Hindawi
Applied Computational Intelligence and Soft Computing
Volume 2023, Article ID 3236617, 10 pages
https://doi.org/10.1155/2023/3236617

Research Article

A Comparative Analysis of Traditional SARIMA and Machine Learning Models for CPI Data Modelling in Pakistan

Moiz Qureshi[1] **Arsalan Khan**,[2] **Muhammad Daniyal**,[3] **Kassim Tawiah**,[4,5] **and Zahid Mehmood**[6]

[1]*Department of Statistics, Shaheed Benazir Bhutto University, Shaheed Benazirabad, Nawabshah, Pakistan*
[2]*Department of Statistics, Quaid-i-Azam University, Islamabad, Pakistan*
[3]*Department of Statistics, The Islamia University of Bahawalpur, Bahawalpur, Pakistan*
[4]*Department of Mathematics and Statistics, University of Energy and Natural Resources, Sunyani, Ghana*
[5]*Department of Statistics and Actuarial Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana*
[6]*Department of Management Science, National College of Business Administration and Economics, Lahore, Pakistan*

Correspondence should be addressed to Kassim Tawiah; kassim.tawiah@uenr.edu.gh

Received 13 November 2022; Revised 12 October 2023; Accepted 17 October 2023; Published 7 November 2023

Academic Editor: Francesco Taglino

Background. In economic theory, a steady consumer price index (CPI) and its associated low inflation rate (IR) are very much preferred to a volatile one. CPI is considered a major variable in measuring the IR of a country. These indices are those of price changes and have major significance in monetary policy decisions. In this study, different conventional and machine learning methodologies have been applied to model and forecast the CPI of Pakistan. *Methods*. Pakistan's yearly CPI data from 1960 to 2021 were modelled using seasonal autoregressive moving average (SARIMA), neural network autoregressive (NNAR), and multilayer perceptron (MLP) models. Several forms of the models were compared by employing the root mean square error (RMSE), mean square error (MSE), and mean absolute percentage error (MAPE) as the key performance indicators (KPIs). *Results*. The 20-hidden-layered MLP model appeared as the best-performing model for CPI forecasting based on the KPIs. Forecasted values of Pakistan's CPI from 2022 to 2031 showed an astronomical increase in value which is unpleasant to consumers and economic management. *Conclusion*. The increasing CPI trend observed if not addressed will trigger a rising purchasing power, thereby causing higher commodity prices. It is recommended that the government put vibrant policies in place to address this alarming situation.

1. Introduction

The consumer price index (CPI) measures the monthly price changes in commodities purchased by consumers [1]. The Pakistan Bureau of Statistics (PBS) computes CPI as an average weight of the cost of a basket of goods and services represented by an aggregated Pakistan consumer's expenditure. The choice of the basket of goods and services is based on popular commodities and services mostly purchased by consumers in the area [1]. CPI values are estimated as percentages. A CPI value less than 100 indicates a general reduction in the prices of goods and services in the current year compared with those in the base year [2, 3]. However, values greater than 100 show a general increase in prices compared to those in the base year [2, 3]. CPI values are used to compute the inflation rate (IR) [1, 4].

Inflation rate (IR) values are estimated as percentages [5]. A negative IR value indicates a reduction in the cost of goods and services paid for by consumers, whereas a positive value indicates an increase in the cost of goods and services paid for by consumers [1]. The aftermath of COVID-19 and the Russian-Ukraine war has put the world in a CPI crisis [6]. Costs of goods and services are skyrocketing everywhere, and Pakistan is no exception.

There has been considerable study recently for the prediction and forecasting of CPI using different several competing models. Kharimah et al. [7] modelled and predicted CPI for Indonesia's Lampung Province using different time series and autoregressive integrated moving average (ARIMA) models and compared them using the mean square error (MSE), Akaike information criteria (AIC), and Bayesian information criteria (BIC). They found ARIMA (1, 1, 0) as the overall befitting model for CPI modelling and forecasting in Indonesia's Lampung Province. Mia et al. [8] used both autoregressive moving average (ARMA) and ARIMA models as the appropriate models for CPI data in Bangladesh, thereby settling for ARIMA (2,2,0) as the overall best model in forecasting Bangladesh's CPI [9]. Nyoni [10] used ARMA and ARIMA models to forecast Germany's CPI, establishing ARIMA (1, 1, 1) as the best fit for the given dataset.

Mohamed [11] made a comparative analysis between ARMA and ARIMA models together with regression using ARIMA errors to model and forecast CPI for Somaliland, selecting models based on AIC and BIC, thereby establishing ARIMA (0, 1, 3) as the overall suitable model for forecasting Somaliland's CPI. Norbert et al. [12] applied a similar methodology to forecast the CPI for a short-term period. Their resulting output showed that ARIMA (4, 1, 6) is more suitable for short-term CPI forecasting for Rwanda. Molebatsi and Roboloko [13] proposed ARIMA(1,1,1) as a suitable model for Botwana's CPI data.

In macroeconomics, neural networks have not been thoroughly explored. Kuan and White [14] are among the few with a first attempt at introducing neural network forecasting in macroeconomics. Maasoumi et al. [15] implemented the backpropagation artificial neural network (ANN) model to predict United States (US) macroeconomic variables like CPI, money inflow, unemployment, gross domestic product (GDP), and wages. Aiken [16] proposed an ANN to forecast CPI in the United States of America. Choudhary and Haider [17] showed how powerful ANN models are when forecasting monthly IR for twenty-eight countries in the Organization for Economic Cooperation and Development (OECD). They implemented the ANN together with quasi-ANN approaches. Their results indicated that average neural network models work excellently in forty-five percent of the OECD member countries, whereas basic autoregressive (AR) of order one (AR1) emerges as the best in twenty-three percent of the OECD member countries. They proposed an arithmetical combination of an ensemble of multiple networks for further accuracy.

Moshiri and Cameron [18] performed a comparison of backpropagation ANN (BPANN) models with basic econometric techniques to predict IR. McAdam and McNelis [19] implemented basic as well as complex neural network-based models to forecast IR in the USA, Japan, and Europe based on Phillips curve formulations. The complex models represented cropped mean predictions from numerous neural networks. The complex models performed better than the basic models for normal timing and bootstrapping predictions for numerous indices in Europe and elsewhere. Wang et al. [20] surveyed partly parametric and erratic AR models with exogenic variables depending on neural networks for CPI modelling and forecasting. Thus, more exploration needs to be done in CPI modelling and forecasting with ANN. Several applications of ANN have been seen in CPI analysis and forecasting [21, 22].

The CPI is a widely used measurement of the cost of living [1]. CPI does not only affect the government's monetary, fiscal, consumption, prices, wages, and social security but also closely relates to the daily lives of people in a country [23, 24]. As an indicator for development, it is essential to model and forecast fluctuations in the CPI. In the post-COVID-19 era, almost every country is in a CPI crisis and Pakistan is not exempted from this catastrophic situation. Most of the previous studies in the literature applied conventional modelling techniques for the prediction of CPI [8, 9, 23, 25]. Those that applied neural networks used single models [18, 19]. In our study, we investigated and used the machine learning approaches (i.e., multilayer perceptron (MLP) and neural network autoregressive (NNAR) models) in forecasting CPI [16] and compared them with the seasonal univariate ARIMA (SARIMA) model. The models are compared using root mean square (RMSE), mean square error (MSE), and mean absolute percentage error (MAPE).

The rest of the article is ordered as follows. Section 2 illustrates the source of data and modelling methods. Section 3 indicates the results of the modelling and its discussion. Section 4 presents the conclusions.

2. Data and Methods

2.1. Data. The data used for modelling the yearly CPI span from 1960 to 2021. The data were sourced from the official website of the Pakistan Bureau of Statistics (https://www.pbs.gov.pk/). Figure 1 shows the time series plot, whereas Figure 2 shows the autocorrelation function (ACF) and partial ACF plots of the CPI data. The summary statistics of the data are presented in Table 1.

2.2. Methods

2.2.1. Seasonal ARIMA (SARIMA) Model. Time series ARMA is extended to the ARIMA model when differencing is applied before achieving stationarity [26–29]. When seasonal patterns are factored into an ARIMA model, we have the seasonal ARIMA (SARIMA) model [30].

A time series $\{\mathbf{Y_t}\}$ is said to follow the ARMA $(\mathbf{p}, \mathbf{q})$ $(\mathbf{p}, \mathbf{q})$ model [26–29] if

$$Y_t = \mu + \sum_{n=1}^{p} \boldsymbol{\phi}_\mathbf{n} \mathbf{Y}_{\mathbf{t-n}} - \sum_{n=1}^{q} \boldsymbol{\Theta}_\mathbf{n} \mathbf{e}_{\mathbf{t-n}} + \mathbf{e}_\mathbf{t}. \quad (1)$$

Using the back-shift operator, equation (1) can be written as

$$\boldsymbol{\phi}(\mathbf{B})\mathbf{Y}_\mathbf{t} = \boldsymbol{\Theta}(\mathbf{B})\mathbf{e}_\mathbf{t}, \quad (2)$$

where

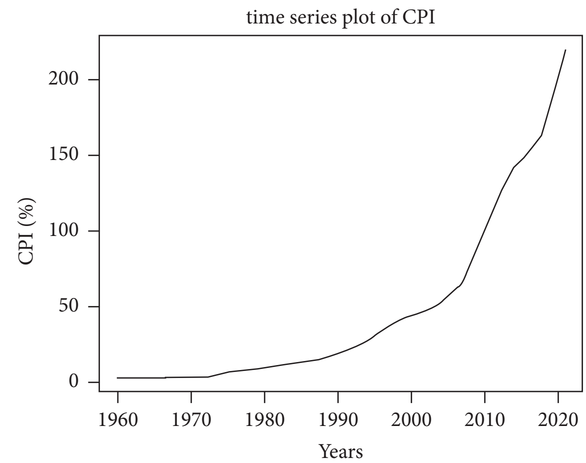

Figure 1: Time series plot of CPI from the year 1960 to 2021.

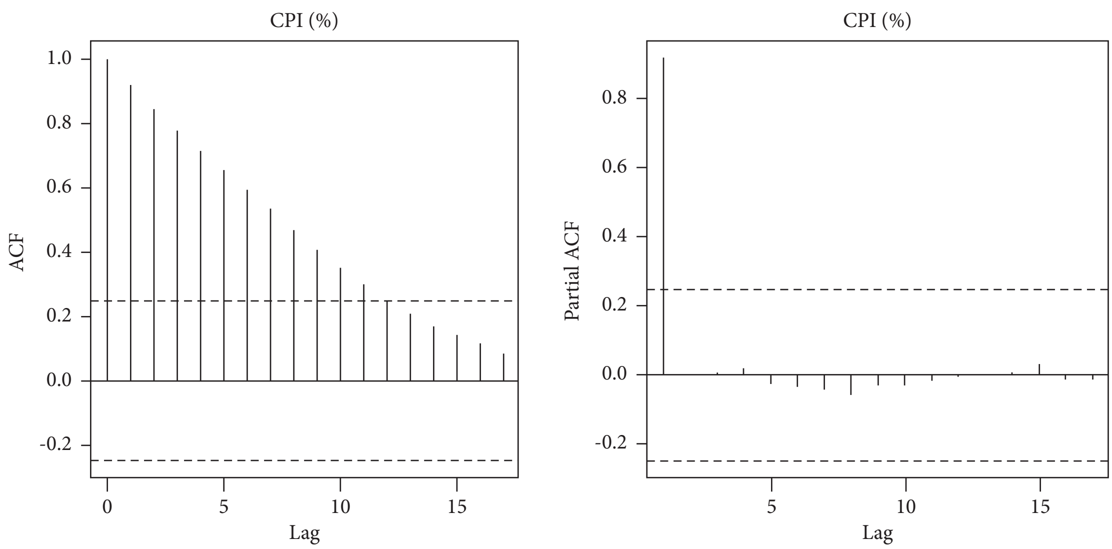

Figure 2: Correlograms of the CPI.

Table 1: Summary statistics of the CPI of Pakistan from the year 1960 to 2021.

	Estimate
Minimum value	2.072
Maximum value	219.079
Median	19.057
Mean	46.888
1st quartile	6.162
3rd quartile	59.092
Standard deviation	57.671

$$\boldsymbol{\phi}(\mathbf{B}) = \mathbf{1} - \boldsymbol{\phi}_\mathbf{1}\mathbf{B}^\mathbf{1} - \boldsymbol{\phi}_\mathbf{2}\mathbf{B}^\mathbf{2} - \ldots - \boldsymbol{\phi}_\mathbf{p}\mathbf{B}^\mathbf{p} = \mathbf{1} - \sum_{n=1}^{p} \boldsymbol{\phi}_\mathbf{n}\mathbf{B}^\mathbf{p},$$

$$\boldsymbol{\Theta}(\mathbf{B}) = \mathbf{1} + \boldsymbol{\Theta}_\mathbf{1}\mathbf{B}^\mathbf{1} + \boldsymbol{\Theta}_\mathbf{2}\mathbf{B}^\mathbf{2} + \ldots + \boldsymbol{\Theta}_\mathbf{q}\mathbf{B}^\mathbf{q} = \mathbf{1} + \sum_{n=1}^{q} \boldsymbol{\Theta}_\mathbf{n}\mathbf{B}^\mathbf{q}, \tag{3}$$

where **p** and **q** are greater than zero and **p** refers to the AR part while **q** refers to the MA part and $\mathbf{e_t}$ is the white noise term of the model. μ is a constant that can be zero or not and $\mathbf{e_t}$ is the white noise having a mean 0 and variance σ^2 [31–33].

For the nonstationary time series, first, we convert it by taking the difference of the series to obtain the ARIMA model. Denoting the number of differencing of the series by **d**, the ARIMA **(p**, **d**, **q)** model [26–29] is given by

$$\boldsymbol{\phi}(\mathbf{B})(\mathbf{1} - \mathbf{B})^\mathbf{d}\mathbf{Y_t} = \boldsymbol{\Theta}(\mathbf{B})\mathbf{e_t}. \tag{4}$$

When the ARIMA model has an extra lag offset for seasonality as an additional component of the autoregressive and moving average, the seasonal ARIMA (SARIMA) is obtained [31–33].

With the backward shift, SARIMA **(p**, **d**, **q)** $\times$ $(\mathbf{P}, \mathbf{D}, \mathbf{Q})_\mathbf{s}$ [26–29] is given by

$$\boldsymbol{\phi}(\mathbf{B})\vartheta(\mathbf{B}^\mathbf{s})(\mathbf{1} - \mathbf{B})^\mathbf{d}(\mathbf{1} - \mathbf{B}^\mathbf{s})^\mathbf{D}\mathbf{Y_t} = \boldsymbol{\Theta}(\mathbf{B})\boldsymbol{\varphi}(\mathbf{B}^\mathbf{s})\mathbf{e_t}, \tag{5}$$

where

$$\begin{aligned}\phi(\mathbf{B}) &= \mathbf{1} - \phi_1\mathbf{B}^1 - \phi_2\mathbf{B}^2 - \ldots - \phi_p\mathbf{B}^P,\\ \Theta(\mathbf{B}) &= \mathbf{1} + \Theta_1\mathbf{B}^1 + \Theta_2\mathbf{B}^2 + \ldots + \Theta_q\mathbf{B}^Q,\end{aligned} \tag{6}$$

with **P** being the autoregressive seasonal term, **Q** being the moving average seasonal term, and **D** being the differencing seasonal term based on s seasonal periods. Figure 3 shows the flowchart of SARIMA methodology.

We can, therefore, write SARIMA $(\mathbf{p}, \mathbf{d}, \mathbf{q}) \times (\mathbf{P}, \mathbf{D}, \mathbf{Q})_\mathbf{s}$ [34, 35] in the form

$$Y_t = \mu + \left(\sum_{n=1}^{p} \phi_\mathbf{n}\mathbf{Y}_{\mathbf{t-n}} + \sum_{n=1}^{P} \vartheta_\mathbf{n}\mathbf{Y}_{\mathbf{t-ns}} - \sum_{n=1}^{p}\sum_{\mathbf{m=1}}^{\mathbf{P}} \vartheta_\mathbf{n}\phi_\mathbf{n}\mathbf{Y}_{\mathbf{t-ms-n}}\right) + \left(\sum_{n=1}^{q} \Theta_\mathbf{n}\mathbf{e}_{\mathbf{t-n}} + \sum_{n=1}^{Q} \varphi_\mathbf{n}\mathbf{e}_{\mathbf{t-ns}} + \sum_{n=1}^{q}\sum_{m=1}^{Q} \varphi_\mathbf{n}\Theta_\mathbf{n}\mathbf{e}_{\mathbf{t-ms-n}}\right) + \mathbf{e}_\mathbf{t}. \tag{7}$$

2.2.2. Neural Network Autoregressive (NNAR) Model. The neural network autoregressive (NNAR) [36–38] model is an application of neural networks in supervised classification, prediction, and nonlinear time series forecasting. A simple feedforward neural network's design can be characterized as a network of neurons arranged in input, hidden, and output layers in a specific order [36]. Each layer uses weights that are acquired using a learning method to relay information to the subsequent layer [37]. The NNAR model is a variation of the straightforward ANN model created specifically for challenges involving time series datasets [38]. The time series' lagged values are used as inputs in the NNAR model together with fixed number of hidden neurons. The NNAR $(\mathbf{p}, \mathbf{k})$ model applies one hidden layered feedforward neural network with k hidden units to time series data with p-lagged inputs [39]. Let **f** be a function of a neural network with the following design, and let **x** represent a vector of p-lagged inputs [38]; then,

$$\mathbf{f}(\mathbf{x}) = \mathbf{C_0} + \sum_{\mathbf{j=1}}^{\mathbf{k}} \mathbf{w_j}\varnothing\left(\mathbf{a_j} + \mathbf{b_j'}\boldsymbol{x}\right), \tag{8}$$

where $\mathbf{C_0}$, $\mathbf{a_j}$, and $\mathbf{w_j}$ are linking adjustable weights, $\mathbf{b_j}$ is a p-dimensional weight vector, and a is a nonlinear sigmoidal function with a bounded domain (e.g., logistic function or tangent hyperbolic activation function).

The structure of the NNAR model is illustrated in Figure 4, while the flowchart for NNAR modelling is illustrated in Figure 5 [37, 38].

2.2.3. Multilayer Perceptron (MLP) Model. Similar to the NNAR model, the multilayer perceptron (MLP) model also uses artificial neurons to migrate processed information from one layer to another [40, 41]. The hidden layers receive the processed information from the input layers and pass it through an interconnected processed fact in a random ramification to the output layers in a manner that will ensue reciprocation of a feedforward system with disjoint layers [19]. The MLP network function [40, 41] is given by

$$x = g_w\left[\sum_{n=0}^{N} k_{1n}^0\left(f\sum_{t=0}^{T} k_{nj}^i d_j + c_j\right)\right], \tag{9}$$

where d_j is the input network and represents the bias of the network, c_j. The intermediate layers have g as the function of activation and g_w the output layer function of activation. x is the signal output, and k_{nj}^i are the weights for the intermediation layer, while k_{1n}^0 denote the connections of the neuron's output [15]. Figure 6 illustrates the structure of an MLP model while Figure 7 shows the flowchart for the MLP modelling procedure [41].

These models have been applied to complete CPI data in Pakistan and compared with MSE, RMSE, and MAE. Expressions for these measures of performance are

$$\begin{aligned}\text{MSE} &= \frac{1}{K-M}\sum_{t=M+1}^{K}\left(Y_t - \widehat{Y}_t\right)^2,\\ \text{RMSE} &= \sqrt{\frac{1}{K-M}\sum_{t=M+1}^{K}\left(Y_t - \widehat{Y}_t\right)^2},\\ \text{MAPE} &= \frac{1}{K-M}\sum_{t=M+1}^{K}\left|Y_t - \frac{\widehat{Y}}{Y_t}\right|,\end{aligned} \tag{10}$$

where $Y_1, \ldots, Y_M$ as well as $Y, \ldots, Y_K$ is a subdivision of our data. The model having the least MSE, RMSE, and MAE is chosen as the preferred model with our data [36–38]. R version 4.3.1 was used for all analysis.

3. Results and Discussion

Figures 1 and 2 clearly show that the data are nonstationary. The series was differenced once and plotted to observe the trend as well as the ACF and the PACF. To check the stationarity of our data statistically, the Augmented Dicky–Fuller (ADF) [42] test was applied under the hypothesis of a 0.05 level of significance.

H_0: the series has a trend and is nonstationary

H_1: the series has no trend and is stationary

The results of the analysis show that H_0 is rejected in favor of H_1 (since the p value is less than the 0.05 significance level) and conclude that the series is stationary. Due to the extra lag present, we applied the second differencing to correct it. Figure 8 shows the time series plot of the second differenced series, while Figure 9 shows the ACF and PACF plots of the second differenced series [33]. Figure 10 shows the ACF and PACF of the competing models, and Figure 11 illustrates the Q-Q plot. Thus, differencing the series

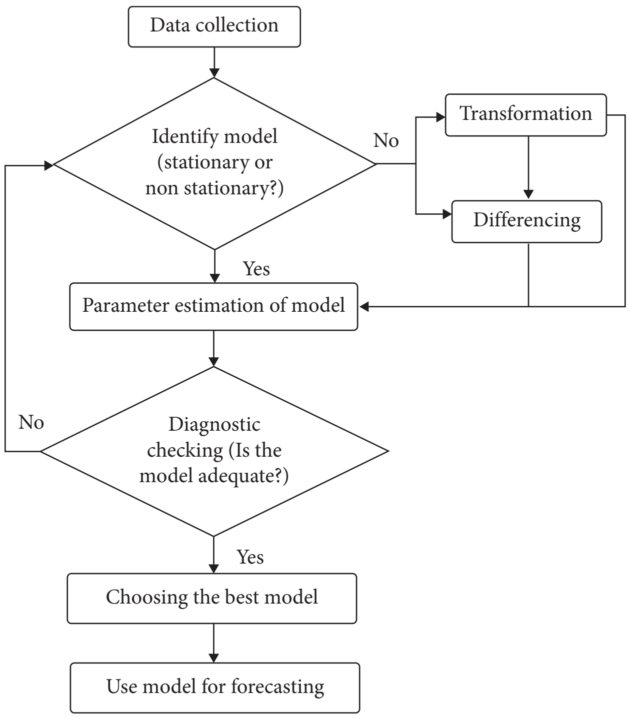

Figure 3: Flowchart for SARIMA modelling.

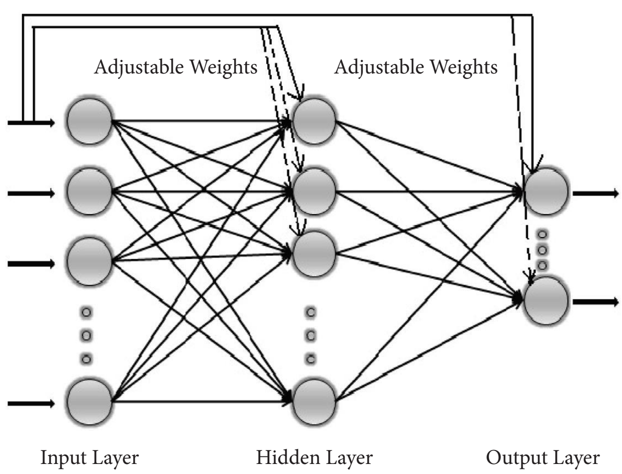

Figure 4: Structure of a NNAR model (source: AL-Allaf and AbdAlKader [37]).

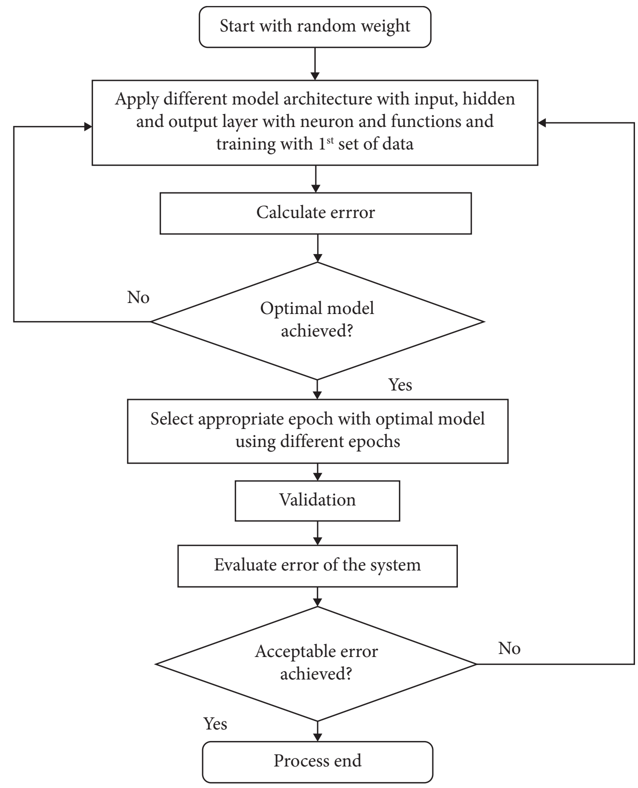

Figure 5: Flowchart for NNAR modelling (source: Chang et al. [38]).

improved the qualities of the series, thereby making it better. Different combinations of the SARIMA model are obtained, and their performance indicators are checked. The various combinations were SARIMA $(3,1,3)(0,1,0)_{12}$, SARIMA $(2,1,2)(1,1,0)_{12}$, and SARIMA $(2,1,2)(0,1,0)_{12}$. The correlogram for the selected model for full sample data is given in Figure 9, whereas the differenced series is shown in Figure 8. To check the normality of the model's residuals, we applied the Shapiro–Wilk normality test at 5% significance level to the hypotheses [30]:

H_0: the residuals are normally distributed

H_1: the residuals are not normally distributed

The results in Table 2 suggest that the null hypothesis is not rejected (since the p value is greater than the 0.5 significance level) and conclude that the residuals are normally distributed, which validates our results. After checking all possible accurate combinations of the SARIMA, different iterations of the NNAR model were applied and the best three were selected among the different iterations. The best-selected iterations for the NNAR were 20, 30, and 40. The performance indicators for all three iterations were computed. The machine learning MLP model was next to be implemented on the CPI data. We set the hidden layers to 5, 10, and 20. We also computed the performance indicators for all possible combinations of the MLP. The results of all competing models are presented in Table 3.

Table 4 shows the performance indicators for all combinations of SARIMA, NNAR, and MLP. It is evident from Table 4 that the 20-hidden-layered MLP outperformed all other competing models since it had the least RMSE, MSE, and MAPE. Figure 12 portrays the fitted as well as the original values, whereas Figure 13 shows the CPI values forecasted using the 20-hidden-layered MLP. Our findings are in contrast with the results of Qin et al. [43] and Hwang [39].

From Figure 13, the 20-hidden-layered MLP model gives multiple horizon forecasts as it indicates that the series may behave in numerous directions with restrictions [43]. Table 4 shows the annual forecasted CPI values from 2022 to 2031. The forecasted values show an increasing trend with high values. We entreat Pakistan authorities to initiate policies to

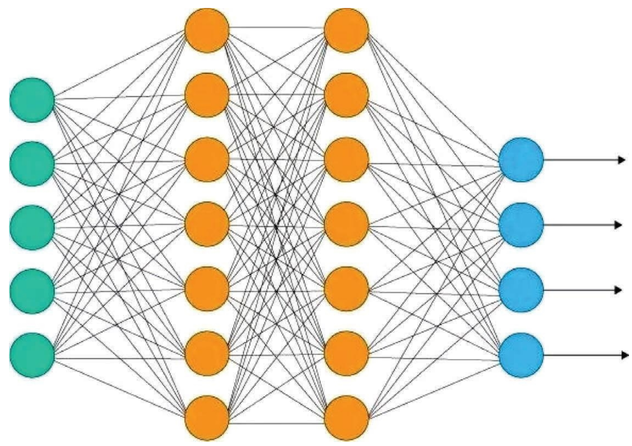

FIGURE 6: Structure of the MLP model with m hidden layers.

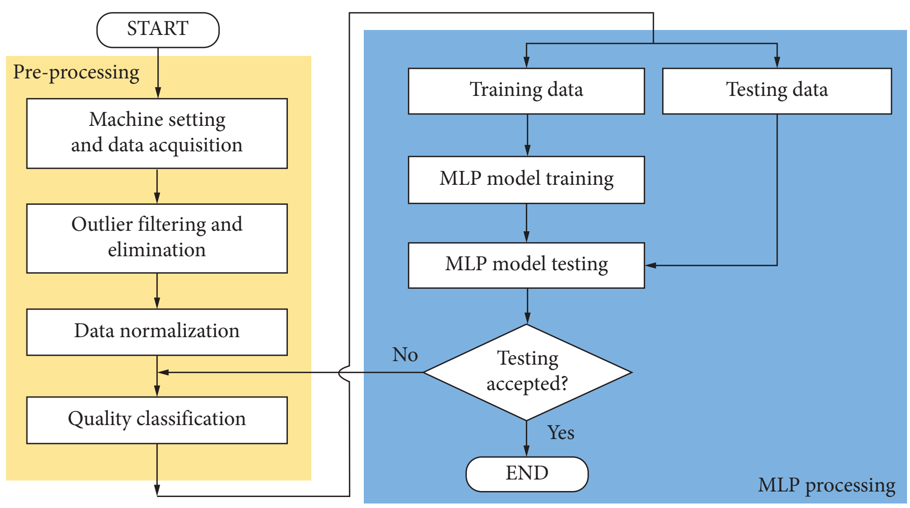

FIGURE 7: Flowchart of MLP modelling (source: Ke and Huang [41]).

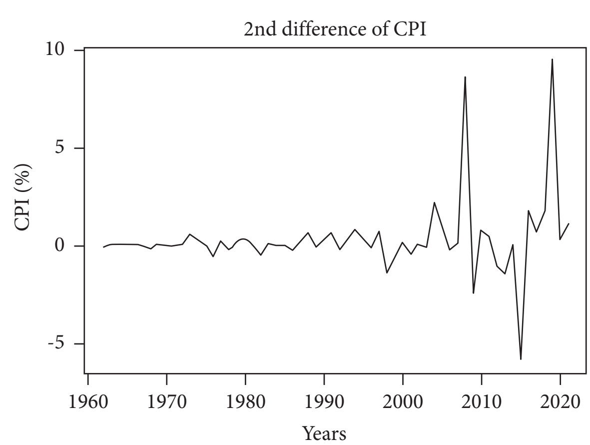

FIGURE 8: Time series plot of second differenced series.

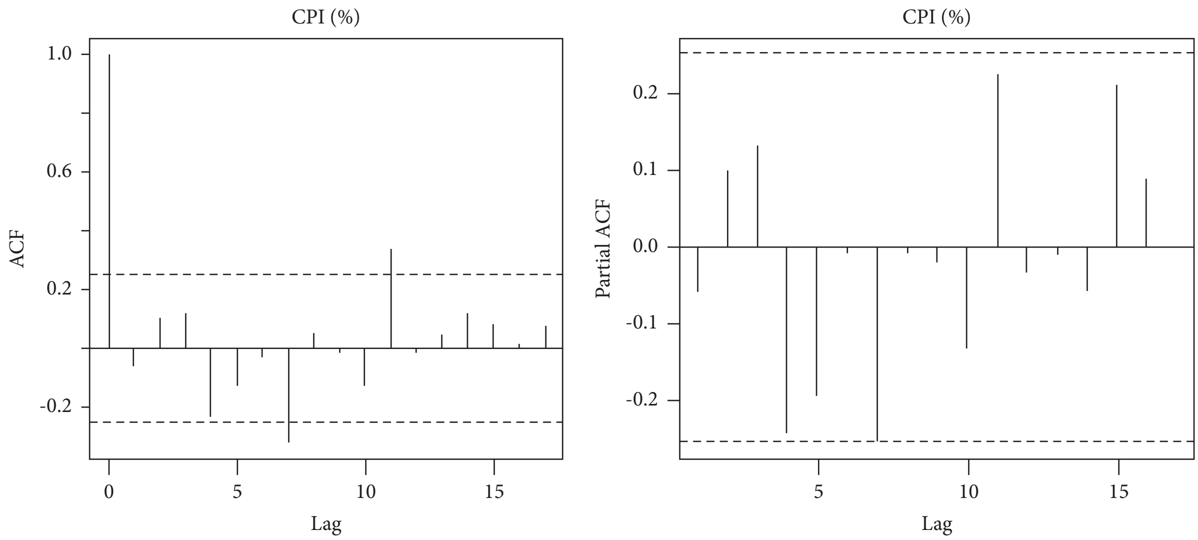

Figure 9: Correlogram of the second differenced series.

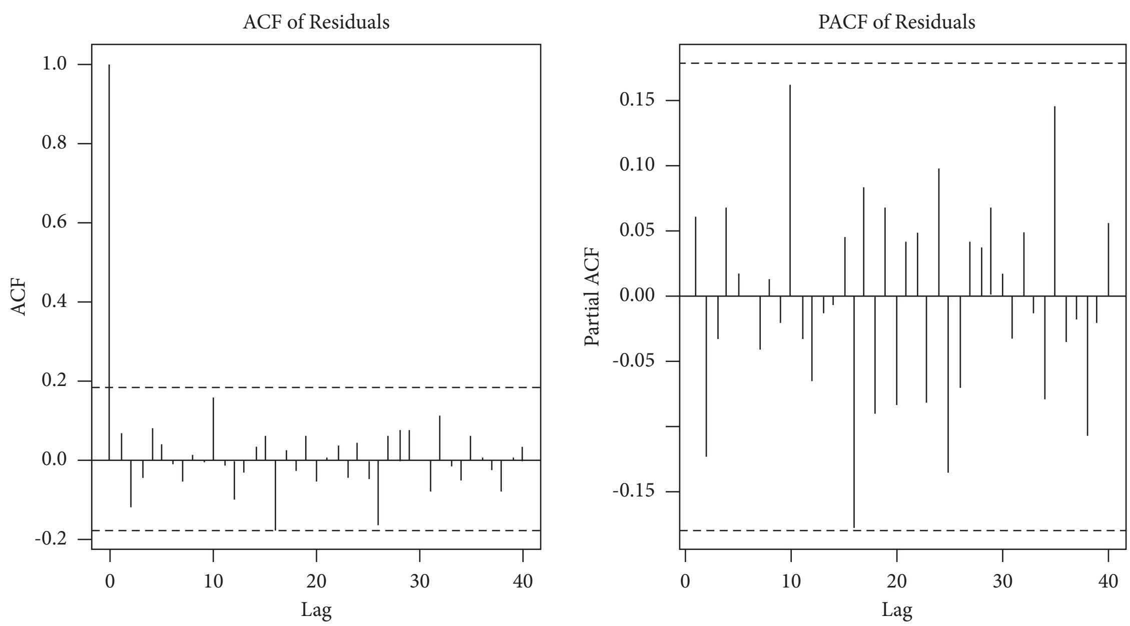

Figure 10: Correlogram of the candidate model.

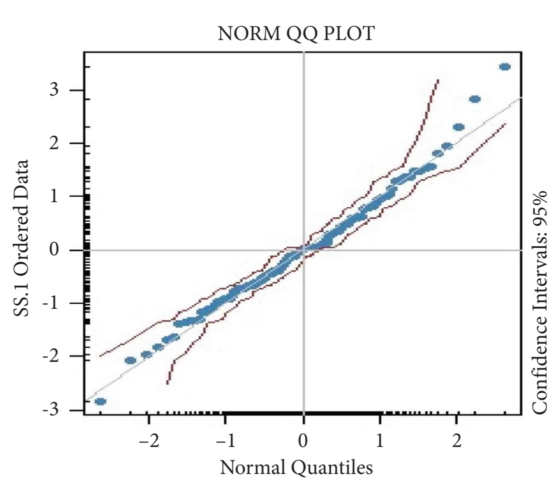

Figure 11: Q-Q norm plots of the candidate model for CPI.

Table 2: Shapiro–Wilk normality test results.

	Estimate
W	0.98633
p value	0.2694

Table 3: Estimated candidate models for CPI (%) from the year 1960 to 2021.

Candidate models	RMSE	MSE	MAPE
SARIMA (2, 1, 2) $(0, 1, 0)_{12}$	2.06	4.24	2.201
SARIMA (2, 1, 2) $(1, 1, 0)_{12}$	1.91	3.64	1.890
SARIMA (3, 1, 3) $(0, 1, 0)_{12}$	1.88	3.55	2.188
NNAR (iterations = 20)	2.56	6.55	6.970
NNAR (iterations = 30)	2.59	6.71	7.054
NNAR (iterations = 40)	2.55	6.50	7.142
MLP with 5 hidden layers	1.88	3.54	0.031
MLP with 10 hidden layers	1.76	3.09	0.024
MLP with 20 hidden layers	1.32	1.75	0.021

Table 4: Forecasted CPI values for the year 2022 to 2031 with the MLP with 20 layers.

Year	Forecasted CPI (%)
2022	239.58
2023	262.19
2024	287.29
2025	315.51
2026	343.25
2027	375.12
2028	408.48
2029	442.77
2030	477.61
2031	512.77

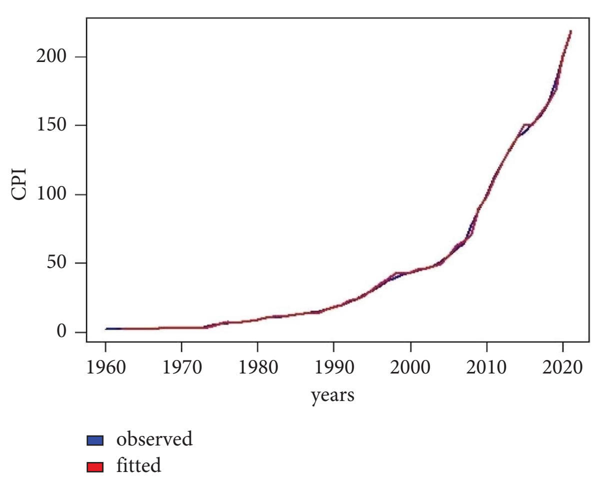

Figure 12: Observed versus fitted time series plot of CPI for MLP (20 hidden layers).

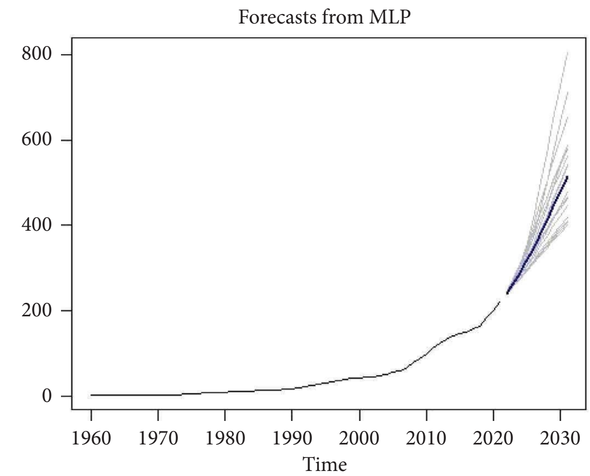

Figure 13: Forecast values of yearly CPI (%) from MLP (20 hidden layers).

reduce these figures as it is not healthy for consumers and the general population. A similar result was obtained by Ansar and Asghar [44]. The computation of CPI takes into account basic commodities like transportation, medical services, goods, and food that can easily be purchased by all consumers. CPI is labelled as a representative of inflation and used as a major indicator of economic growth. CPI is an important variable that is used to measure the IR [39]. The prices paid by consumers or households are represented by the CPI. Additionally, the changes in the purchasing power of money in a country are traced by the CPI [25]. Stock prices, exchange rates, and interest rates highly affect inflation, while the rise in the prices of yield and fall in the prices of bonds causes unexpected inflation [24, 43]. Stock prices are negatively affected by the increase in the interest rate. Our result therefore reflects an increasing trend in CPI values in Pakistan that, if not checked, will adversely cripple Pakistan's economy.

4. Conclusion

This study delves into the critical domain of CPI analysis, recognizing its paramount importance in gauging economic stability and its ramifications for households and individuals. To provide a robust understanding and prognosis of CPI dynamics in the context of Pakistan, a spectrum of time series forecasting models was employed, including SARIMA, NNAR, and MLP. These models were used for modelling and analyzing the historical CPI data spanning from 1960 to 2021. In addition to constructing these models, rigorous diagnostic assessments were conducted to ascertain their suitability and reliability. These diagnostic steps were pivotal in establishing the adequacy and robustness of the selected model. Utilizing the selected model, the study proceeded to generate short-term forecasts for annual CPI values in Pakistan, traversing the horizon from 2022 to 2031. These projections unveiled a discernible and persistent upward trajectory in the CPI over this time frame. This observation holds considerable implications for purchasing power dynamics as it implies a continuous escalation in the cost of living. The situation could potentially exert financial strain on individuals and households, particularly if income levels and wages remain stagnant throughout this period. This rigorous study makes a substantial contribution to comprehending the intricate behaviour of CPI in the specific context of Pakistan and its potential macroeconomic and microeconomic repercussions. It is of paramount importance for all stakeholders to meticulously contemplate the implications of escalating CPI when making financial, investment, and economic decisions to proactively mitigate the potential consequences on purchasing power, economic stability, and overall welfare of the less privileged in Pakistan. The effect of this high CPI is a higher cost of living, thereby increasing poverty levels [44]. The government should devise economic policies and put in initiatives in such a way that the increasing trend of CPI can be minimized so that the burden on the poorest class of people in Pakistan can be minimized, thereby reducing poverty.

Data Availability

The data used to support the findings of this study are available on the official website of the Pakistan Bureau of Statistics (https://www.pbs.gov.pk/).

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Authors' Contributions

Arsalan Khan, Moiz Qureshi, Muhammad Daniyal, and Zahid Mehmood were responsible for data curation and formal analysis. Kassim Tawiah and Muhammad Daniyal were responsible for review and editing. All authors were responsible for conceptualization, methodology, validation, visualization, and original draft preparation.

References

[1] Consumer Price Index Releases, "United state of America Bureau of statistics," 2022, https://www.bls.gov/news.release/cpi.htm.

[2] D. Gujarati, *Basic Econometrics*, McGraw-Hill Inc, Singapore, 1995.

[3] W. Enders, *Applied Econometric Time Series*, John Wiley & Sons, Inc, Hoboken, NJ, USA, 2004.

[4] S. E. Alnaa and F. Ahiakpor, "ARIMA (autoregressive integrated moving average) approach to predicting inflation in Ghana," *Journal of Economics and International Finance*, vol. 3, no. 5, pp. 328–336, 2011.

[5] A. K. Uko and E. Nkoro, "Inflation forecasts with ARIMA, vector autoregressive and error correction models in Nigeria," *European Journal of Economics, Finance and Administrative Sciences*, vol. 50, pp. 71–87, 2012.

[6] R. Blundell, R. Griffith, P. Levell, and M. O'Connell, "Could COVID-19 infect the consumer prices index?" *Fiscal Studies*, vol. 41, pp. 357–361, 2020.

[7] F. Kharimah, M. Usman, W. Widiarti, and F. A. Elfaki, "Time series modeling and forecasting of the consumer price index Bandar Lampung," *Science International*, vol. 27, pp. 4619–4624, 2015.

[8] M. S. Mia, A. H. M. M. Rahman Nabeen, and M. M. Akter, "Modelling and forecasting the consumer price index in Bangladesh through econometric models," *American Academic Scientific Research Journal for Engineering, Technology, and Sciences*, vol. 59, no. 1, pp. 118–127, 2019.

[9] F. Faisal, "Forecasting Bangladesh's inflation using time series ARIMA models," *World Review of Business Research*, vol. 2, no. 3, pp. 100–117, 2012.

[10] T. Nyoni, *ARIMA Modeling and Forecasting of Consumer Price Index (CPI) in Germany*, Munich Personal RePEcArchive(MPRA), Germany, 2019.

[11] J. Mohamed, "Time series modeling and forecasting of Somaliland consumer price index: a comparison of ARIMA and regression with ARIMA errors," *American Journal of Theoretical and Applied Statistics*, vol. 9, no. 4, pp. 143–153, 2020.

[12] H. Norbert, A. Wanjoya, and A. Waititu, "Modeling and forecasting consumer price index (Case of Rwanda)," *American Journal of Theoretical and Applied Statistics*, vol. 5, 2016.

[13] K. Molebatsi and M. Raboloko, "Time series modelling of inflation in Botswana using monthly consumer price indices," *International Journal of Economics and Finance*, vol. 8, no. 3, p. 15, 2016.

[14] C. M. Kuan and H. White, "Artificial neural networks: an econometric perspective," *Econometric Reviews*, vol. 13, no. 1, pp. 1–91, 1994.

[15] E. Maasoumi, A. Khotanzed, and A. Abaye, "Artificial neural networks for some macroeconomic series: a first report," *Econometric Reviews*, vol. 13, no. 1, pp. 105–122, 1994.

[16] M. Aiken, "Using a neural network to forecast inflation," *Industrial Management and Data Systems*, vol. 99, no. 7, pp. 296–301, 1999.

[17] M. A. Choudhary and A. Haider, "Neural network models for inflation forecasting: an appraisal," *Applied Economics*, vol. 44, no. 20, pp. 2631–2635, 2012.

[18] S. Moshiri and N. Cameron, "Neural network versus econometric models in forecasting inflation," *Journal of Forecasting*, vol. 19, no. 3, pp. 201–217, 2000.

[19] P. McAdam and P. McNelis, "Forecasting inflation with thick models and neural networks," *Economic Modelling*, vol. 22, no. 5, pp. 848–867, 2005.

[20] W. Wang, T. Wang, and Y. Shi, "Factor analysis on consumer price index rising in china from 2005 to 2008," in *Proceedings of the International Conference on Management and Service Science*, pp. 1–4, Beijing, China, September 2009.

[21] A. Wanto, M. Fauzan, D. Suhendro et al., "Epoch analysis and accuracy 3 ANN algorithm using consumer price index data in Indonesia," in *Proceedings of the 3rd International Conference of Computer, Environment, Agriculture, Social Science, Health Science, Engineering and Technology (ICEST)*, pp. 35–41, Medan, Indonesia, October 2021.

[22] M. F. Rohmah, I. K. G. D. Putra, R. S. Hartati, and L. Ardiantoro, "Comparison four kernels of svr to predict consumer price index," *Journal of Physics: Conference Series*, vol. 1737, no. 1, Article ID 012018, 2021.

[23] W. Wang, T. Wang, and Y. Shi, "Factor analysis on consumer price index rising in china from 2005 to 2008," in *Proceedings of the International Conference on Management and Service Science*, pp. 1–4, Beijing, China, September 2009.

[24] M. N. Jamil, "Monetary policy performance under control of exchange rate and consumer price index," *Journal of Environmental Science and Economics*, vol. 1, no. 1, pp. 28–35, 2022.

[25] W. Dongdong, "The consumer price index forecast based on arima model," in *Proceedings of the WASE International Conference on Information Engineering*, pp. 307–310, Beidai, China, August 2010.

[26] G. Box, G. Jenkins, and G. Reinsel, *Time Series Analysis*, Wiley, Hoboken, NJ, USA, 4th edition, 2008.

[27] J. D. Cryer and K. S. Chan, *Time Series Analysis with Applications in R*, Springer, New York, USA, 2nd edition, 2008.

[28] D. C. Montgomery, C. L. Jennings, and M. Kulahci, *Introduction to Time Series Analysis and Forecasting*, John Wiley & Sons, NewYork, NY, USA, 2008.

[29] P. J. Brocwell and R. A. Davis, *Introduction to Time Series and Forecasting*, Springer, New York, NY, USA, 2002.

[30] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time Series Analysis: Forecasting and Control*, John Willey and Sons, New Jersey, NJ, USA, 2016.

[31] Z. Xiao, "CPI prediction based on ARIMA model," in *Proceedings of the 7th International Conference on Education, Management, Information and Computer Science (ICEMC 2017)*, June 2016.

[32] L. Poulos, A. Kvanli, and R. Pavur, "A comparison of the accuracy of the Box- Jenkins method with that of automated forecasting methods," *International Journal of Forecasting*, vol. 3, no. 2, pp. 261–267, 1987.

[33] E. J. Hannan, "The estimation of the order of an ARMA process," *Annals of Statistics*, vol. 8, no. 5, pp. 1071–1081, 1980.

[34] C. Chatfield, *The Analysis of Time Series an Introduction*, Chapman & Hall/CRC, New York, NY, USA, Sixth edition, 2004.

[35] W. S. Wei, *Time Series Analysis Univariate and Multivariate Methods*, Pearson education Inc, Canada, Second edition, 2006.

[36] M. Daniyal, K. Tawiah, S. Muhammadullah, and K. Opoku-Ameyaw, "Comparison of conventional modeling techniques with the neural network autoregressive model (NNAR): application to COVID-19 data," *Journal of Healthcare Engineering*, vol. 2022, Article ID 4802743, 9 pages, 2022.

[37] O. N. Al-allaf and S. A. AbdAlKader, "Nonlinear Autoregressive neural network for estimation soil temperature: a comparison of different optimization neural network algorithms," *UbiCC Journal*, vol. 6, pp. 43–51, 2011.

[38] Y. K. Chang, M. S. Mahmud, J. Shin, T. Nguyen-Quang, G. W. Price, and B. Prithiviraj, "Comparison of image texture based supervised learning classifiers for strawberry powdery mildew detection," *AgriEngineering*, vol. 1, no. 3, pp. 434–452, 2019.

[39] H. B. Hwarng, "Insights into neural-network forecasting of time series corresponding to arma (p,q) structures," *Omega*, vol. 29, no. 3, pp. 273–289, 2001.

[40] M. Qureshi, M. Daniyal, and K. Tawiah, "Comparative evaluation of the Multilayer perceptron approach with conventional ARIMA in modeling and prediction of COVID-19 daily death cases," *Journal of Healthcare Engineering*, vol. 2022, Article ID 4864920, 7 pages, 2022.

[41] K.-C. Ke and M.-S. Huang, "Quality classification of injection-molded components by using quality indices, grading, and machine learning," *Polymers*, vol. 13, no. 3, p. 353, 2021.

[42] Y.-W. Cheung and K. S. Lai, "Lag order and critical values of the augmented Dickey–Fuller test," *Journal of Business & Economic Statistics*, vol. 13, no. 3, pp. 277–280, 1995.

[43] F. Qin, T. Ma, J. Wang, H. Liang, T. Zhang, and H. Zhang, "The CPI forecast based on GA-SVM," in *Proceedings of the International Conference on Information, Networking and Automation (ICINA)*, pp. 142–147, Kunming, China, October 2010.

[44] I. Ansar and N. Asghar, "The impact of oil prices on stock exchange and CPI in Pakistan," *IOSR Journal of Business and Management*, vol. 7, no. 5, 2013.