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Forecasting the Future: Neural Networks vs. Time Series in Pakistan's CPI

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Abstract
In this paper, diverse models used in the prediction and projection of the consumer price index in Pakistan are reviewed. The data used for the analysis include monthly data from July 2016 to February 2024. We employed both basic time series models like; ARIMA and SARIMA, as well as advanced models; Neural Network Autoregressive (NNAR) and the Multilayer Perceptron (MLP) models. We used differencing as was justified by the Augmented Dickey-Fuller test to handle non-stationary features of the Consumer Price Index series. The correctness of the model attracted the use of performance measures including Mean Correct Squared and Root Mean Correct Squared Error. The SARIMAX (4,1,4)(0,1,[1],12) was found to outperform other more conventional models considerably. The MLP model yielded the lowest RMSE and MSE therefore it is said to have a higher prediction accuracy. Forecasting showed the potential to increase the CPI, an aspect of inflation. In light of these realizations, it becomes clear that only fiscally positive economic initiatives should be used as inflation checkers plus control mechanisms to foster economic stability. In this study, the authors evaluated the power of machine learning models for CPI projection and found their results invaluable for policymakers. Next studies should consider other macroeconomic variables and examine the mixed models to enhance the expected performance of the CPI.

Keywords: Consumer Price Index (CPI), SARIMA Model, Neural Network Autoregressive (NNAR), Multilayer Perceptron (MLP)

JEL classification: C45, C49, C43

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1. Introduction

The CPI is an essential means for assessing the relative monthly shifts in the price of goods and services the consumers typically buy Shapiro and Wilcox (1996). The Punjab Bureau of Statistics defined the CPI as the overall indicator of Consumer expenditure on a bag of goods and services. This index gives important information concerning the prices. A figure below 100 signifies a decline, and a figure above 100 signifies an increase from the base year. With global upheavals including the effects of Covid-19 and the ongoing war in Ukraine and Russia, there is an observation of a large-scale CPI crisis across the globe. These crises are straining the situation concerning the economy Blundell et al. (2020). These crises are observable in the escalating prices of items that must be provided in society and needed in today's economy, which promises significant difficulties in these concerns and in the economy's stability as a whole. Several studies have been conducted and devoted to developing predicting model for CPI. Pakistan has witnessed persistent inflationary trends over the last decade, largely driven by exchange rate volatility, supply shocks, and energy price fluctuations. Given that the CPI directly affects monetary policy, real income, and poverty levels, accurate CPI forecasting is vital for Pakistan's economic stability. Moreover, Pakistan's developing economy, with its frequent structural changes, makes it a unique case where both traditional and machine learning models can be contrasted for inflation prediction.

It is equally widely known that the straightforward models based on reflective time series, namely ARIMA and its seasonal version, have been widely applied to forecasts in the field of economics and finance. Jenkins and Box (1976) were the first to develop the ARIMA methodology, as it is evident from the fact that it possesses qualities of modeling and forecasting the time series components by the incorporation of AR and MA together with the differencing to achieve stationarity. On this basis, the strength of the ARIMA model is in the correct consideration of the features of time series data, including the presence of a trend or seasonality. Many have engaged in forecasting using the ARIMA models since they are simple and easily understandable. Nihan and Holmesland (1980) consider the application of the more recent forms of time series methods for the forecasting of short-run traffic intensity. To this end, the present research focuses on Pakistan. Farooqi (2014) stresses the significance of the forecast for economic planning. Using the method of ARIMA and the statistical tools of R programming, the study determines that progressive values lie in the future for both imports and exports.

In a study done by Zhang (2003) focused on the simulation of economic time series data using neural networks as being more advantageous than the standard models in capturing non-linear patterns. The addition of autoregressive components improves the use of NNAR models when projecting applications such as CPI. Tkacz (2001) described the effectiveness of the NNAR model in exploring the inflation trend successfully and attributed the victory to the temporal relationships that the model can learn about. Feedforward neural networks known as MLP models have shown great effectiveness in several different forecasting tasks due in part to their high levels of deep learning. An MLP construction allows for the representation of complex patterns through the application of concealed layers and nonlinear activation functions. Hyndman and Athanasopoulos (2018) looked at the performance of ARIMA, SARIMA, and the neural network models as applied to forecasting the affiliated economic indicators. Many neural networks captured higher accuracy and flexibility than the conventional models, as identified in the study. Rosado et al. (2021) employs distinct LSTM neural network architecture and integrate CNN to enhance feature learning; The author achieved enhanced and more accurate prediction of the CPI using data collected from Ecuador than ordinary LSTM networks. The approach involves the use of higher mathematical functions that are multidimensional and involve both spatial and temporal characteristics. This

approach therefore establishes how spatial and temporal modeling can complement each other in terms of predicting yields of CPI. The future values of the US CPI are assumed in Nguyen et al. (2023) with a help of various statistical models as support vector regression, multivariate linear regression, multivariate adaptive regression and autoregressive distributed lag splines. These models are trained and tested by datasets from January 2017 to February 2022. The metrics used in the evaluation show that the models are very accurate. Among all these models, MARS shows the best Forecasting Performances which play a very crucial role in deciding near about all the economic policies and the national development projects. Previous cross-sectional research results have pointed to the lower effectiveness of time series models compared to ML approaches for predicting CPI. In most of these analyses, researchers employ average quantitative measures, including MSE and RMSE, to quantify the model's precision. The authors propose a new method of flexible BMA for predicting CPI inflation. This methodology combines methods of time series analysis that were developed by applying machine learning approaches. By combining the features and the potential intricacies in the determination of inflation using Bayesian Model Averaging (BMA), analysis results from data retrieved from the US and the Euro Area is evidence that BMA improves the precision of short-term inflation forecasts. Qureshi et al. (2023) present a comparative analysis of traditional SARIMA and machine learning models for CPI data modelling in Pakistan. In another study by C. Zhang et al. (2024), the comparison of SARIMA and MLP models for CPI forecasting in China was well done. This research suggested that, in terms of lower MSE and RMSE, the MLP model is superior to the SARIMA model. Therefore, the MLP model was considered more reliable in making forecasts. Hu et al. (2024) specifically examine the spectral analysis forecasting methodologies of SARIMA and ARIMA in depicting the seasonality of time series data. The paper discusses the approaches to robust control and the recent probabilistic tools before reviewing the pros and cons of the mitigation measures as well as their complications on emerging grid planning and management.

The machine learning has introduced new methods for modeling the nonlinear interaction and the underlying complex dependencies arising in time series. NNAR and MLP models have steadily gained popularity because of these qualities and primarily because of their ability to learn from large datasets. They therefore include NNAR models, which are unique types of NN that are applied in the analysis of time series, and these models have proven useful in the field of economic prediction. Sibai et al. (2024) try to explain the annual prediction of the CPI in Saudi Arabia. The authors then contrast six categories of methods that use ML with traditional statistical methods like the ARIMA method. With the help of the Orange 3 data mining tool and CPI data from January 2013 to November 2020, different machine learning algorithms like Decision Tree, k–NN, Linear Regression, Neural Network, Random Forest and SVM were compared. Finally, the results show that the MLP well performs for the years 2021-2024 close to the actual CPI values and IMF estimation. This means that MLP has potential in predicting CPI up to 3 years ahead of the most recent data used in training the model. Barkan et al. (2023) focus on how machine learning strategies outcompete traditional techniques in forecasting trends for economic decisions. Forecasting of disaggregated components of the CPI is addressed with a new Hierarchical Recurrent Neural Network (HRNN). Results of experiments on a more structured empirical dataset, namely, a US CPI-U demonstrate that the HRNN performs better than conventional baselines. The HRNN uses information from higher level CPI's for making forecasts at lower levels; such information is important for policy-making and other business entities. The subject under investigation was to utilize MLP and NNAR to make a forecast of CPI and compare their performance with the ARIMA and SARIMA models. The comparisons of the models are based on evaluation measures such as the RMSE and the MSE.

The main contributions of this study are threefold. First, it provides a comparative analysis between classical time series models and advanced neural network models in forecasting CPI for Pakistan. Second, it empirically evaluates how nonlinear learning models such as MLP and NNAR outperform traditional methods in accuracy. Finally, it offers insights for policymakers by forecasting inflation trends that can inform future monetary and fiscal decisions.

In the next part of this article, Section 2, the source of data and modeling procedures involved is mentioned. The results of the modeling and the analysis are discussed in Section 3. Section 4 contains concluding remarks. As such, while applying a rigorous research paradigm, this work aims to make a positive and useful contribution to the advancement of existing knowledge in the domain of CPI modeling and forecasting.

2. Data and methodology

2.1. Data acquisition

The information used for the annual CPI spans from July 2016 to February 2024. The data, obtained from the Pakistan Bureau of Statistics, covers a wide range of time. Figure 1 depicts the time series plot, while Figures 2 illustrate the ACF and PACF plots generated from the CPI dataset. Furthermore, Table 1 presents a summary of the statistical properties of the dataset.

Table 1 - Summary statistics of dataset (summary statistics of CPI for Pakistan, Jul 2016- Feb 2024)

Count	92
Mean	147.7
Standard Deviation	44.8
Minimum	102.8
1st Quartile	112.3
Medium	131.9
3rd Quartile	162.5
Maximum	260.0

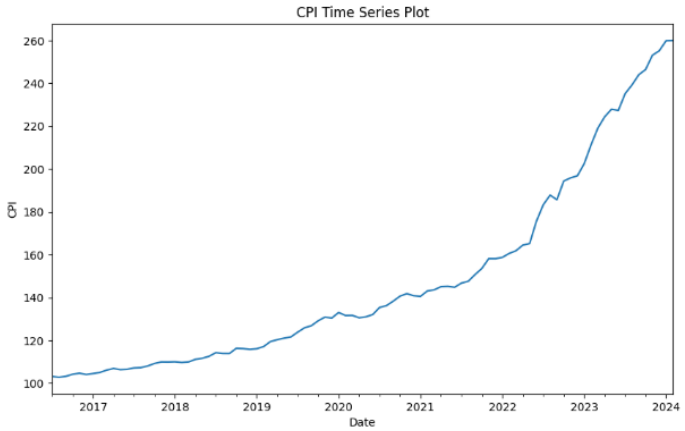

Figure 1 - Time series plot from Jul 16 till Feb 24

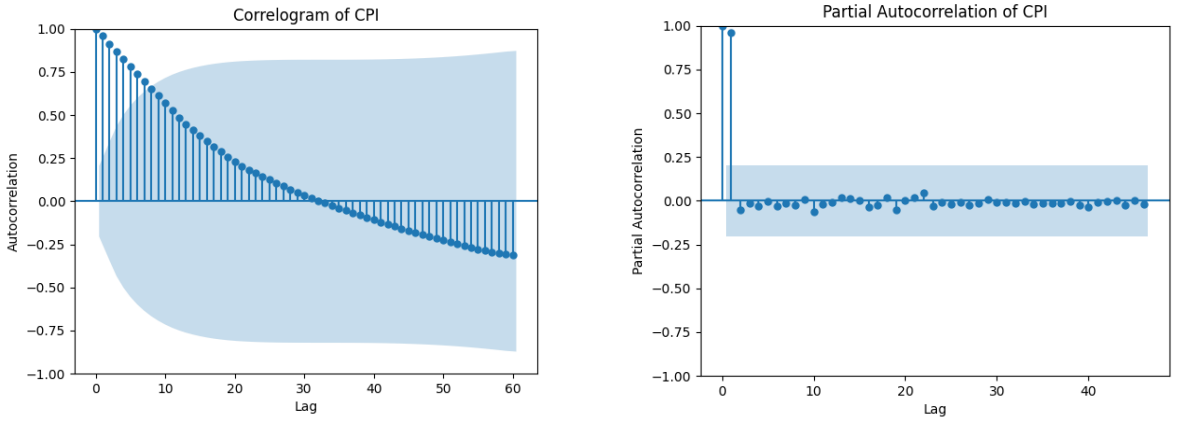

Figure 2 - ACF and PACFof CPI data

2.2. Methods

2.2.1. Autoregressive Integrated Moving Average Model

ARIMA is a common time series approach that has a high level of application within the current economy. Elements that are represented in the model include AR and MA parts together with differencing for non-stationary sections. ARIMA models can work very well to capture the dependencies and patterns inherent in any time series (Montgomery et al., 2008). ARIMA (p, d, q) model describes a time series {Yt}, where the p stands for the order of the autoregressive model, d as the order of differencing and q for the order of the moving average model. The ARIMA model has been defined as:

$$(1-\phi_1 B-\phi_2 B^2-\ldots-\phi_p B_p)(1-B)^d Y_t = (1+\theta_1 B+\theta_2 B^2+\ldots+\theta_q B_q)\varepsilon_t \quad (1)$$

where:
B is the backshift operator, $\phi_1, \phi_2, \ldots, \phi_p$ are the autoregressive coefficients, $\theta_1, \theta_2, \ldots, \theta_q$ are the MA coefficients, d is the differencing order, Y_t is the observed time series, ε_t is the error term assumed to be white noise.
The ARIMA model incorporates both the autoregressive and MA terms along with differencing to account for the temporal structure and non-stationarity in the time series data. By estimating the model parameters $\phi_1, \phi_2, \ldots, \phi_p$ and $\theta_1, \theta_2, \ldots, \theta_q$, the ARIMA model can be used for forecasting future values of the time series.

2.2.2. Seasonal ARIMA (SARIMA) model

The SARIMA model is the advanced form of the ARIMA model to help identify and include the presence of seasonality in the modeling exercise. SARIMA models are highly advantageous for capturing cyclic patterns in time series data, especially on data that trends in economical and climate. A SARIMA(p, d, q)(P, D, Q)s model is specified by the following equations:

$$(1-\phi_1 B-\phi_2 B^2-\cdots-\phi_p B^p)(1-\boldsymbol{\phi}_1 B^s-\boldsymbol{\phi}_2 B^{2s}-\cdots-\boldsymbol{\phi}_P B^{Ps})(1-B)^d(1-B^s)^D Y_t=(1+\theta_1 B+\theta_2 B^2+\cdots+\theta_q B^q)(1+\Theta_1 B^s+\Theta_2 B^{2s}+\cdots+\Theta_Q B^{Qs})\varepsilon_t \quad (2)$$

where:

$\phi_1, \phi_2, \ldots, \phi_P$ are the seasonal autoregressive coefficients, $\Theta_1, \Theta_2, \ldots, \Theta_Q$ are the seasonal MA coefficients and *D* is the seasonal differencing order.

The SARIMA model combines autoregressive, MA, and differencing components at both non-seasonal and seasonal frequencies to capture the temporal patterns in the data. By estimating the model, the SARIMA model can effectively model and forecast time series data with seasonal fluctuations.

2.2.3. The Neural Network Autoregressive model

It is a modified version of AR modeling that incorporates the neural network architecture to capture complex and nonlinear relationships in time series data. While traditional AR models generally express this in terms of a linear combination of past observations, NNAR models are similar to other models, in that they use neural networks to identify and model the temporal structures of the data, not least of all to allow for the inclusion of non-linearity into the AR process. The primary idea of the NNAR model is based on the idea to use a neural network to predict the next value in the time series taking into account a set of the previous values with a time delay. The neural network takes lagged observations for input and produces the forecast of the next time point. The topology defining the layout of the neural network can vary depending on how complex we want the input to be, and how accurately we want to model it. Mathematically, the NNAR model is as:

$$Y_{t+1} = f(Y_t, Y_{t-1}, \ldots, Y_{t-k}) + \varepsilon_{t+1} \quad (3)$$

where:

f represents the neural network function, which takes as input the lagged observations $Y_t, Y_{t-1}, \ldots, Y_{t-k}$ and produces the predicted value Y_{t+1} and ε_{t+1} is the prediction error.

The NNAR model utilizes the adaptability and cognitive capacities of neural networks to deliver precise forecasts for time series data, especially when the underlying dynamics are nonlinear and complex.

2.2.4. The Multilayer Perceptron (MLP) model

The MLP model is a kind of ANN with more than one layer of nodes called the neurons of connectionism organized in feedforward architecture. Every neuron within a certain layer is linked to every neuron within the subsequent layer, and every link has an assigned value, known as weight. Generally, MLPs have been employed in a number of learning problems such as regression and classification because the model is good at expressing nonlinear relationships in data. The computation of the output of a neuron in a MLP is determined mathematically in the following manner:

$$Y_j = \sigma \sum_{i=1}^{n} w_{ij} x_i + \sigma b_j \quad (4)$$

where:

Y_j is the output of the neuron *j* in the current layer, σ is the activation function which introduces nonlinearity into the model and allows it to approximate arbitrary functions, w_{ij} is the weight associated with the connection between neuron *i* in the previous layer and neuron *j* in the current

layer, x_i is the input to neuron j from neuron i in the previous layer and b_j is the bias term associated with neuron j which allows the model to learn an offset from zero.

An MLP model is made of a series of links of neurons whereby each nexus of neurons is connected to the next link of neurons. The input layer takes the attribute values of the inputs and the output layer gives the analytic outcomes respectively. While intermediate layers are called hidden layers, these contain neurons, which transform the input data through nonlinear operations. The number of hidden layers and the number of neurons in each layer chosen in a network are the two typical hyperparameters of the networks. In the training phase of an MLP, the weights and the biases are optimized by such techniques as; gradient descent. It is used to control the growth of any strong muscle and the intent is to minimize a loss function which determines the difference between the actual outputs of a model and the theoretic what should be known as the targets. This is because through the process, the MLP gets the ability of making iterative change, thus mapping for the outcomes for those data that had not been previously used in the process. At present, MLP models are effective at recognizing the interactions between the variables within the data and have been implemented in numerous fields including time series analysis, picture recognition, natural language processing.

An attempt was also made to evaluate the gap-fill capability of MLP and NNAR models in the forecast of Pakistan's CPI. The validity of this model was evaluated based on two main parameters namely the MSE and the RMSE. These measurements are crucial when representing the levels of the accuracy and reliability of the models about the data of the CPI. The model with the lowest MSE and RMSE values is determined as the best model in the study for completing the CPI data. These give a numerical measure of the performance of the given models and help in the selection of the most accurate model for the given task.
All computations and assessments were performed using Python for the analysis.

3. Results and discussions

The analysis of Figures 1 and 2 unequivocally illustrates the lack of stability in the CPI statistics in Pakistan. In order to tackle this issue, the series was differenced once, and then additional plots were created to visualize any patterns, as well as the ACF and PACF. To statistically verify the stationarity of the data, the ADF test was utilized, with a significance level of 0.05.
The null hypothesis (H_0) of the ADF test stated that the series exhibited a trend and was not stationary, whereas the alternative hypothesis (H_1) proposed the lack of a trend and the presence of stationarity. The test results supported the rejection of the null hypothesis (H_0) in favor of the alternative hypothesis (H_1), suggesting that the series was confirmed to be stationary. However, to address the problem caused by an additional delay, a second differencing was implemented. Figures 3 and 4 display the time series, as well as the plots for the ACF and PACF of the second differenced series.

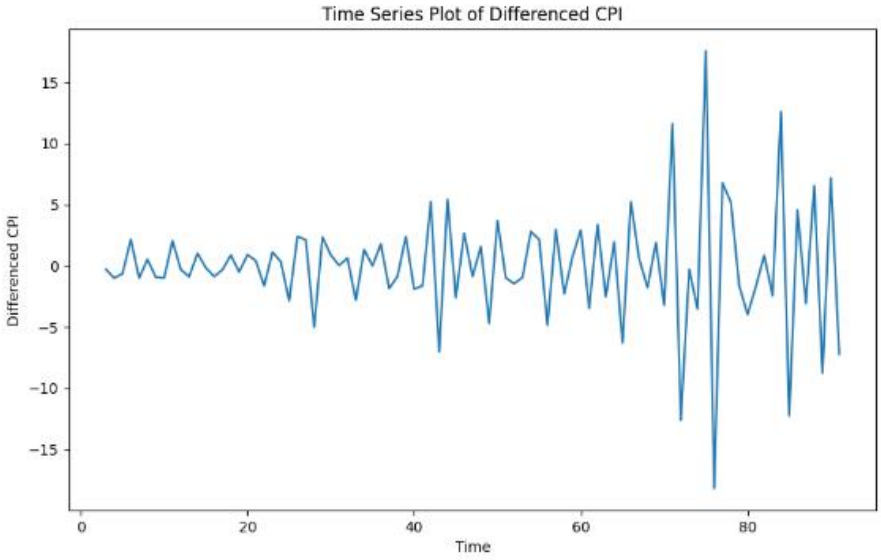

Figure 3 - Time series plot of differenced CPI

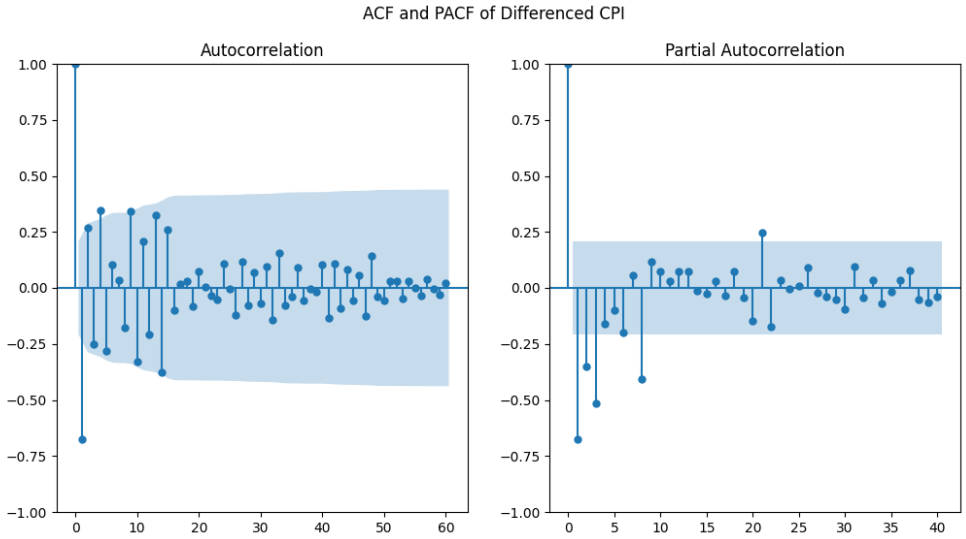

Figure 4: ACF and PACF of Differenced CPI

The Shapiro-Wilk normality test was used to assess the normality of the model's residuals. The test was conducted at a significance level of 5% to test the following hypotheses:
H_0: The residuals follow a normal distribution
H_1: The residuals do not follow a normal distribution.
Also

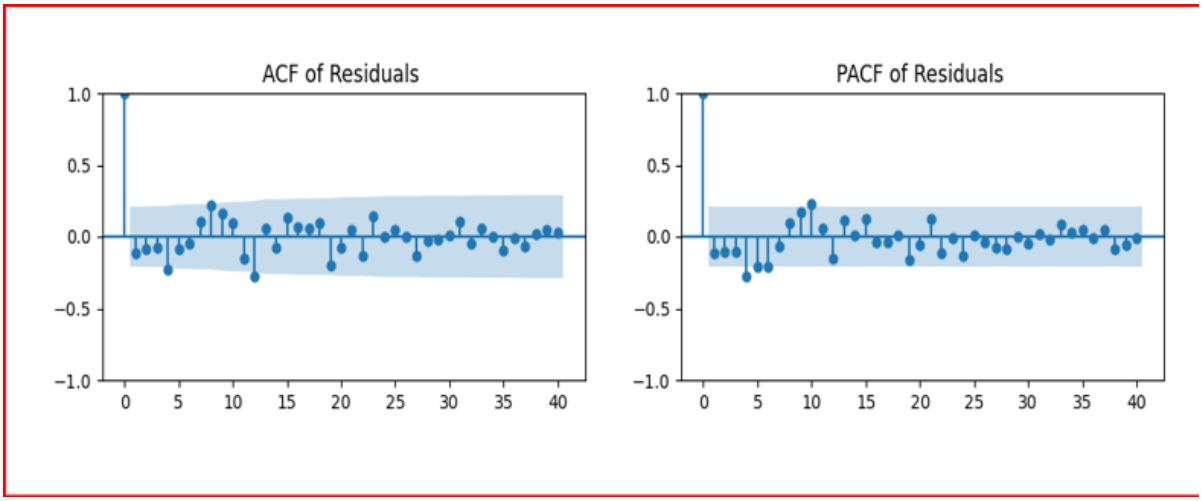

Figure 5 - ACF and PACF of Residuals

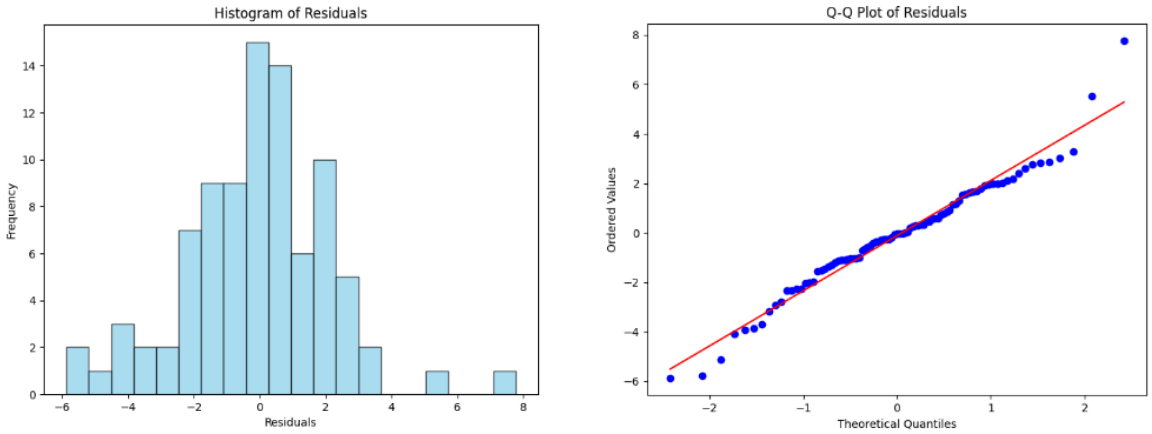

Figure 6 - Histogram and QQ plot of residuals

Figure 5 shows ACF and PACF of residuals. In Figure 6, we have checked the normality of data using histogram and QQ plot.

Further analysis involved exploring different combinations of the ARIMA and SARIMA model to improve the quality of the series. Various iterations of the ARIMA and SARIMA model were tested and their performance indicators were evaluated. These combinations included ARIMA (2,1,2), ARIMA(4,1,4), ARIMA(3,1,3), SARIMA (3, 1, 3)(0, 1, 0)12, SARIMA(2, 1, 2)(1, 1, 0)12, and SARIMA(4, 1, 4)(0, 1, 1)12. Some best performing model results in Table 2 are as:

Table 2 - AIC and BIC of some models

Model	Order	AIC	BIC
SARIMAX	(4, 1, 4)(0, 1, [1], 12)	380.977	404.285
ARIMA	(2, 1, 2)	483.971	496.357
ARIMA	(4, 1, 4)	414.628	436.924

Once the best-performing SARIMA models were identified, iterations of the NNAR model were applied and evaluated. The top-performing models were selected based on their performance indicators. The MLP model is a form of machine learning was implemented on the CPI data. Different configurations of the MLP including varying numbers of hidden layers were tested and their performance was assessed. MLP with three hidden layers outperformed other models. Results from competing models were compiled and presented in Table 3 for comparison.

Table 3 - Comparison of models

Models	MSE	RMSE
ARIMA (2, 1, 2)	11.94	3.46
ARIMA (4, 1, 4)	4.51	2.12
SARIMAX (4, 1, 4)(0, 1, [1], 12)	4.94	2.22
NNAR	0.46	0.68
MLP	0.03	0.19

Upon analysis, it was found that the MLP model with 3 hidden layers outperformed all other models, exhibiting the lowest values for RMSE and MSE. Figure 7 depicts the fitted and original values using the MLP model to visualize the results.

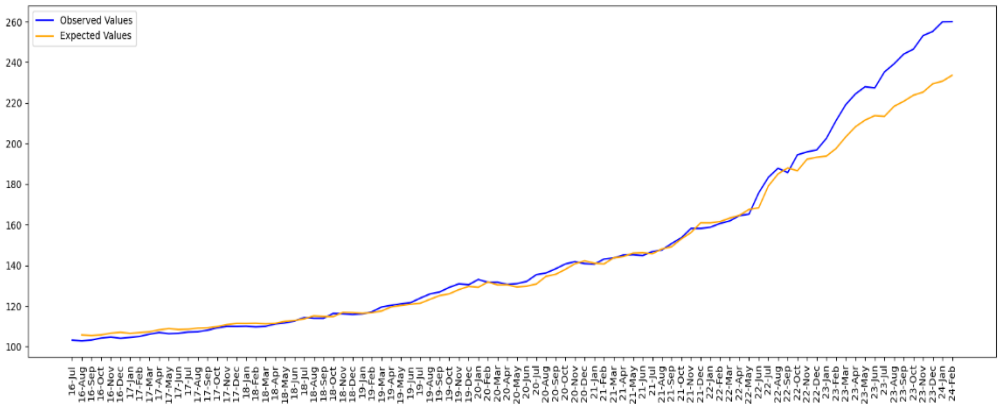

Figure 7 - Observed vs Expected plot using MLP

The forecasted CPI values from March 2024 to February 2026 displayed an increasing trend with high values indicating potential inflationary pressures (see Table 4).

Table 4 - Forecasted CPI values from March 2024 to February 2026

Mar 24	Apr 24	May 24	June 24	July 24	Aug 24	Sep 24	Oct 24
268.47	276.10	282.98	289.16	294.70	299.67	304.14	308.17
Nov 24	Dec 24	Jan 25	Feb 25	Mar 25	Apr 25	May 25	June 25
311.81	315.07	318.20	320.68	323.07	325.23	327.19	328.97
July 25	Aug 25	Sep 25	Oct 25	Nov 25	Dec 25	Jan 26	Feb 26
330.57	332.02	333.34	334.53	335.60	336.57	337.46	338.26

Recommendations were made for Pakistani authorities to implement policies aimed at mitigating these trends to safeguard consumers and the overall economy. These findings align with previous research highlighting the importance of CPI as a key economic indicator and its significant implications for inflation and economic growth.

The obtained findings are consistent with prior studies such as Zhang (2003) and Qureshi et al. (2023), which reported that neural network-based approaches outperform ARIMA-type models in handling nonlinearity in economic data. Similarly, our results support Sibai et al. (2024), who demonstrated that MLP models predict CPI more accurately in Middle Eastern economies. This confirms that machine learning models offer a powerful alternative to traditional time series forecasting in emerging markets like Pakistan.

4. Conclusion

This study examined different models to predict and anticipate the CPI in Pakistan, utilizing data from 1960 to 2021. We utilized ARIMA, SARIMA, NNAR, and MLP models, evaluating their effectiveness using measures such as MSE and RMSE. The study we conducted indicated that the CPI series is not stationary. To make it stationary, differencing was necessary, as demonstrated by the ADF test. The SARIMAX (4, 1, 4)(0, 1, [1], 12) model demonstrated superior performance compared to other conventional time series models. The MLP model with three hidden layers shows superior performance compared to all other models showcasing the lowest RMSE and MSE values. The CPI numbers reflect a consistent increasing trajectory that indicates the possibility of inflationary pressures. These findings emphasize the significance of proactive economic policy in reducing inflation and ensuring economic stability. The MLP model demonstrated significant efficacy in predicting CPI provides policymakers with useful information. We can integrate supplementary macroeconomic variables and hybrid models in order to improve the accuracy of CPI forecasts in future research. The findings have important policy implications. As inflation remains a key economic concern in Pakistan, accurate CPI forecasting can support the State Bank and Ministry of Finance in designing timely monetary policies. By adopting advanced forecasting models like MLP, policymakers can better anticipate inflationary pressures, implement preemptive measures, and maintain price stability to protect consumer welfare.

5. Limitations and future work

Despite the promising results, this study has certain limitations. The analysis relies solely on CPI data without incorporating exogenous macroeconomic variables such as exchange rate, oil prices, and interest rates, which may affect inflation dynamics. Additionally, the study focuses only on univariate models and does not explore hybrid or ensemble approaches. Future work should

consider integrating these macroeconomic indicators and developing hybrid models combining statistical and neural network frameworks for improved predictive accuracy.

Conflicts of interest

The authors declare that they have no conflict of interest.

Data accessibility statement

The dataset utilized in this study is from July 2016 to February 2024 obtained from the PBS. The dataset contains monthly CPI values which offer a full time series for study.
The data and analytic scripts can be provided upon request to guarantee the transparency and repeatability of the results.

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