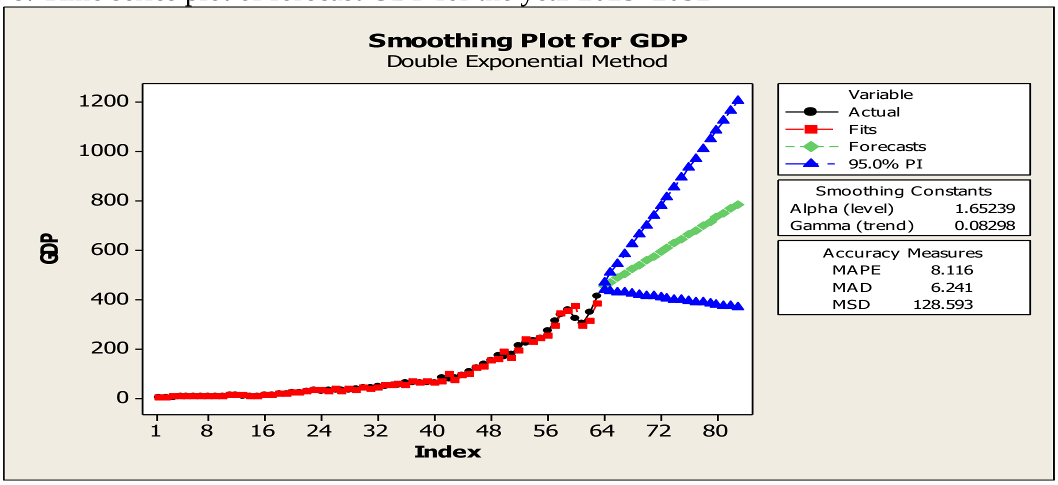


Table-5: Forecast for the years 2023 to 2032 at 95% limits

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

4.3. Multilayer Perceptron (MLP)

Figure 9 shows the hidden input and output for MLP. Figure 10 shows the maximum prediction regarding MLP beyond 2020, and it seems to increase every year. Table-6 displays the GDP prediction using MLP. After examining the data, the maximum prediction appears to be seen in 2032 compared to all reported years from 2023 onward till 2031.

Figure 9: Structure of the MLP modelling technique

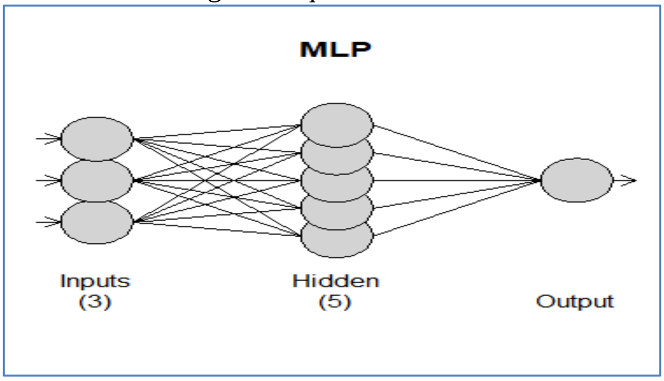


Figure 10: Forecasts from MLP for the year 2023 to 2032

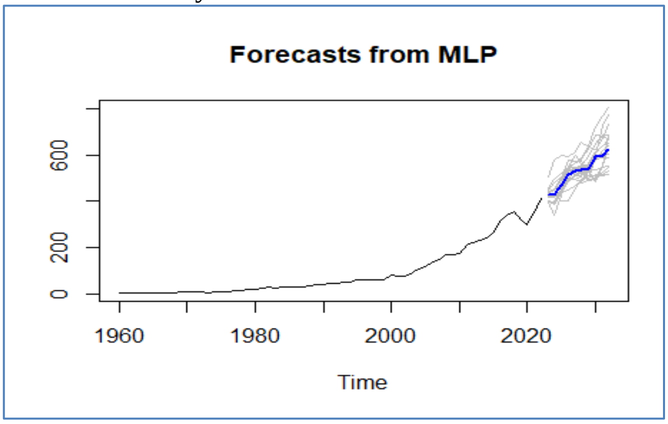


Table-6: Forecast for the year 2023 to 2032 using MLP

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

4.4. Neural Network Auto-Regressive (NNAR)

Figure 11 prominently shows NNAR model no (1,1). Table-7 shows predictions for the years 2023 to 2032 using the NNAR model. Outcomes show that maximum GDP is visible in 2023 compared to the coming years from 2024 onward, which shows that the NNAR model is not a very pertinent model for predicting future GDP.

Figure 11: Forecasts from NNAR for the year 2023 to 2032

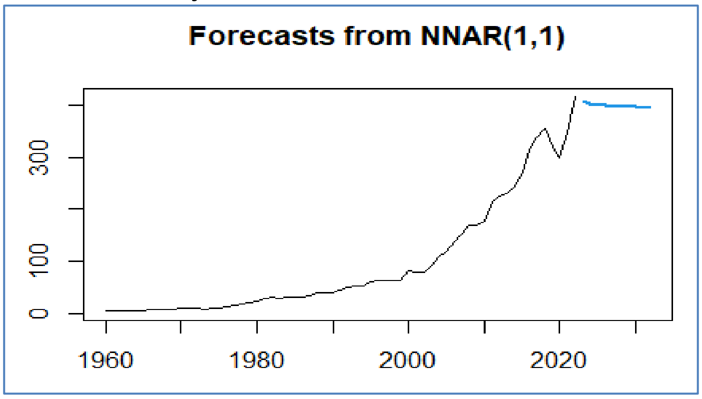


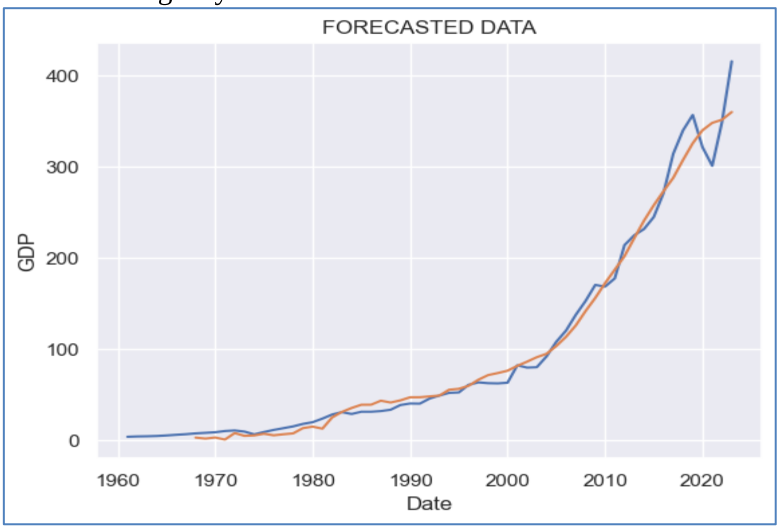
Table-7: Forecast for the year 2023 to 2032

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

4.5. Hybrid model

Figure 12 shows the forecasting data for the mentioned years by using hybrid model. It is visible that the prediction of GDP is much higher within the range of 400 plus beyond 2020, which seems to be more in the year 2021 onward.

Figure 12: Forecasted data using a hybrid model



5. Accuracy measures

Numerous researchers have utilised various accuracy measures and tests of statistics to assess the efficiency of prediction models in the empirical data. Nevertheless, in this research, we have selected to employ three accuracy mean errors - the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), and the Mean Absolute Error Percentage (MAEP) - for evaluating all sixteen combination models. The arithmetical equations for these mean errors are given below.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{n}} \tag{7}$$

$$MAE = \frac{\sum_{i=1}^{n} |\, \hat{x} - x_i|}{n} \tag{8}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \tag{9}$$

The data given in the Table-8 compares double exponential smoothing, multilayer perceptron, and neutral network auto-regressive models. According to the calculations, NNAR appears to be the better model.

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 Auto-Regressive (NNAR)	12.45796	6.479029	8.417001
Hybrid model	16.11520	8.457237	---

6. Discussion

From the outcomes, it seems that the given data for this current research is non-stationary throughout the research. Out of all potential models of ARIMA, MLP, NNAR and hybrid, the (2,2,2) model of ARIMA is better; its AIC value is lower, which projects it as an optimal model to forecast any GDP. This result is well supported by Wabomba *et al.* (2016) and Ghazo (2021), who concluded that ARIMA (2,2,2) is best to predict for a sample as close as 5 percent to the actual value. GDP is raised during the predicted years 2023 to 2032. The 2030 year predicted the highest GDP compared to other years.

It is even debated from the outcomes that maximum prediction is reported for the year 2032, which is much better than the years from 2023 to 2031. It's an ideal future prediction for any GDP by focusing on the MLP model. This finding is in line with Shams *et al.* (2024) who utilized the MLP model and concluded that this model is better performer than other potential model with R value of 99 percent to predict. The finding also shows that the prediction of GDP by using MLP is maximum in the year 2032 as compared to all reported years from 2023 onward till 2031.

Table-7 shows predictions for the years 2023 to 2032 by using the NNAR model. The outcome shows that the maximum GDP is visible in 2023 as compared to the coming years from 2024 onward. This shows that the NNAR model is not pertinent for predicting future GDP. This outcome is supported by Almarashi *et al.* (2024), who opined that the NNAR model, as a nonlinear advance, downsizes all other potential models and shows the lowest figure. Another finding is that among double exponential smoothing, multilayer perceptron and neutral network auto-regressive models, the better model appears to be NNAR according to the outcomes as reported by the current study.

7. Conclusion

In conclusion, this study intended to create projections for the years 2023 to 2032 to offer useful insights into Pakistan's real Gross Domestic Product (GDP) growth. Based on data spanning from 1960 to 2022, many forecasting models, including Auto-Regressive Integrated Moving Average (ARIMA), double exponential smoothing, Multilayer Perceptron (MLP), Neural Network Auto-Regressive (NNAR), and a model of hybrid, were utilised. RStudio and Jupiter Notebook were used in this research project for analysis and forecasting. The MLP within the Artificial Neural Network (ANN) framework was created to be the finest model through comparative investigation. The evaluation of root means square error and mean absolute error among the many forms 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. Machine learning algorithms produced more precise predictions than traditional methods, 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. This study's results help improve forecasting procedures and demonstrate how machine learning can generate more precise forecasting in practical situations.

Declaration of conflict of interest

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