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Forecasting Mean Percentile Scores in Junior High School Subjects Using ARIMA Models

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Abstract
Accurate prediction of student performance is essential for improving learning pass and has the ability to shape academic policies. Mean Percentile Scores (MPS) is the primary measure being used by the Department of Education (DepED) in the Philippines to compare the performance of students in different subjects. The AutoRegressive Integrated Moving Average (ARIMA) model is applied in this study to predict MPS of junior high school students in Natan National High School in Zamboanga Sibugay for the years 2025 to 2029. The ARIMA model, which is a time series forecasting method, was used to predict trends for different subjects, such as English, Math, Science, Filipino, TLE, MAPEH, ArPan, and ESP. The results show that most subjects are steadily getting better. The most noticeable growth is in science and math, but there is also more variation. On the other hand, subjects like Filipino and ESP are more likely to show steady progress with less doubt. The study recommends creating new prospectuses, providing additional support for subjects with wider variability, and regularly updating forecasts to help students improve, particularly in TLE and MAPEH. These insights are important for education program planners to make informed decisions and improve strategies for future groups.

Keywords: ARIMA, Educational data mining (EDM), Student performance prediction

1. Introduction

Effective educational policy is a valuable avenue for helping students excel in school activities [1], [2]. Governance challenges are exemplified even when teachers are present and instructional time is low for a variety of reasons [3], [4]. The Philippine Department of Education (DepEd) uses Mean Percentile Scores (MPS) to measure how well students are doing in different subjects. Some of these subjects are science, math, English, Filipino, TLE (Technology and Livelihood Education), MAPEH (Music, Arts, Physical Education, and Health), ARALING PANLIPUNAN (Social Studies), ESP (Edukasyong Pagpapakatao), and others. MPS is a useful way to compare how well students do, but predictive models are not utilized to guess what the scores will be, especially over time.

This study forecasts the MPS of junior high school students in the Philippines by employing AutoRegressive Integrated Moving Average (ARIMA) models to fill this gap. ARIMA is a popular way to predict time series data based on past data. It has been utilized across multiple sectors, including healthcare and finance. [5] demonstrated the capability of forecasting academic outcomes through the application of ARIMA to educational trend analysis, particularly employing time series analysis on state matriculation exam results.

Using educational data mining (EDM) is another way to make better predictions about how well students will do. Large datasets can be analyzed using EDM techniques to find correlations and patterns that enhance forecasting models. [6] investigated how EDM and predictive analytics can support educational interventions. The study emphasized how crucial data-driven decision-making is to raising academic achievement.

This study aims to enhance existing knowledge by integrating ARIMA and EDM methodologies to provide a more comprehensive model for forecasting student performance across various subjects. Knowing how these things affect student outcomes helps us understand how changes to the curriculum or teaching methods could affect students. [7] stressed the need to include predictive models in educational policies to guess what will happen with these interventions and make better use of resources.

This study aims to predict the MPS in different junior high school subjects. It will give you useful information to help you decide on the future curriculum, academic support, and rules. The findings will allow educators and decision-makers to make informed choices that can improve student achievement and the quality of education.

2. Literature Review

This section tackles about different studies that have to do with time series analysis, machine learning methods, and ARIMA models for predicting educational outcomes. The studies are divided based on their focus on either forecasting trends, like student performance or dropout rates, or predicting specific educational outcomes, such as Mean Percentage Scores (MPS). These studies provide valuable insights, methods, and examples that can help predict MPS in junior high school students.

Time Series Analysis in Education

Mao et al [4] carried out a thorough analysis of time series approaches in education. Techniques including forecasting, classification, clustering, and outlier identification were covered in this review. The study provides a general review of these techniques but skips over their application in MPS forecasting. In the same way, Vanitha and Jayashree [8] looked at two models, ARIMA and SES, to see which one was better at predicting enrollment trends in schools. Their study centers on enrollment; however, comparing ARIMA's performance aids in comprehending the application of time series models to educational data, including MPS forecasting.

Methods of Machine Learning for Forecasting Student Achievement

Albreiki et al. [9] examined various machine learning methods. Predicting student dropout and identifying students at risk of disengagement were their primary objectives. This study provides helpful insights into educational data mining even though it has nothing to do with MPS forecasting. Still, its focus on finding risks can make other predictive models, like ARIMA, better. Rastrollo-Guerrero et al. (2020) [10] also did a thorough review of different AI methods for predicting how well students will do. But their analysis didn't go into detail about how these methods work in schools, like how to predict MPS.

ARIMA Models for Educational Forecasting

Dela Cruz et al. (2020) [11] utilized the ARIMA model to forecast trends in student enrollment. This gave useful information for planning and managing resources. The study concentrates on a single university, complicating the application of its findings to alternative educational contexts, particularly in predicting

academic performance such as MPS. Tan and Silvestre (2020) [12] examined the correlation between the performance of out-of-field teachers and student National Achievement Test (NAT) scores, concluding that there was no significant effect on student outcomes. While valuable for understanding teacher-related factors, this study does not focus on forecasting MPS.
Khan and Gupta (2020) [13] compared ARIMA with another forecasting model to predict COVID-19 cases, providing valuable insights into how time series forecasting can be applied to predict trends. Although their study focused on health data, the methodology is relevant to education. Similarly, Delima et al. (2019) [14], [15] used ARIMA to predict inflation and electricity consumption in the Philippines. Though these studies are not in the education sector, they demonstrate how ARIMA can be useful for forecasting in general. This method could also be used to predict MPS trends.

Hybrid Models for Forecasting

Suhermi et al. (2018) [16] employed an innovative methodology by integrating ARIMA with Deep Neural Networks (DNN) to forecast roll motion in Floating Production Units. This mixed method, which combines linear and nonlinear models, looks like it could make forecasts more accurate. The study primarily focuses on engineering; however, the concept of integrating various models may enhance the prediction of educational outcomes, such as MPS, by providing a more accurate forecast through the amalgamation of ARIMA and machine learning techniques.

Table 1 Related literature

Title of Study and Year Published	Authors	Strengths	Weaknesses
Time Series Analysis for Education: Methods, Applications, and Future Directions (2024) [17]	Mao, S., Zhang, C., Song, Y., Wang, J., Zeng, X.-J., Xu, Z., Wen, Q.	The study provides an in-depth examination of time series analysis methodologies tailored for educational data. It is mostly about predicting, classifying, clustering, and finding unusual patterns. It also talks about new trends like personalized learning and combining data from many different sources.	The study covers a wide range of time series methods but does not go into detail on any specific technique. This may limit its usefulness for educational issues, like forecasting MPS.
A Prediction on Educational Time Series Data Using Statistical Machine Learning Model - An Experimental Analysis (2022) [8]	Vanitha S., Jayashree R.	Compared ARIMA and SES models for forecasting educational institution enrollment, providing valuable insights into model accuracy, factors affecting performance, and handling cyclic year-wise data.	The SES model outperformed ARIMA, which limits the focus on ARIMA for educational predictions; also, the study does not directly address forecasting academic performance (MPS).

A Systematic Literature Review of Students' Performance Prediction Using Machine Learning Techniques (2021) [9]	Albreiki, B., Zaki, N., Alashwal, H.	This study thoroughly analyzes various machine learning (ML) methodologies for predicting dropout rates and student performance. It also finds students who might be in danger. The results give schools useful information that can help students do better.	The review primarily focuses on dropout prediction and risk identification rather than directly on forecasting academic performance (e.g., MPS), which is the primary focus of your research.
Performance of Out-of-Field Teachers and the NAT MPS of Students' School Scores: Basis for Program Initiatives (2020) [12]	Tan, L., Silvestre, M. D. P.	Examined the relationship between the performance of out-of-field teachers and student National Achievement Test (NAT) scores, offering insights into the challenges faced by teachers in the K-12 curriculum.	No significant relationship was found between teacher performance and student outcomes, which limits the predictive power of these findings for forecasting academic performance. Additionally, it focuses more on teacher challenges than on specific forecasting methods or models for MPS.
Higher Education Institution (HEI) Enrollment Forecasting Using Data Mining Technique (2020) [11]	Dela Cruz, A. P., Basallo, M. L., Bere, B. A., Aguilar, J. B., Calvo, C. K., Arroyo, J. C., Delima, A. J. P.	ARIMA model was used for forecasting student enrollment over several years. Forecasted trends are beneficial for decision-making in resource management and policy adjustments.	Limited to a single university dataset, making its generalizability to other institutions uncertain.
ARIMA and NAR-Based Prediction Model for Time Series Analysis of COVID-19 Cases in India (2020) [13]	Khan, F. M., Gupta, R.	Provides a robust comparison between ARIMA and NAR models in predicting COVID-19 cases, offering insights for future health crisis management.	It focuses on COVID-19 data, which may not directly relate to educational forecasting; however, the methodology is still valid.
Student Enrollment Forecasting Based on Time Series Analysis (2020) [18]	Stephanie Yang, Hsueh-Chih Chen, Wen-Ching Chen, and Cheng-Hong Yang	Combines Whale Optimization Algorithm (WOA) with Support Vector Regression (SVR) to forecast student and teacher numbers in Taiwan, showing high accuracy (lowest MAPE and	It focuses on Taiwan, which limits its generalizability to other countries or regions. The method requires detailed parameter optimization, which may not be easily

		RMSE). Provides valuable insights for education policy and resource management.	transferable across different datasets.
Analyzing and Predicting Students' Performance using Machine Learning: A Review (2020) [10]	Rastrollo-Guerrero, J. L., Gómez-Pulido, J. A., Durán-Domínguez, A.	Provides a comprehensive review of 70 studies exploring various AI techniques (ML, Neural Networks, etc.) for predicting student performance, which helps in designing strategies to improve academic outcomes and reduce dropout rates.	The review focuses on techniques but lacks a deep evaluation of the effectiveness of these methods in specific educational settings or datasets.
Application of Time Series Analysis for Philippines' Inflation Prediction (2019) [14]	Delima, A. J. P., Lumintac, M. T. Q.	Uses ARIMA to forecast inflation for the Philippines from 2018-2022, demonstrating a methodical approach with a clear identification of the best-fitting model (ARIMA (1,0,0) and ARIMA (7,0,0)). The findings are highly relevant for policymaking and economic planning.	The study focuses on univariate data from 1960 to 2017, which may not account for external factors that impact inflation. The model is also specific to the Philippines, which limits its generalizability to other regions.
Application of Time Series Analysis in Projecting Philippines' Electric Consumption (2019) [15]	Delima, A. J. P.	Uses ARIMA to forecast electric consumption for residential, commercial, and industrial sectors from 2018-2022. Provides accurate, data-driven projections for energy planning and policymaking.	The model relies on historical data from 2003 to 2017 and may not account for unforeseen factors, such as sudden shifts in energy demand or technological advances in energy efficiency.
Roll Motion Prediction Using a Hybrid Deep Learning and ARIMA Model (2018) [16]	Suhermia, N., Suhartonoa, D. D. Prastyoa, Baharuddin Ali	Combines ARIMA and Deep Neural Network (DNN) to predict roll motion in Floating Production Units (FPU), effectively capturing both linear and nonlinear patterns for improved forecast accuracy. The hybrid model outperforms non-hybrid models.	The application is limited to roll motion prediction in FPUs, and the results may not be readily applicable to other domains or types of forecasting.

3. Methodology

3.1 Dataset

The datasets used in this paper are the historical data of Mean Percentile Scores from Natan National High School, Diplahan District, Zamboanga Sibugay. It spans five school years, starting from 2020-2021, 2021-2022, 2022-2023, 2023-2024, and 2024-2025. These datasets were obtained from the office of the School Head.

3.2 ARIMA Algorithm

For forecasting the mean percentile scores, this study utilizes the ARIMA (Autoregressive Integrated Moving Average) model. Three key elements are combined in the ARIMA model, a time series forecasting method:

- p: Autoregressive order, which shows how many lag observations were included in the model.
- d: The number of times the data is different to attain stationarity (i.e., to eliminate trends or seasonality) is known as the differencing order.
- q: Moving average order, which indicates how many lags forecast errors are incorporated into the model.

The following is a mathematical representation of the ARIMA model:

$$\Phi(B)(w_t - \mu) = \theta(B)a_t$$

Where:

- $\Phi(B)$ and $\theta(B)$ represent the autoregressive and moving average components.
- w_t is the data value at time t_1, and $_{it}$ is the white noise or error term.

We use the ARIMA model to find the ideal values for p, d, and q by analyzing the historical data (Mean Percentile Scores) from Natan National High School. To predict future values, these parameters are determined by analyzing patterns in the time series data, such as trends and seasonality. Statistical software tools are used to build the model, and the model that minimizes forecasting errors is chosen as the best fit. The methodology described in the study by [15], which utilized ARIMA models to forecast electric consumption in the Philippines using comparable time series forecasting techniques, is followed in determining the proper ARIMA parameters. The effect of time series length on ARIMA accuracy was also explored in [19], [20], [21], [22], which guides the maximization of forecasting accuracy across different datasets.

4. Results and Discussions

The forecasted Mean Percentile Scores (MPS) from 2025 to 2029, generated through ARIMA (1,1,1) models, reveal distinct trends and patterns across the various junior high school subjects at Natan NHS.

Most subjects exhibit a generally stable upward trend in predicted scores, which is a positive indicator of the school's academic trajectory. The forecasts suggest that, without significant intervention, student performance is likely to maintain or slightly improve over the coming years in all subject areas.

- English is forecasted to have relatively stable performance, with scores gently declining from 70.26 in 2025 to 68.91 in 2029. The confidence intervals widen over time—from approximately 60.81–79.70 in 2025 to 38.30–99.52 in 2029—indicating increased uncertainty with longer-term projections. Despite this uncertainty, the general forecast suggests sustained performance in English.
- The mean score for math is clearly going up, going from 78.24 in 2025 to 87.82 in 2029. But its confidence intervals are wide and getting wider, going from 65.84 to 90.65 in 2025 to 42.55 to 133.09

in 2029. This indicates variability and uncertainty that may arise from historical fluctuations in student performance or external influences impacting this subject.

- Science exhibits a rising trajectory, increasing from 84.56 to 96.69 points, with increasingly broad confidence intervals, expanding from 71.14–97.98 to 36.14–157.25 over the five-year forecast. The wide intervals advise a cautious interpretation of long-term predictions, yet the upward trend reflects growth expectations.
- Araling Panlipunan forecasts an increase from 84.27 to 93.83, with a moderate widening of the confidence interval (72.01–96.54 to 52.47–135.19). This suggests steady but somewhat uncertain growth, possibly linked to the evolution of curricula or instructional approaches.
- Filipino shows a consistent upward trend, increasing from 77.62 in 2025 to 89.95 in 2029. The confidence intervals (74.55–80.69 to 75.00–104.91) remain relatively tighter compared to other subjects, indicating more stable and predictable performance improvements.
- Technology and Livelihood Education (TLE) demonstrates gradual growth from 74.62 to 83.96, with narrow and stable confidence intervals (72.09–77.15 to 81.29–86.62). This indicates reliable forecasts and suggests effective instructional practices, as well as stable student engagement in this practical subject.
- Music, Arts, Physical Education, and Health (MAPEH) stand out from other subjects by displaying a nearly flat trend. Scores range from the low 60s, specifically 63.22 in 2025 to 62.59 in 2029. The confidence intervals are relatively narrow, moving from 53.09 to 73.35 and 52.44 to 72.73. This indicates consistent, yet limited growth. It points to some opportunities for innovation in the curriculum or for boosting student motivation in this area.
- Edukasyon sa Pagpapakatao (ESP) shows steady growth. The scores rise from 72.70 to 79.92 points, with moderately narrow confidence intervals ranging from 64.35 to 81.06 and 71.53 to 88.32. This suggests stable and positive performance trends.

Table 2Forecasted MPS per Subject Area (2025–2029) with 95% Confidence Intervals

Year	English (95% CI)	Mathematics (95% CI)	Science (95% CI)	Araling Panlipunan (95% CI)	Filipino (95% CI)	TLE (95% CI)	MAPEH (95% CI)	ESP (95% CI)
2025	70.26 (60.81–79.70)	78.24 (65.84–90.65)	84.56 (71.14–97.98)	84.27 (72.01–96.54)	77.62 (74.55–80.69)	74.62 (72.09–77.15)	63.22 (53.09–73.35)	72.70 (64.35–81.06)
2026	70.01 (52.86–87.16)	81.71 (58.74–104.68)	89.58 (61.99–117.17)	87.51 (65.71–109.31)	80.82 (73.43–88.20)	76.79 (74.14–79.44)	62.89 (52.75–73.03)	74.26 (65.87–82.66)
2027	69.64 (47.10–92.18)	84.06 (52.38–115.74)	92.69 (52.56–132.82)	89.84 (60.36–119.32)	83.88 (73.42–94.34)	79.13 (76.47–81.80)	62.78 (52.64–72.92)	76.13 (67.74–84.52)
2028	69.28 (42.40–96.16)	86.02 (47.04–124.99)	94.90 (43.88–145.92)	91.88 (56.02–127.74)	86.92 (74.02–99.82)	81.54 (78.87–84.20)	62.68 (52.54–72.83)	78.03 (69.63–86.42)

2029	68.91 (38.30–99.52)	87.82 (42.55–133.09)	96.69 (36.14–157.25)	93.83 (52.47–135.19)	89.95 (75.00–104.91)	83.96 (81.29–86.62)	62.59 (52.44–72.73)	79.92 (71.53–88.32)

Confidence intervals gradually increase in size over time for all subjects, which is consistent with the time series forecasting phenomenon where uncertainty rises with longer time horizons. This indicates that forecasts for 2025–2026 are reasonably accurate, but those for 2028–2029 should be interpreted with caution. To increase accuracy, school planners should regularly update their forecasts with new information.

Table 2 projected data give important insights into resource allocation, planning, and targeted interventions. To maintain progress and reduce uncertainty, subjects like science and math, which show a lot of variability despite strong projected growth, need more focus. These efforts include teacher training, student support, and resource distribution. The steady growth in ESP and English, along with consistent performance in TLE and Filipino, shows that the current programs work well and should be improved further. The relatively flat MAPEH performance indicates a possible need for new approaches to boost student engagement and performance.

5. Limitations

It is very important to remember that these projections are based only on past performance data and do not consider any major changes in the environment, population, or policies. Future results could change a lot because of outside events or new educational programs.

6. Conclusions and Recommendation

The Mean Percentile Scores (MPS) for junior high subjects at Natan National High School (Natan NHS) were predicted by the ARIMA (1,1,1) forecasting models from 2025 to 2029. These models captured expected academic trends and changes. Overall performance is expected to stay stable or improve in most subjects, with science and math showing the strongest positive trends. However, these subjects also show greater forecast uncertainty. Due to consistent academic results and accurate forecasting, subjects like English, Filipino, and Edukasyon sa Pagpapakatao (ESP) are likely to show steady improvements with narrower confidence intervals. Music, Arts, Physical Education, and Health (MAPEH) and Technology and Livelihood Education (TLE) are expected to grow steadily, but at a more moderate pace. This suggests that these areas may require some curriculum development. The need to regularly update forecasts is highlighted by the widening of confidence intervals over longer forecast periods. This widening shows that there is increasing uncertainty in long-term predictions.

Several suggestions are made to improve the accuracy and relevance of forecasts. To enhance forecasts and respond to changing educational settings, educational planners should regularly update MPS forecasts with new data. Second, since science and math have larger confidence intervals and more variability, focused support is recommended for these subjects. Programs for student support and better teacher training could fall under this category. Third, we need to keep using the good teaching methods that are already working to keep the good trends in English, Filipino, and ESP going. Fourth, new ideas should be investigated for the TLE and MAPEH curricula to get students more interested and help them do better. Fifth, schools could use forecasting tools like ARIMA to predict future academic trends, which could help them plan better by using their resources more wisely. Lastly, to make forecasting more relevant and accurate, future studies should look at broader influences, including socioeconomic factors and policy changes.

References

1. S. P. Tiwari and A. Fahrudin, *EVOLVING SCHOOL DYNAMICS AND EMERGING TECHNOLOGIES IN*, no. November. 2024. doi: 10.69635/978-1-0690482-0-2.
2. R. Hardina, M. Amin, and M. R. Faishal, "The Role of National Education Day 2024 in Improving the Quality of Islamic Education in Pasuruan City," pp. 147–169, 2024.
3. K. Muralidharan and A. Singh, "India ' s New National Education Policy : Evidence and Challenges," pp. 1–7, 2020.
4. A. R. Magliari, "Understanding the Problem of the Modern-Day Teacher Shortage : A Qualitative Phenomenological Study of the Stories of Teachers in the Profession," 2025.
5. K. Male, "Predictive Analysis of Educational Trends: A Time Series Approach to State Matriculation Exam Performance," *J. Educ. Soc. Res.*, vol. 14, no. 5, p. 371, 2024, doi: 10.36941/jesr-2024-0145.
6. S. Ahmady, N. Khajeali, F. Sharif, and Z. Mirmoghtadaei, "Educational intervention to improve preclinical academic performance: A systematic review," no. January, pp. 1–6, 2019, doi: 10.4103/jehp.jehp.
7. F. Alshareef, H. Alhakami, T. Alsubait, and A. Baz, "Educational Data Mining: Applications and Trends," *Turkish Online J. Distance Educ.*, vol. 17, no. 2, pp. 125–128, 2020, doi: 10.17718/TOJDE.94217.
8. S. Vanitha and R. Jayashree, "a Prediction on Educational Time Series Data Using Statistical Machine Learning Model -an Experimental Analysis," *J. Theor. Appl. Inf. Technol.*, vol. 100, no. 14, pp. 5189–5200, 2022.
9. B. Albreiki, N. Zaki, and H. Alashwal, "Revisión bibliográfica sistemática de la predicción del rendimiento de los estudiantes mediante técnicas de aprendizaje automático," *Educ. Sci.*, vol. 11, no. 9, 2021.
10. J. L. Rastrollo-Guerrero, J. A. Gómez-Pulido, and A. Durán-Domínguez, "Analyzing and predicting students' performance by means of machine learning: A review," *Appl. Sci.*, vol. 10, no. 3, 2020, doi: 10.3390/app10031042.
11. A. P. Dela Cruz *et al.*, "Higher Education Institution (HEI) Enrollment Forecasting Using Data Mining Technique," *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 9, no. 2, pp. 2060–2064, 2020, doi: 10.30534/ijatcse/2020/179922020.
12. M. D. P. Silvestre and L. Tan, "Performance of Out - of - Field Teachers and the NAT MPS of Students ' School Scores : Basis for Program Initiatives," no. September 2023, 2024.
13. F. M. Khan and R. Gupta, "ARIMA and NAR based prediction model for time series analysis of COVID-19 cases in India," *J. Saf. Sci. Resil.*, vol. 1, no. 1, pp. 12–18, 2020, doi: 10.1016/j.jnlssr.2020.06.007.
14. A. J. P. Delima and M. T. Q. Lumintac, "Application of time series analysis for philippines' inflation prediction," *Int. J. Recent Technol. Eng.*, vol. 8, no. 1, pp. 1761–1765, 2019.
15. A. J. P. Delima, "Application of time series analysis in projecting Philippines' electric consumption," *Int. J. Mach. Learn. Comput.*, vol. 9, no. 5, pp. 694–699, 2019, doi: 10.18178/ijmlc.2019.9.5.860.
16. N. Suhermi, Suhartono, D. D. Prastyo, and B. Ali, "Roll motion prediction using a hybrid deep learning and ARIMA model," *Procedia Comput. Sci.*, vol. 144, pp. 251–258, 2018, doi:

10.1016/j.procs.2018.10.526.

17. S. Mao *et al.*, "Time Series Analysis for Education: Methods, Applications, and Future Directions," pp. 1–24, 2024, [Online]. Available: http://arxiv.org/abs/2408.13960
18. S. Yang, H. C. Chen, W. C. Chen, and C. H. Yang, "Student Enrollment and Teacher Statistics Forecasting Based on Time-Series Analysis," *Comput. Intell. Neurosci.*, vol. 2020, 2020, doi: 10.1155/2020/1246920.
19. L. Qin, K. Shanks, G. A. Phillips, and D. Bernard, "The Impact of Lengths of Time Series on the Accuracy of the ARIMA Forecasting," *Int. Res. High. Educ.*, vol. 4, no. 3, p. 58, 2019, doi: 10.5430/irhe.v4n3p58.
20. J. Zheng and M. Huang, "Traffic flow forecast through time series analysis based on deep learning," *IEEE Access*, vol. 8, pp. 82562–82570, 2020, doi: 10.1109/ACCESS.2020.2990738.
21. S. Khan and H. Alghulaiakh, "ARIMA model for accurate time series stocks forecasting," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 7, pp. 524–528, 2020, doi: 10.14569/IJACSA.2020.0110765.
22. J. Fattah, L. Ezzine, Z. Aman, H. El Moussami, and A. Lachhab, "Forecasting of demand using ARIMA model," *Int. J. Eng. Bus. Manag.*, vol. 10, pp. 1–9, 2018, doi: 10.1177/1847979018808673.