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Research Paper

Forecasting the consumer price index in the regions of the Philippines using machine learning for time series models

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ABSTRACT

The core objective of this study is to showcase the enhanced forecasting capabilities of a hybrid model that combines the strengths of Artificial Neural Networks (ANN) and Autoregressive Integrated Moving Average (ARIMA) in predicting the Consumer Price Index (CPI). By harnessing the intricate non-linear pattern capturing ability of ANN and the capabilities of ARIMA in modeling linear and autoregressive components, the hybrid model aims to outperform the standalone ARIMA model in accurately forecasting the CPI. Real-world CPI data will be utilized for empirical evaluation and comparison, providing valuable insights into the effectiveness and practical applicability of the hybrid ARIMA-ANN approach in improving CPI forecasting accuracy. The performance of Box Jenkins Models which gives the resulted value of R-squared values for both stationary and non-stationary data are high, indicating that the models explain a significant portion of the variability in the CPI data. The RMSE, MAPE, and MAE values are relatively low, suggesting that the Box-Jenkins models' predictions are close to the actual values. The Ljung-Box Q statistic indicates that all Box-Jenkins models best fit their respective CPI data. The study also employs rigorous statistical methods of machine learning model accuracy assessment, including the Akaike Information Criterion (AIC), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE), to assess the forecasting performance of both models. The results demonstrate that the hybrid ARIMA-ANN model consistently outperforms the standalone ARIMA model, delivering more accurate and reliable forecasts over an extended forecast horizon. The integration of Artificial Neural Networks (ANN) using Multilayer Perceptron (MLP) in the ARIMA models improved the accuracy of the fitted and forecasted values. RMSE and MSE values for the Hybrid ARIMA-ANN models are lower compared to the original Box-Jenkins/ARIMA models, validating the goal of enhancing accuracy through ANN integration.

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1. INTRODUCTION

In many developing countries, inflation is a significant macroeconomic concern, and the Philippines is no exception. The Consumer Price Index (CPI) plays a crucial role in determining the nation's inflation rates. In the Philippine context, the CPI serves as a vital indicator, reflecting the average expenses of households for goods and services. Inflation, characterized by a sustained rise in the overall price level of goods and services, can be influenced by various factors, such as an increase in the money supply, rising production costs, or heightened demand for goods and services [1]. Understanding and effectively managing inflation, through a thorough analysis of the CPI, is imperative for making informed economic policies and ensuring the country's economic stability.

The Philippine Statistics Authority (PSA) highlights that inflation continues to pose a significant threat to the country's macroeconomic stability. In August 2022, inflation in the Philippines declined to 6.3 percent, breaking a streak of five consecutive months of increase. The 4.9 percent average inflation rate for the period of January up to August 2022 stood, taking into account the inflation figure for August. In comparison, the official inflation rate for August 2021 was 4.4 percent. The ARIMA approach is frequently preferred in many studies for forecasting economic statistics like the Consumer Price Index (CPI). This choice is due to ARIMA effectiveness in short-term forecasting. However, it is important to acknowledge that ARIMA may have limitations when used for long-term forecasting, as it could generate constant results [2]. The time series data initial characteristics, including identifying yearly seasonality and studying autocorrelation functions to uncover underlying patterns. ARIMA has shown effectiveness in making short-term predictions of stock prices, as highlighted in a study by [3]. While ARIMA is a time series model designed for linear data, it is essential to acknowledge that not all time series phenomena are strictly linearly related. In fact, some phenomena exhibit nonlinear characteristics. To tackle these nonlinear problems, alternative methods are required, as emphasized in the research conducted [4]. Artificial Neural Networks (ANNs) offer an alternative method for solving complex problems, as demonstrated in the research conducted [5]. ANNs are designed to simulate the functioning of the human brain's neural network, making them capable of handling various data patterns and relationships, as emphasized [6].

An innovative approach was proposed, integrating ARIMA with multilayer perceptrons and support vector machines to enhance forecasting performance [7], [8]. This hybrid system proved to be promising in addressing complex forecasting tasks. The implied relationship between the consumer price index (CPI) and inflation suggests that as the index rises, the likelihood of experiencing higher inflation also increases. This relationship holds several implications, as inflation can have both positive and negative effects. While some levels of inflation can be beneficial for economic growth, excessive inflation can lead to economic instability. Moreover, the rate of inflation influences investors' decisions, impacting their choices in investment products and the timing of their investments. As a result, accurately predicting the CPI becomes crucial for guiding investors and financial institutions in their decision-making processes. Structural inflation, income disparities, and the adverse effects of inflation on low- and middle-income individuals are some of the challenges that arise from fluctuating inflation rates. Current literature predominantly focuses on conventional econometric models, thereby neglecting the exploration of the capabilities of machine learning models, such as artificial neural networks, random forests, and support vector machines, in enhancing the accuracy and robustness of CPI forecasts. This research gap calls for an in-depth investigation into the effectiveness of machine learning techniques as a viable alternative for improving CPI forecasting accuracy, considering their capacity to capture intricate nonlinear patterns, handle large datasets, and potentially mitigate the limitations of traditional methods [9].

1.1 Research Elaborations

The first step involves conducting tests for trend, seasonality, and stationarity, which will be further explained in the methodology section. If the data is found to be non-stationary, appropriate transformations are applied. Moving on to the second step, two models were employed for the study: ARIMA (Autoregressive Integrated Moving Average) and ANN (Multi-Layer Perceptrons). As indicated in Figure 1, each model follows distinct steps in its application. Once the models are calculated, the next phase involves integrating them and comparing their performance using metrics such as RMSE, MAPE. The objective of this study is to enhance the forecasting capabilities of the conventional ARIMA model by integrating it with ANN, specifically MLPs, for predicting the consumer price index in different regions of the Philippines. Through this hybrid ARIMA-ANN approach, we aim to leverage the strengths of both methods to achieve more accurate and reliable time series forecasts. By combining the ANN's ability to capture intricate non-linear patterns with ARIMA's expertise in modeling linear and autoregressive components, we intend to demonstrate that the hybrid model outperforms the standalone ARIMA model in terms of forecast accuracy and predictive performance. The Consumer Price Index (CPI) plays a vital role in measuring inflation and provides valuable insights into the standard of living and socio-economic development of the population. Accurate modelling of inflation through scientific analysis of goods and services costs is essential for effective control and management of price increases [10]. [11] Highlights the significant role of accurate prediction results in informing government policies and emphasizes the indispensability of economic forecasting in the economic sector.

The Consumer Price Index (CPI) stands as a critical economic indicator, providing valuable data on consumer-paid prices for goods and services. This study utilizes both the ARIMA time series model and Artificial Neural Network (ANN), specifically Multilayer Perceptrons (MLPs), for machine learning model treatment. The data obtained is quantified and evaluated to fulfill the study objectives. The primary goal of this study is to enhance the forecasting capabilities of the conventional ARIMA (AutoRegressive Integrated Moving Average) model by incorporating Artificial Neural Networks (ANN), particularly Multilayer Perceptrons (MLPs). Through this hybrid ARIMA-ANN approach, the study aims to capitalize on the strengths of both methods to achieve more precise and reliable time series forecasts. The hybrid ARIMA-ANN model shows promise as a robust technique in time series analysis, with potential for enhancing forecasting tasks, as previously demonstrated in relevant literature [12], [13].

2. RESULTS AND DISCUSSION

To verify if hybrid ARIMA-ANN model consistently outperforms the standalone ARIMA model, delivering more accurate and reliable forecasts over an extended forecast horizon. The integration of Artificial Neural Networks (ANN) using Multilayer Perceptron (MLP) in the ARIMA models improved the accuracy of the fitted and forecasted values. RMSE and MSE values for the Hybrid ARIMA-ANN models are lower compared to the original Box-Jenkins/ARIMA models, validating the goal of enhancing accuracy through ANN integration [14].

Table 1. Summary Metrics of Box-Jenkins Models

CPI	Model Type	Stationary R-Squared	R-Squared	RMSE	MAPE	MAE	Normalized BIC	Ljung Box Q	Sig.
Philippines	ARIMA (1,1,0)	0.196	0.994	0.379	0.279	0.297	-1.796	18.363	0.366
NCR	ARIMA (1,1,0)	0.196	0.994	0.379	0.279	0.297	-1.796	17.703	0.408
CAR	ARIMA (0,1,1)	0.287	0.994	0.374	0.273	0.287	-1.819	10.431	0.885

Region I	ARIMA (0,1,1)	0.151	0.991	0.461	0.323	0.341	-1.405	10.476	0.882
Region II	ARIMA (0,1,1)	0.181	0.988	0.631	0.443	0.474	-0.775	17.309	0.434
Region III	ARIMA (0,1,1)	0.093	0.99	0.556	0.387	0.419	-1.029	12.037	0.798
Region IVA	ARIMA (0,1,0)	0	0.988	0.551	0.432	0.459	-1.12	20.018	0.332
Region IVB	ARIMA (0,1,1)	0	0.990	0.618	0.439	0.439	-0.815	9.685	0.916
Region V	ARIMA (0,1,0)	0.178	0.99	0.618	0.406	0.439	-0.815	9.685	0.916
Region VI	ARIMA (0,1,1)	0	0.989	0.506	0.361	0.383	-1.288	13.4	0.767
Region VII	ARIMA (0,1,1)	0.17	0.993	0.557	0.42	0.456	-1.025	14.855	0.606
Region VIII	ARIMA (0,1,0)	0	0.990	0.505	0.359	0.359	-1.222	7.606	0.974
Region IX	ARIMA (0,1,0)	0	0.954	0.873	0.589	0.617	-0.199	4.415	1
Region X	ARIMA (0,1,0)	0	0.992	0.447	0.339	0.358	-1.538	18.322	0.435
Region XI	ARIMA (1,1,0)	0.171	0.987	0.553	0.408	0.43	-1.041	6.989	0.984
Region XII	ARIMA (0,1,0)	0	0.989	0.606	0.419	0.446	-0.929	14.74	0.68
Region XIII	ARIMA (1,1,0)	0.139	0.991	0.52	0.363	0.384	-1.163	9.19	0.934
BARMM	ARIMA (0,1,0)	0	0.989	0.453	0.31	0.328	-1.509	12.037	0.845

The ARIMA (1, 1, 0) for Philippines, NCR, Region XI, and Region XIII model is applied for predicting the monthly consumer price index (CPI). The ARIMA (1, 1, 0) model indicates that it includes a first-order differencing component (d = 1), which helps in achieving stationarity and correcting the trend, and a moving average (MA) component of order q = 0, implying there is no need for additional moving average terms. The AR component is not explicitly mentioned here, but it is implicitly included as ARIMA (1, 1, 0) indicates the presence of an autoregressive (AR) component of order p = 1. For Regions IV-A, V, VIII, IX, X, XII, and BARMM, ARIMA (0, 1, 0) is the suitable model in fitting and forecasting the CPI. This indicates that autoregressive and moving average terms are not needed. For CAR, Regions I, III, IV-B, VI, and VII, the SPSS expert modeler applied the ARIMA (0, 1, 1) for forecasting and fitting the CPI values. This suggests that an Autoregressive Component is not applicable to these time series data. By looking at the results of the modelling phase performed by SPSS Modeler, the 3 different Box-Jenkins models were applied widely across different CPI's. This suggests that those Regions that share the same Box-Jenkins models display similar characteristics in terms of the progression and variation of values as shown during the exploratory phase of inspecting the individual CPI's per Region. Moreover, this gives an insight that those Regions with same Box-Jenkins model may also expect to have the same properties in terms of their individual economic indicators that one way or another directly or indirectly influence the CPI values.

The models' performances are evaluated using various metrics such as the stationary R-squared, R-squared, RMSE (Root Mean Squared Error), MAPE (Mean Absolute Percentage Error), MAE (Mean Absolute Error), Normalized BIC (Bayesian Information Criterion), Ljung-Box Q statistic, and significance (Sig.) level. The R-squared values for both stationary and non-stationary data are high, indicating that these models generated by the SPSS expert modeler can explain a significant portion of the variability in the CPI data. The RMSE, MAPE, and MAE values are relatively low, suggesting that the model's predictions are close to the actual values. The Ljung-Box Q statistic checks the residuals' autocorrelation, and the significance (Sig.) level helps in determining the presence of residual autocorrelation. Lower values of the Ljung-Box Q statistic and higher significance (Sig.) levels indicate better model fit. All Box Jenkins model flagged nonsignificant Ljung-Box Q statistics, suggesting that all of the respective Box-Jenkins models per Regions best fit their respective CPI.

Table 2. Model Specifications and Performance Metrics of the Hybrid Models

CPI	Activation Function–Hidden Layer	Activation Function–Output Layer	Error Function	Initial Lambda	Initial Sigma	SSE–Training	Relative Error Training	SSE–Testing	Relative Error Testing
Philippines	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.137	0.007	0.042	0.006
NCR	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.344	0.02	0.276	0.014
CAR	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.121	0.006	0.037	0.012
Region I	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.141	0.008	0.062	0.012
Region II	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.302	0.018	0.11	0.008
Region III	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.175	0.009	0.145	0.018
Region IVA	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.18	0.009	0.137	0.064
Region IVB	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.184	0.009	0.119	0.016
Region V	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.276	0.015	0.087	0.014
Region VI	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.199	0.011	0.047	0.007
Region VII	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.135	0.007	0.066	0.011
Region VIII	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.206	0.011	0.073	0.01
Region IX	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	1.125	0.062	1.791	0.052
Region X	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.203	0.01	0.031	0.011
Region XI	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.285	0.015	0.117	0.027
Region XII	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.233	0.014	0.114	0.009
Region XIII	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.182	0.009	0.094	0.011
BARMM	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.291	0.015	0.043	0.012

The input covariate wherein the ANN will be trained are the fitted and forecasted CPI values from the Box-Jenkins models, with the observed CPI per Regions were used as the Dependent Variables. The purpose of integrating an ANN through Multilayer Perceptron in the Box-Jenkins Models is to further lower the RMSE and MSE values which will ensure that the fitted and forecast values are getting closer to the observed values. The ANN model uses the hyperbolic tangent as the activation function in the hidden layer and the identity function in the output layer. It employs the sum of squares as the error function. The model is trained and tested using SSE (Sum of Squared Errors) values and relative errors for both training and testing phases. Several measures, including SSE Training, Relative Error Training, SSE-Testing, and Relative Error-Testing, are used to evaluate the performance of the ANN model. SSE stands for the sum of squared errors (measured separately for the training and testing phases) between the predicted and actual CPI values. Relative error values, on the other hand, provide a thorough assessment of the model's performance by providing information about the precision of the model's predictions during both training and testing.

Table 3. Summary table for Accuracy Metrics – RMSE and MSE

CPI	MSE-ARIMA	MSE-MLP	RMSE-ARIMA	RMSE-MLP
Philippines	80.0591	79.6249	8.9480	8.9233
NCR	54.7953	53.3633	7.4022	7.3050
CAR	76.1891	75.0711	8.7286	8.6644
Region I	87.9855	86.3576	9.3803	9.2929
Region II	115.9745	114.9051	10.7687	10.7194
Region III	88.1376	86.0281	9.3882	9.2751
Region IVA	83.5809	82.6184	9.1426	9.0895
Region IVB	148.2607	147.3107	12.1762	12.1372
Region V	145.3612	142.8057	12.0566	11.9501
Region VI	84.3886	83.8957	9.1863	9.1595
Region VII	44.1607	43.4164	6.6453	6.5891
Region VIII	80.7360	79.6696	8.9853	8.9258
Region IX	46.2747	46.1342	6.8026	6.7922
Region X	95.6175	95.4172	9.7784	9.7682
Region XI	82.9621	81.6552	9.1084	9.0363
Region XII	107.3028	107.2420	10.3587	10.3558
Region XIII	91.4085	88.7048	9.5608	9.4183
BARMM	106.5025	101.7140	10.3200	10.0853

For the RMSE (Root Mean Squared Error) and MSE (Mean Squared Error) are both commonly used performance metrics to assess the accuracy of predictions or forecasts in various fields, including statistics, machine learning, and data analysis. These accuracy metrics are undeniably sound in evaluating the fitted values generated by the Hybrid ARIMA-ANN models for each Regions' CPI. Upon inspection, it can be clearly seen that the RMSE and MSE values across all MLP (Hybrid ARIMA-ANN) models are relatively lower compared to those of the fitted values from the original Box Jenkins/ARIMA models. These results further validate the primary goal of this analysis wherein the fitted values are to be made more accurate through the integration of ANN in the ARIMA models.

Table 4. Forecasted CPI's from September – December 2022

CPI	Sep. 2022 ARIMA Forecast	Oct. 2022 ARIMA Forecast	Nov. 2022 ARIMA Forecast	Dec. 2022 ARIMA Forecast	Sep. 2022 MLP Forecast	Oct. 2022 MLP Forecast	Nov. 2022 MLP Forecast	Dec. 2022 MLP Forecast
Philippines	116.7	117.1	117.5	117.8	115.7	115.9	116.1	116.3
NCR	113.8	114.2	114.6	114.9	113.1	113.3	113.5	113.7

CAR	116.34	116.68	117.01	117.35	115.96	116.19	116.4	116.62
Region I	117.1	117.4	117.8	118.1	116.0	116.3	116.5	116.7
Region II	118.4	118.8	119.2	119.6	117.6	117.9	118.1	118.3
Region III	118.58	118.95	119.31	119.67	117.89	118.16	118.41	118.66
Region IVA	116.6	117.0	117.3	117.7	115.5	115.7	115.9	116.1
Region IVB	121.0	121.4	121.8	122.2	120.3	120.6	120.9	121.3
Region V	121.75	122.19	122.63	123.07	120.22	120.5	120.77	121.03
Region VI	117.56	117.93	118.29	118.65	116.96	117.19	117.41	117.62
Region VII	112.68	112.96	113.24	113.52	111.44	111.51	111.58	111.64
Region VIII	116.84	117.2	117.56	117.92	115.99	115.99	116.33	116.48
Region IX	115.22	115.54	115.86	116.18	114.09	114.2	114.3	114.39
Region X	117.47	117.83	118.2	118.57	117.37	117.68	117.97	117.97
Region XI	118.51	118.94	119.33	119.72	118.19	118.39	118.57	118.73
Region XII	119.39	119.79	120.18	120.57	118.83	119.13	119.42	119.7
Region XIII	118.58	118.96	119.34	119.72	118.26	118.55	118.83	119.1
BARMM	115.65	116.0	116.35	116.7	114.52	114.73	114.93	115.12

Using the ARIMA and ANN (Multilayer Perceptron) machine learning models developed, the forecasted Consumer Price Index (CPI) for each region, including the CPI of the Philippines as a whole, was presented. Notably, Regions IV and V exhibited relatively higher CPI values compared to other regions in terms of year-on-year changes. Conversely, Regions IX and NCR showed relatively lower CPI among all regions considered in the analysis. The high CPI values in Regions IV and V can be influenced by various factors, as evident from the raw data and PSA reports. The headline inflation rate at the regional level showed a slightly faster growth in November 2022 compared to October. The housing, water, electricity, gas, and other fuels with 6.7 percent inflation, and food and nonalcoholic beverages with 10.5 percent inflation were primarily the main drivers due to the acceleration of other commodity groups, implying that the said commodities were the major contributing factor in the increase of the consumer price index. These commodity groups, along with other fixed expenses, significantly influence the prices of goods and services in these regions. For Bicol Region, the inflation rate in February 2022 slightly increased to 2.8% from 2.7% in the previous month, while inflation in February the previous year was higher at 7.2%. Based on the raw data provided by the PSA (Philippines Statistics Authority), the housing, water, electricity, gas, and other fuels category saw an increase of 5.1% from 4.1%, which also contributed to the upward movement of other commodity groups.

According to the recent report from the Philippine Statistics Authority (PSA) in 2023, the overall downtrend in inflation can be attributed to various factors. One of the primary drivers of this downtrend was the housing, water, electricity, gas, and other fuels category, which recorded a lower inflation rate of 1.8 percent in April 2023, compared to 5.6 percent in March. This category had a significant impact on the overall decrease in inflation during April 2023. Another contributing factor to the decelerated inflation was the food and non-alcoholic beverages category, which registered an inflation rate of 6.5 percent in April, down from 7.7 percent in previous months. Similarly, the transport category played a role in the inflation deceleration, with an inflation rate of 4.2 percent in April, compared to 6.5 percent in previous periods.

In July 2022, it was the second-lowest inflation in the region for the National Capital Region (NCR). The following commodities, such as housing, water, electricity, gas, and other fuels index, which declined to 3.6 percent from 5.9 percent in the previous month, were significantly responsible for the reduction of inflation in NCR during that time. Indicators of health at 1.3 percent and of personal care and other goods and services at 2.0 percent showed lower annual growth.

Moreover, the factors that influenced the inflation trend were external, such as the world economy and currency exchange. These external factors also played a role in shaping the overall inflation dynamics during the given period.

3. CONCLUSION

The study successfully developed and evaluated Hybrid ARIMA-ANN models for forecasting the CPI of the Philippines and its regions for 2022. The models demonstrated promising accuracy in capturing the underlying patterns in the CPI data, providing valuable insights into the economic indicators' influence on CPI values. The integration of ANN in ARIMA models significantly improved the accuracy of the forecasts, making it a suitable approach for future CPI predictions.

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Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
John Philip Omol Echevarria	✓	✓	✓	✓		✓		✓	✓	✓	✓			
Peter John Berces Aranas		✓				✓	✓				✓	✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

Conflict of Interest Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Informed Consent

All participants were informed about the purpose of the study and their voluntary consent was obtained prior to data collection.

Ethical Approval

Not applicable.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] Monetary Economy (Ekonomi Moneter). Book II. Yogyakarta: BPFE-UGM, 1987.

[2] D. Djawoto, 'Advanced Forecasting of Inflation with Auto Regressive Integrated Moving Average (ARIMA) Method', Jurnal Ekonomi dan Keuangan, vol. 14, no. 4, pp. 524-538, 2010. doi.org/10.24034/j25485024.y2010.v14.i4.176

[3] A. A. Ariyo, A. O. Adewumi, and C. K. Ayo, 'Stock price prediction using the ARIMA model', in 2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation, Cambridge, United Kingdom, 2014. doi.org/10.1109/UKSim.2014.67
[4] S. N. Janah, W. Sulandari, and S. B. Wiyono, 'Application of The ARIMA Backpropagation Hybrid Model for Price Forecasting of Indonesian Gabah', Media Statistika, vol. 7, no. 2, pp. 63-69, 2014. doi.org/10.14710/medstat.7.2.63-69
[5] B. E. Fitriani, D. Ispriyanti, and A. Prahutama, 'Forecasting Loads of Electricity Usage in Central Java and the Special Region of Yogyakarta Using Hybrid Autoregressive Integrated Moving Average - Neural Network', Jurnal Gaussian, pp. 745-754, 2015.
[6] D. Susilokarti, S. S. Arif, S. Susanto, and L. Sutiarso, 'Comparative Study of Rainfall Prediction Fast Fourier Transformation (FFT) Method, Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Network (ANN). agriTECH', pp. 241-247, 2015. doi.org/10.22146/agritech.9412
[7] Mehandzhiyski, V. (2020). What is SARIMAX Model? https://365datascience.com/tutorials/python-tutorials/sarimax/
[8] Dalinina, R. (2017). Introduction to Forecasting with ARIMA in R.
[9] A. G. Robles and F. G. Estrada, 'Forecasting inflation using machine learning algorithms', Journal of Applied Research in Business and Economics, vol. 17, no. 1, pp. 16-26, 2019.
[10] O. Shinkarenko, A. Hostryk, L. Shynkarenko, and L. Dolinskyi, Forecasting the consumer price index using time series model. 2020. doi.org/10.1051/shsconf/202110710002
[11] M. Grogan, neuralnet: Train and Test Neural Networks Using R. 2018.
[12] Dalinina, R. (2017). Introduction to Forecasting with ARIMA in R.
[13] A. G. Robles and F. G. Estrada, 'Forecasting inflation using machine learning algorithms', Journal of Applied Research in Business and Economics, vol. 17, no. 1, pp. 16-26, 2019.
[14] A. Y. A. Diaz and B. V. C. Mendoza, 'Forecasting Philippine inflation: A comparative analysis of ARIMA, ETS, and LSTM', Asia Pacific Journal of Multidisciplinary Research, vol. 8, no. 3, pp. 17-24, 2020.

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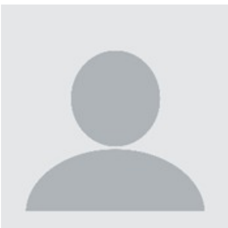
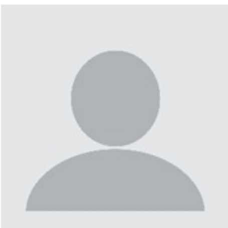
BIOGRAPHIES OF AUTHORS

	**John Philip Omol Echevarria,** is a graduate researcher at the Polytechnic University of Manila, with research interest in machine learning time series forecasting, and economic data analytics. His work leans on hybrid computational models like ARIMA-ANN, and it helps with improving prediction accuracy for economic indicators, including inflation related studies. He has also contributed to research that blends artificial intelligence, statistical modelling, and predictive analytics, for socio economic and financial uses. Email: jpoechevarria@pup.edu.ph
	**Peter John Berces Aranas,** is affiliated with the University of the Philippines Diliman, under the School of Statistics. His academic and research background includes statistical modelling, econometrics, data science, and machine learning applications for economic forecasting. He has taken part in studies on consumer price index prediction, inflation analysis, and the merging of AI techniques with conventional statistical methods to make forecasting results more dependable and to support decision making processes.