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Evaluation of machine learning approach in modelling and forecasting real gross domestic product growth: a comparative study

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ABSTRACT

This study aims to provide an efficient and accurate machine-learning approach for modelling and forecasting the real gross domestic production (GDP) in the context of Pakistan. The study forecasts Pakistan's GDP growth rate using different forecasting models, such as naïve, seasonal naïve (SNaive), smoothing, and k-nearest neighbors (k-NN). Machine learning algorithms provide additional advice for data-driven decision-making. According to the findings, the k-NN-based forecasting gives minimum mean absolute percentage error (MAPE), root mean square error (RMSE), and mean absolute error (MAE) compared to the other three models. Economic policymakers can use accurate models to measure significant economic activity and formulate plans. The results indicate that the model produced accurate projections of future GDP levels for Pakistan.

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1. INTRODUCTION

Data from the World Bank (WB) suggest that Pakistan’s gross domestic product (GDP) stood at US$346.34 billion at the end of 2021. Pakistan is ranked among lower-middle-income countries with a GDP per capita of US$1,537.9. The WB estimated Pakistan’s growth rate at 6.0% in 2021 [1].

One method for evaluating an economy's output and national income is to look at the GDP or gross domestic income (GDI). The total market value of all the goods and services produced in a nation during a specific period is the GDP (usually a calendar year). Furthermore, it is regarded as the total value added at each level of production (the intermediate stages) of all completed goods and services produced within a state over a specific period, and it is assigned a monetary value [2].

GDP is computed as:

$$DP = consumption + gross\ investment + government\ spending + (exports - imports)$$

GDP growth rate measures the relative change in GDP in the current year using the previous year's GDP as the base. The GDP growth rate is computed as:

$$GDP\ growth\ rate = \frac{GDP\ in\ current\ year - GDP\ in\ previous\ year}{GDP\ in\ previous\ year} \times 100$$

GDP and GDP growth rate are significant indicators of an economy's overall economic picture. Monetary policy directly impacts every economy and has long and fluctuating lags.

Accurate predictions of economic activity are essential for formulating current and future macroeconomic policies. Sustainable economic growth is of utmost importance for every economy, especially the emerging ones that frequently experience difficulties. Thus, economists have concentrated on examining how GDP may enhance economic growth. Three methods, the income approach, the spending approach, and the product approach, can be used to describe GDP. According to the rule of income approach, each manufacturer's income must match the value of their product, and the GDP is calculated by adding the incomes of all producers [3]. Financial forecasting undoubtedly includes evaluating the economy's current status because it serves as the platform for a longer-term study. This is relevant all the more, considering that quarterly GDP growth and longer-term predictability have decreased [4]. Though there is no doubt that forecasting significantly functions in many areas of business, government, and policymaking, Pilström and Pohl [5] claims that the topic has been overlooked. Pilström and Pohl [5] also claims that few economics departments offer training in the area and that most econometric and growth theory texts only briefly address the issue. A lot of literature has suggested several methods for predicting GDP. The macroeconomic literature that examines this subject using a time series approach primarily employs various vector autoregressive (VAR) specifications [6]. Forecasting enhancements can be made using the proper Bayesian shrinkage procedures, as highlighted in Babura [7].

Many scholars believe that the yield curve, which provides insight into future economic activity, should be considered one of the potential economic indicators that must be employed by GDP forecasters [8]. Another group of studies demonstrated that projections based on multiple indications perform significantly better than those based on only one indicator [9]. The implementation of forecast combination methods is the second contribution of our investigation. For combining leading indicator forecasts for IP, we use a variety of weighting techniques, including simple averaging schemes (mean and median forecast), trimmed means (due to historical out-of-sample performances), forecasts based on in-sample criteria, weights calculated by relative mean square forecast errors, ordinary least square (OLS) weights, and shrinkage techniques [10].

Machine learning (ML) has made enormous improvements in the last few years, especially for jobs involving recognition. It has been demonstrated that ML is extremely efficient at handling huge amounts of data and performing algorithms in an adequate amount of time, all while maintaining a bit inexpensive costs [11]. Beyond speech and image recognition, it has also demonstrated potential in prediction tasks. In the ML model, no need to require the stationarity assumptions, nonlinear time series data may be predicted very well using ML models, such the k-nearest neighbors (k-NN) approach. However, traditional time series forecasting methods, which rely on stationarity assumptions, usually fail when it comes to real-world data that exhibits significant variations [12].

ML algorithms have been used more recently to forecast the Pakistan GDP; these algorithms reveal more adaptability than traditional predictive models. ML algorithms are capable of making predictions based on historical data, independent of preconceived notions or judgments. Over the past few decades, technology has advanced exponentially, enabling it to handle enormous amounts of data in milliseconds and extract valuable insights from billions of inputs. That being said, this trend has not been fully adopted by Pakistan's non-financial industries. In Pakistan, traditional techniques such as beta, standard deviation, conditional value at risk (CVaR), and value at risk (VaR) have been the mainstays of risk prediction. Artificial intelligence approaches have not been employed significantly to address risk in the financial and non-financial industries, despite these conventional methods [13].

The research stated by [14] show that the SVM approach has been extensively utilized to anticipate real GDP in many regions of the world in order to make swift economic judgment. Several research propose frameworks based on ML for coordinating the coordinated management of inventory at each node in the supply chain. Their methods find nearly-optimal ordering strategies by applying different reinforcement learning algorithms, such Q-learning.

k-NN has been used to forecast health card distribution [15], traffic speed [16], and stock price [17]–[19]. Compared to decision trees and Naive Bayes, k-NN prediction results have demonstrated more accuracy in forecasting data and predictions [20]–[23]. In this study, we modeled Pakistan's GDP growth rate to produce preliminary estimates of the current yearly GDP growth rate and immediate forecasts of the following years' GDP. We applied the mean, naïve, seasonal naïve (SNaive), exponential smoothing, and k-NN foresting techniques to achieve better forecasting and capture different patterns and trends in the data. By applying these techniques, this study aims to support prudent economic planning and the development of policies that improve the key economic indicators of the Pakistani economy.

The aim of this study is to evaluate the forecasting Pakistan GDP price by the new approach k-NN based on the ML to gain the high forecasting accuracy. The ML approach has no assumption about the stationary series, so the new ML forecasting has proved the optimal forecasting accuracy where the time series data is nonstationary series. Using a novel ML strategy, specifically the k-NN algorithm, the purpose of this study is to assess the accuracy with which GDP forecasts for Pakistan can be made. The naive forecasting method, seasonal naive forecasting method, and simple exponential smoothing method are examples of conventional time series forecasting techniques that make assumptions regarding the stationarity of the time series data. The statistical properties of the time series, such as the mean and variance, must be stationary in order to be considered stationary. However, underlying trends, seasonal effects, and abrupt structural changes frequently cause non-stationary behavior in real-world economic data, such as GDP. Classical forecasting techniques, which either require pre-processing steps to convert non-stationary data into stationary form or require data to be stationary, can suffer greatly from this inherent non-stationarity. Interestingly, the k-NN strategy doesn't force severe presumptions about the stationarity of the time series information. k-NN is a type of instance-based learning that uses similarities between new and previously observed instances to make predictions. k-NN is able to handle non-stationary data more effectively as a result of this adaptability, capturing intricate patterns and relationships without the need for extensive data transformation or detrending procedures. To show the prevalence of the k-NN approach for determining Pakistan's Gross domestic product, this study directs a relative examination against conventional strategies. The dataset utilized incorporates authentic Gross domestic product figures from the world bank, which are separated into preparing and testing sets. Standard metrics like root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are used to evaluate the forecasting performance of the k-NN model on the testing set. By quantifying the average magnitude of the forecast errors on both the absolute and relative scales, these metrics provide a comprehensive evaluation of the model's accuracy.

In the remaining parts of the paper, section 2 describes the data and the models applied, while section 3 presents the data analysis results and its discussions. Section 4 ends the paper with conclusions and recommendations of the study.

2. DATA AND METHODS

2.1. Data

The data used is Pakistan's GDP growth rate data from 1990 to 2022 from the WB's official website [1]. The summary statistics of our data are presented in Table 1. Table 1 shows the average GDP growth rate for the period under consideration is 4.067 percent, while the minimum and maximum GDP growth rates were -1.300 and 7.710 percent, respectively.

Table 1. summary statistics of Pakistan’s GDP growth rate from 1990 to 2022

Minimum	First quartile	Median	Mean	Third quartile	Maximum	Standard deviation	Skewness	Kurtosis
-1.300	2.700	4.067	4.067	5.125	7.710	1.96	-0.431	3.324

2.2. Methods

This article estimates Pakistan's GDP for the upcoming years by comparing two distinct forecasting approaches: traditional forecasting techniques and ML methods. The traditional methods applied include the simple exponential smoothing (SES), SNaive, and naïve forecasting methods. Additionally, the study uses k-NN, a ML technique, to predict Pakistan's GDP. These methods are evaluated and compared to determine their forecasting accuracy and suitability for predicting future GDP growth.

2.2.1. Mean forecasting method

The mean forecast (MF) method is a very simple technique in which all future values predicted are equal to the previous data's average (or "mean"). If the data set of observations is denoted by $y_1, \dots, y_T$ then the forecast value is calculated by (1).

$$y_{T+h|T} = \bar{y} = \frac{y_1 + y_2 + y_3 \dots y_t}{T} \quad (1)$$

The arithmetic mean of all prior observations, the mean forecasting method is a clear and easy time series forecasting approach that makes predictions for the upcoming time period. For stationary time series data those whose mean does not change over time this strategy is especially helpful since it assumes that future values will roughly equal the average of past values. With data that exhibit trends or seasonal patterns, however, its efficacy is reduced. One of its main advantages is that it is simple and easy to apply, but it may miss recent changes in the data since it considers all previous observations identically [19].

2.2.2. Naive forecasting method

A naive forecast (NF) entails using the previous observation without modification as the basis for the forecast. Estimating techniques in which the previous period's actuals are utilized as the forecast for a current period without being adjusted or attempting to determine causal elements [21], [24]. It is solely useful for comparison with projections made by more advanced (sophisticated) approaches. It is frequently called the persistence forecast because the earlier observation persists. This straightforward method can be significantly modified for seasonal data [22]. The NF is sometimes known as a random walk forecast since an NF is a correct approach when data a random walk, and the $RW()$ function can be used instead of naïve. This is the best that can be done for many time series, including most stock price data, and even if it is not a good forecasting method, it provides a useful benchmark for other forecasting methods.

2.2.3. SNaive forecasting method

In the SNaive forecasting (SNF) method, we set the most current data from the same season as the baseline for each estimation (*e.g.*, the same month of the previous year) [25]. The estimate for the time $T + h$ is written as (2).

$$y_{T+h|T} = y_{T+h-m(k+1)} \tag{2}$$

where m is the seasonal period or time, and k is the integer part of $h - \frac{1}{m}$. It seems more difficult than it is. For instance, when using monthly data, the forecast for all upcoming February values is the same as the most recent February value recorded. When using quarterly data, the prediction of all upcoming Q2 values equals the most recent Q2 value observed (where Q2 means the second quarter). The same rules would apply for additional months, quarters, and other seasonal times [25].

2.2.4. Simple exponential smoothing method

Generally, the simple exponential smoothing (SES) model is predicated on the idea that a time series' level should oscillate around a set level or fluctuate around a constant level [23], [26], [27]. The following equation gives the SES model:

$$y(t) = \beta(t) + \varepsilon(t) \tag{3}$$

where $\beta(t)$ takes a constant at the time t and may change slowly over time; $\varepsilon(t)$ is a random variable used to describe the effect of stochastic fluctuation.

2.2.5. k-NN method

Computational intelligence and other ML methods [28] in forecasting time series have been increasingly common in recent decades. Two intriguing features of computational intelligence and ML that distinguish them from conventional statistical models are nonlinearity and the lack of an underlying model (also known as non-parametricity) [29]. The k-NN regression-based approach is non-parametric and requires no prior assumptions about the nature of the data [30]. Its ability to learn complicated functions fast and accurately is its main benefit. The following $\hat{y}$ result for a given x from the training data is obtained by taking the mean of the responses to these k independent variables, taking into account k training data observations with x_i close to x:

$$\hat{y}(x) = \frac{1}{k} \sum_{x_1 \epsilon N} y_1 \tag{4}$$

where *N* stands for the k spots that are closest. In actuality, a wide variety of distance measures may be used to assess the proximity of two sites. In particular, the Euclidean distance was applied in our work. Giving different factors in the near region varying degrees of weight is beneficial. We employed a density distribution based on the Gaussian distribution as these data are computed using a density function.

We employed the following performance metrics to evaluate each forecasting model's performance: MAPE, MAE, and RMSE [30]–[32]. The following is an explanation of these measurements: observed values and estimated or anticipated values are shown. The average of all absolute errors is known as the MAE [33]. The following formula is expressed as:

$$\text{MAE} = \frac{1}{N}\sum_{t=1}^{N} |y_t - \widehat{y_t}| \tag{5}$$

RMSE is a widely utilized metric among practitioners and academics for evaluating the precision of forecasting models. RMSE quantifies the disparity between observed and expected values, determined using the subsequent formula.

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \widehat{y_t})^2} \tag{6}$$

The MAPE is the mean or average of the absolute percentage errors of forecasts [34], [35]. The difference between the predicted and actual values is called the error. To calculate MAPE, the percentage errors are added together regardless of their sign. The following formula expresses it:

$$MAPE = \frac{1}{N}\sum_{t=0}^{N} |\frac{y_t-\widehat{y_t}}{y_t}| \times 100 \tag{7}$$

From 2023 through 2026, predictions will be based on the best-selected model, which will be determined using the RMSE, MAE, and MAPE criteria. All models were analyzed in R using the packages $tknn()$, $tseries()$, $stats()$, $forecast()$, $asta()$, and $ggplot()$.

3. RESULTS AND DISCUSSION

Predicting Pakistan's annual GDP growth rate is crucial for strategic economic planning and policy formulation. In this study, we assess several forecasting methods using an in-sample dataset to determine the most accurate approach. Among the models evaluated are traditional time series methods like the mean forecast method, naïve forecast method, seasonal naïve forecast method, and seasonal exponential smoothing method, alongside the modern ML technique known as the k-NN approach. The evaluation criteria focus on metrics such as RMSE, MAE, and MAPE, which are essential for gauging predictive accuracy. Our findings reveal that the k-NN method consistently achieves the lowest error rates across these metrics compared to the classical time series models. This superior performance underscores the k-NN approach as the optimal choice for forecasting Pakistan's GDP growth rate, offering robust and reliable predictions that outpace traditional forecasting methods. The comprehensive analysis ensures a rigorous comparison, providing insights into the effectiveness of contemporary ML techniques in economic forecasting contexts.

Table 2 evaluates the performance of different approaches to forecasting Pakistan's annual GDP growth rate using the in-sample data set. It is evident that the RMSE, MAE, and MAPE values on the basis of the k-NN technique had the minimum than all other four-time series models such as the mean forecast method, naïve forecast method, seasonal naïve forecast method, and seasonal exponential smoothing method. Therefore, the k-NN method is considered the best method for foresting the annual Pakistan gross domestic product growth rate. Then, all other classical time series approaches are based on the data under consideration.

Table 2. Evaluation of the performance of different methods in predicting Pakistan’s annual GDP growth rate

Methods	RMSE	MAE	MAPE
Mean	1.896	1.493	56.901
Naïve	2.443	1.817	69.007
SNaive	2.838	2.185	83.711
Exponential smoothing	1.896	1.493	56.904
k-NN forecast method	1.704	1.270	42.050

The similar exhibition of different anticipating methods for anticipating Pakistan's yearly GDP development rate, involving in-example information. RMSE, MAE, and MAPE are the evaluation criteria. Table 2 gives an itemized assessment of the presentation of various gauging techniques for foreseeing

Pakistan's yearly gross domestic product development rate, involving in-example information. RMSE, MAE, and MAPE are the evaluation metrics. The forecasting models' accuracy can only be evaluated using these metrics, with lower values indicating better performance. When compared to the other approaches, the k-NN method performed the best and had the lowest RMSE, MAE, and MAPE values. This suggests that forecasts made using the k-NN method are more accurate and trustworthy. The mean forecast method, nave forecast method, seasonal nave forecast method, and seasonal exponential smoothing method, on the other hand, had higher error rates. These traditional techniques frequently depend on presumptions about information, for example, stationarity, which may not hold in certifiable financial information portrayed by vacillations and non-direct patterns. The k-NN method's superior performance can be attributed to its ability to identify intricate data patterns without relying on presumptions about the data's distribution or stationarity. k-NN's ability to handle non-linear time series data, which is common in economic forecasting, is enhanced by its flexibility. By showing lower mistake measurements, the k-NN approach ends up being more exact in determining Pakistan's GDP development rate. Policymakers and economic planners who rely on precise forecasts to make informed decisions need this improved accuracy. The discoveries feature the capability of AI procedures like k-NN in upgrading gauging exactness and giving more solid financial forecasts, eventually supporting better monetary preparation and strategy detailing.

Figure 1 shows Pakistan's Annual GDP growth rate from 1990 to 2022. In 1990, Pakistan’s GDP growth rate was 4.5 percent, which increased to a peak of 7.7 percent in two years. Some fluctuations were found in the GDP growth rate from 2019 to 2020. However, almost all international markets crashed due to the COVID-19 pandemic; the GDP growth rate decreased to a record low of -1.30 percent. Using 95 percent of our data for testing and 5 percent for forecasting, we present the forecast for all models discussed in the methods section [36]–[38]. Figure 2 shows the annual Pakistan GDP growth rate forecast by the MF, upon which we find the forecast with centroid value in the data set. Forecasts for all predicted prices equal the past data's average (or mean). Figure 3 shows the forecast for NM. It is worth noting that the NF can be implemented in a namesake function. The naive method forecasted values for Pakistan's GDP growth rate for the coming years 2023, 2024, 2025, and 2026, are the same at 4.0 percent.

In Figure 4, the exponential smoothing method (ESS) method forecast values for 2023, 2024, 2025, and 2026 were all the same, just as in the case of the NF. In Table 3, we present the different forecasting methods and their respective Pakistan's gross domestic (GDP) growth rate predictions for 2023, 2024, 2025, and 2026 for all models under consideration. The MF forecasted Pakistan's GDP growth rate for the upcoming years 2023, 2024, 2025, and 2026 at 4.065 percent, respectively. In contrast, the ESS forecasted Pakistan's GDP growth rate for the years 2023, 2024, 2025, and 2026 at 4.064 percent, respectively. The SNF forecasted values are 6.000, 4.000, 4.050, and 6.010 for 2023, 2024, 2025, and 2026, respectively. For the NF, the forecasted values for 2023, 2024, 2025, and 2026 were 4.000 percent, respectively. Using the ML technique, k-NN's forecast value for 2023 is 3.763, while that of 2024, 2025, and 2026 are 3.348, 4.741, and 5.920 percent, respectively. Figure 5 shows the forecasted values of Pakistan’s GDP growth data by the k-NN. We can observe a fluctuating forecast similar to the original series. This shows that Pakistan’s GDP growth rate will continue to decrease in 2023 and increase thereafter, after which it will decrease again.

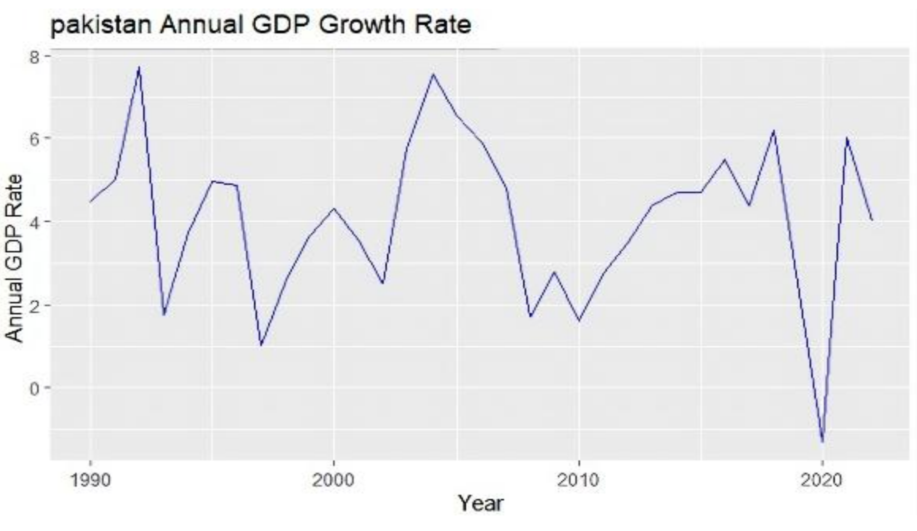

Figure 1. Annual Pakistan GDP growth rate

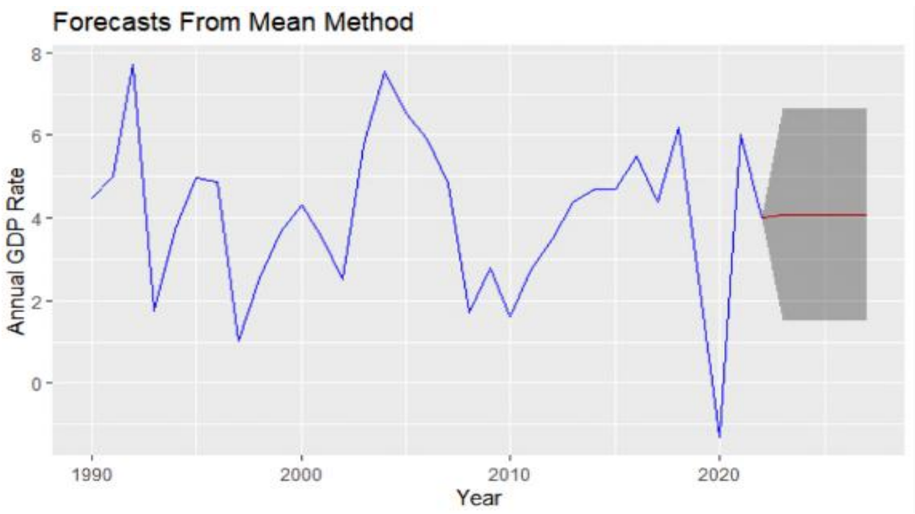

Figure 2. Forecast GDP by the MF

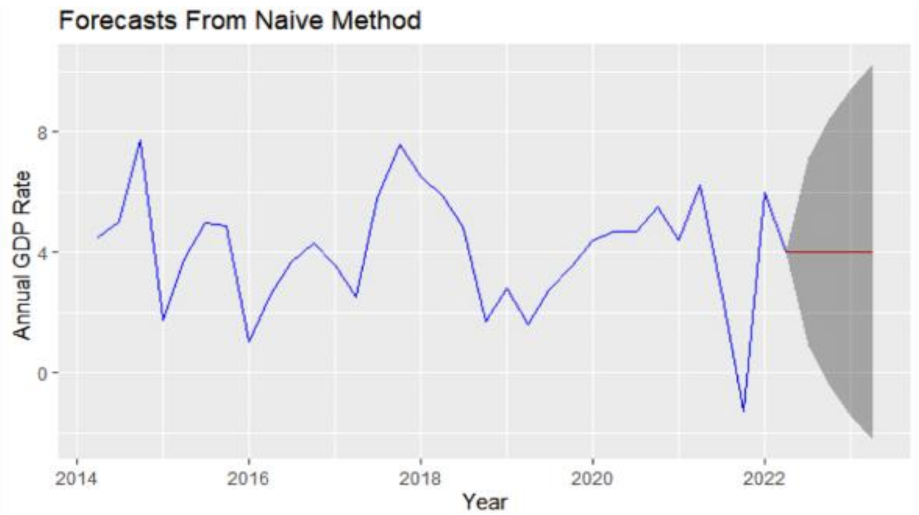

Figure 3. Forecast values Pakistan (GDP) Growth Rate from NF

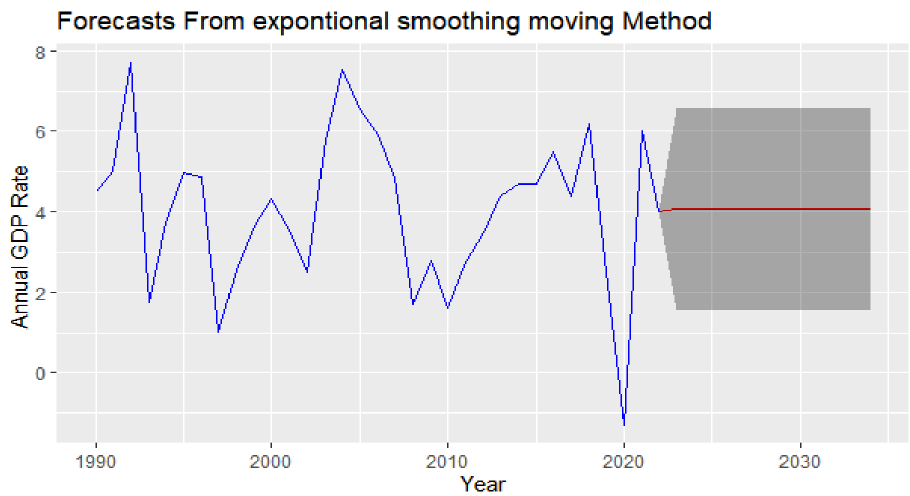

Figure 4. Forecast values Pakistan (GDP) growth rate from SES

Table 3. The forecasted value of GDP data of Pakistan using forecasting methodology

Methods	Year	Forecast value	Lo 80	Hi 80	Lo 95	Hi95
Mean forecast	2023	4.065	1.507	6.623	0.083	8.047
	2024	4.065	1.507	6.623	0.083	8.047
	2025	4.065	1.507	6.623	0.083	8.047
	2026	4.065	1.507	6.623	0.083	8.047
Naïve forecast	2023	4.000	0.868	7.131	-0.788	8.788
	2024	4.000	-0.427	8.427	-2.771	10.771
	2025	4.000	-1.423	9.423	-4.293	12.293
	2026	4.000	-2.262	10.262	-5.576	13.576
SNF	2023	6.000	2.361	9.638	0.436	11.563
	2024	4.000	0.361	7.638	-1.563	9.563
	2025	4.050	-1.144	9.144	-3.868	11.868
	2026	6.010	-0.301	12.301	-3.636	15.023
Exponential smoothing forecast	2023	4.064	1.557	6.572	0.229	7.900
	2024	4.064	1.557	6.572	0.229	7.900
	2025	4.064	1.557	6.572	0.229	7.900
	2026	4.064	1.557	6.572	0.229	7.900
k-NN base forecast	2023	3.763	1.321	3.981	0.067	7.345
	2024	3.348	1.456	3.941	0.076	7.432
	2025	4.741	1.312	3.912	0.078	7.876
	2026	5.920	1.345	3.916	0.089	7.376

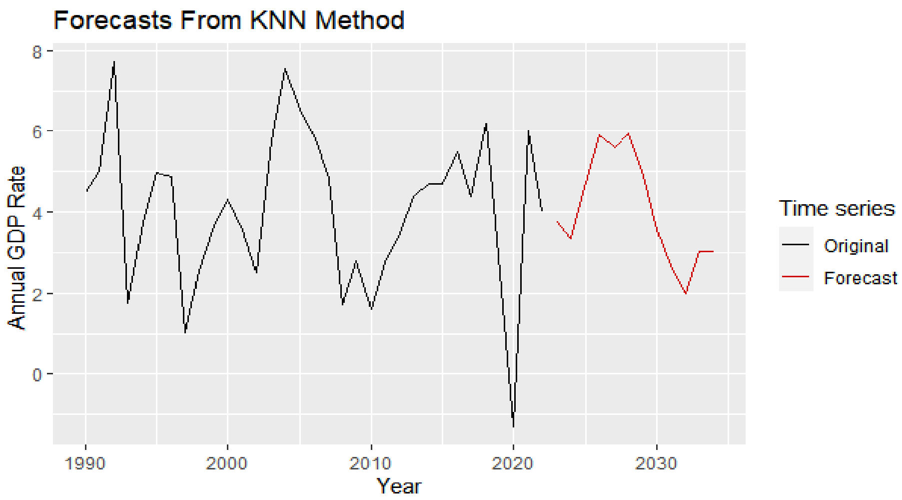

Figure 5. Forecast values Pakistan (GDP) growth rate from k-NN

4. CONCLUSION

In this research, various forecasting techniques is used such as`the MF, NF, SNF, ESS, and the modern k-NN approach were evaluated using data sourced from the World Bank. The evaluation criteria, comprising RMSE, MAPE, and MAE, were employed to determine the most accurate forecasting method. Among these techniques, the ML model is more supportive in the case of non liner time series data.The k-NN method is used to forecasting the Pakistan GDP. This method is more optimal result because it forecast the next value or the one head forecast value on the base of k-NN algorithm. The k-NN method emerged as the optimal choice, consistently demonstrating superior performance across all evaluation metrics. Specifically, it exhibited the lowest RMSE, MAPE, and MAE values compared to the traditional time series methods evaluated. This indicates that the k-NN approach provides robust and reliable forecasts of Pakistan's GDP growth rate, offering precise estimates for the years 2023, 2024, 2025, and 2026: 3.763%, 3.45%, 4.721%, and 5.34%, respectively.

The implications of these findings extend beyond academic research, suggesting practical applications for economic management teams and policymakers. By leveraging the k-NN model, policymakers can anticipate future economic activities more accurately, enabling them to formulate informed strategies and policies to mitigate challenges and promote sustainable economic growth. Furthermore, the study calls upon the government of Pakistan to implement prudent economic policies aligned with these forecasts to enhance economic stability and prosperity.

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No funding was secured for this study.

CONFLICT OF INTEREST

No conflict of interest is declared by the authors.

DATA AVAILABILITY

The data is made up of Pakistan's GDP growth rate from 1990 to 2022, available at *https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?locations=PK*.

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