E-ISSN: 3031-8629
P-ISSN: 3032-3258
Halaman 35-48
Volume 2 Nomor 3 Tahun 2025

# A Comparative Analysis Of Machine Learning Models For Inventory Demand Forecasting In A Food Manufacturing Sme

Igbokwe Nkemakonam Chidiebube[1], Nwamekwe Charles Onyeka[2], Aguh Patrick Sunday[3] and Ezeanyim Okechukwu Chiedu[4]
Department of Industrial and Production Engineering, Nnamdi Azikiwe University, Awka
e-mail: ps.aguh@unizik.edu.ng

Abstract

Inventory demand forecasting is vital for small and medium enterprises (SMEs) in the food manufacturing sector to maintain optimal stock levels, reduce waste, and improve operational efficiency. Traditional statistical methods often fail to capture complex demand patterns, necessitating the adoption of advanced machine learning (ML) approaches. This study conducted a comparative analysis of four ML models Long Short-Term Memory (LSTM), Facebook Prophet, XGBoost, and Gradient Boosting Regressor using a three-year dataset (January 2020–December 2022) from a Nigerian food manufacturing SME. The dataset included monthly demand records for thirteen product categories. Models were evaluated based on Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared ($R^2$). LSTM consistently outperformed other models, achieving the lowest RMSE and MAE values and the highest $R^2$ scores, demonstrating superior capability in capturing non-linear and temporal demand patterns. Facebook Prophet and Gradient Boosting performed moderately, with Prophet offering higher interpretability. XGBoost showed the weakest predictive performance across all metrics. The findings indicate that LSTM is the most effective model for inventory demand forecasting in SMEs with dynamic demand profiles. Incorporating advanced ML techniques like LSTM can enhance forecasting accuracy and support strategic inventory management decisions in food manufacturing SMEs.

Keywords *: Corporate Culture, Employee Productivity, Work Loyalty, Mediation, SEM, PT. Ochiai Menara Indonesia*

## INTRODUCTION

Inventory demand forecasting plays a critical role in supply chain management, particularly for small and medium enterprises (SMEs) in the food manufacturing sector. Effective demand forecasting helps businesses maintain optimal stock levels, reduce waste, and enhance customer satisfaction. Traditional forecasting methods, such as time series models and statistical techniques, have long been employed in this domain. However, the increasing complexity of market demands and the availability of large datasets have necessitated the adoption of more sophisticated approaches, such as machine learning (ML) models (Chikwendu et al., 2023; Vitalis, et al., 2024). Machine learning models offer significant advantages in demand forecasting due to their ability to learn from historical data, capture complex patterns, and improve predictive accuracy over time (Chidiebube, Uzochukwu, et al., 2025). Various Machine Learning models, have demonstrated promising results in demand forecasting applications (Kolková & Ključnikov, 2022). These models can process large volumes of data from multiple sources, including sales records, market trends, and external factors such as seasonality and economic conditions (Vitalis, et al., 2024). For SMEs in the food manufacturing sector, selecting an appropriate ML model for inventory demand forecasting is particularly crucial. Unlike large enterprises with extensive data infrastructure, SMEs often face constraints in computational resources, data availability, and model interpretability (Chidiebube et al., 2024; Chukwutoo & Nkemakonam, 2018; Godwin et al., 2022; Igbokwe et al., 2021; Igbokwe & Godwin, 2021; Igbokwe & Godwin, 2022; Igbokwe & Mba, 2019). Therefore, a comparative analysis of different ML models tailored to the specific needs of SMEs can provide valuable insights into the most effective techniques for improving inventory management and operational efficiency (Al-karkhi & Rza, 2025; Nwamekwe & Okpala, 2025). Despite the growing interest in ML-based demand forecasting, there remains a gap in research focusing on SMEs in food manufacturing (Le Dinh et al., 2025; Oldemeyer et al., 2024; Peretz-Andersson et al., 2024; Phir & Mbale, 2024). Most studies primarily target large corporations with vast datasets and sophisticated analytics capabilities (Chidiebube et al., 2025). By conducting a comparative analysis of ML models in this context, this study

aims to bridge this gap, offering practical recommendations for SMEs to enhance their demand forecasting strategies. The present study evaluates various ML models, xgboot, lstm, fbPhrophet and gradient boosting. The goal is to determine which model provides the highest forecasting accuracy while considering computational efficiency and ease of implementation. The findings from this study will contribute to both academia and industry by informing best practices for inventory demand forecasting in food manufacturing SMEs.

## METHODS

This study utilizes a three-year dataset comprising monthly inventory demand records from a food manufacturing small and medium enterprise (SME). The dataset spans from January 2020 to December 2022 and includes thirteen distinct product categories labeled Product 1 through Product 13. For each product, the data captures the quantity demanded per month and the corresponding date of demand, resulting in a time series structure with 36 monthly observations per product.

Key variables include:

Product ID: Unique identifier for each product (Product 1–Product 13).

Quantity Demanded: Total number of units requested or consumed each month.

Date of Demand: Monthly timestamps indicating the period of demand. The dataset was selected based on its relevance to demand forecasting tasks, aligning with established practices in inventory management and supported by literature on time series forecasting. The demand patterns reflect varying scales, from high-volume staples (e.g., Product 2 and Product 12) to low volume specialized products (e.g., Product 1 and Product 4), providing a diverse test bed for model performance evaluation. This variability in product demand profiles allows for robust comparative analysis of forecasting models under different demand conditions, including seasonality, trend, and volatility.

## RESULTS AND DISCUSSION

The purpose of developing and applying machine learning models for inventory demand forecasting in this study, is to enhance accuracy, optimize inventory levels, reduce costs, improve customer satisfaction, inform strategic decisions, increase efficiency, and gain a competitive advantage. It serves the following critical purposes:

- Improved accuracy in demand prediction
- optimization of inventory levels
- Cost reduction
- Informed decision making
- Enhanced customer satisfaction
- Scalability and Efficiency

The heat map in figure 1.1 illustrates the correlation coefficients between the inventory demands for 13 products over different months. Product 4 and Product 5 have a correlation of 0.92, indicating that their demand tends to increase and decrease together. Product 8 and Product 9 have a correlation of 0.99, showing almost identical demand patterns. Product 7 and Product 8 with a correlation of 0.99, these products also display highly similar demand trends.

Product 2 and Product 3 have a negative correlation of -0.5, indicating that when the demand for Product 2 increases, the demand for Product 3 tends to decrease, and vice versa. Product 2 and Product 8 have a correlation of -0.48, showing an inverse relationship in their demand patterns. Product 13 is strongly related to the monthly pattern with a correlation of 0.79. This means the demand for Product 13 is strongly related to the monthly pattern. There is a slight negative correlation (-0.037), implying that the demand for Product 3 does not significantly follow the monthly trend.

Products such as Product 3, Product 4, Product 5, Product 6, Product 7, Product 8, Product 9, and Product 13 show high positive correlations with each other, indicating similar demand patterns. Products like Product 2 and Product 12 have lower correlations with other products, indicating different demand patterns.

Products with high positive correlations (e.g., Product 8 and Product 9) can be managed together. This could mean ordering these products simultaneously or considering them together in demand forecasting models. Products with negative correlations (e.g., Product 2 and Product 3) could be used to diversify inventory and reduce risk. If one product's demand decreases, the other's increase might balance overall demand variability. Products that correlate strongly with monthly patterns (e.g., Product 13) should be carefully analyzed for seasonal trends. Inventory levels for these products might need adjustment based on the time of year. Products like Product 2, which have a mix of negative and low correlations with others, may require individual attention. Their unique demand patterns suggest they could be influenced by different factors compared to other products.

E-ISSN: 3031-8629
P-ISSN: 3032-3258
Halaman 35-48
Volume 2 Nomor 3 Tahun 2025

The heat map reveals significant insights into the relationships between the demands for different products. High positive correlations suggest similar demand patterns, making these products suitable for joint management. Negative correlations indicate opportunities for diversification. Products with strong correlations to monthly patterns suggest a need for seasonal planning. Finally, products with unique demand patterns may require special attention to ensure efficient inventory management.

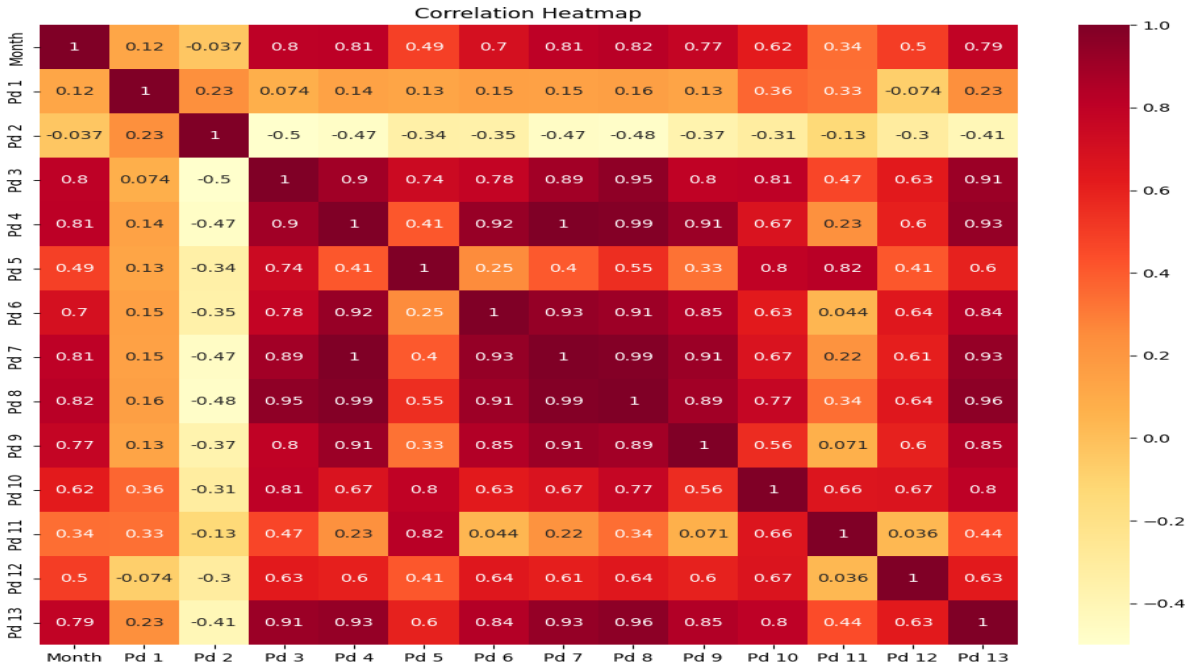



Fig 1.1: Heat Correlation

The applied models Xgboot, LSTM, Prophet and Gradient boosting regressor were evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared ($R^2$). Figure 1.2 illustrates the Mean Absolute Error (MAE) of the four forecasting models ARIMA, Prophet, LSTM, and XGBoost across thirteen products. For Products 1 to 3, all models demonstrated relatively low MAE values, with ARIMA and Prophet achieving similar low errors for Product 1, LSTM recording slightly higher errors, and XGBoost performing the worst. In Product 2, ARIMA and LSTM exhibited the lowest errors, while

Prophet and XGBoost trailed behind. Prophet outperformed the other models for Product 3, followed by ARIMA and LSTM, with XGBoost again showing the highest error. In Products 4 to 6, performance disparities among the models became more pronounced. For Product 4, LSTM achieved the lowest MAE, followed by ARIMA and Prophet, while XGBoost remained the least accurate. In Product 5, Prophet and XGBoost recorded comparable errors, whereas ARIMA and LSTM outperformed them with lower MAEs.While in product 6, Prophet and LSTM have the lowest errors, followed by ARIMA, with XGBoost having the highest error. For Products 7 to 9, LSTM consistently demonstrated superior accuracy with the lowest forecasting errors for Product 7, while ARIMA outperformed others for Products 8 and 9. Prophet closely followed ARIMA in these cases, whereas XGBoost persistently exhibited the highest error rates across all three products. Similarly, for Products 10 to 13, Prophet emerged as the best-performing model for Product 10, while ARIMA and Prophet exhibited comparable low errors for Product 11. For Product 12, both Prophet and LSTM achieved the lowest errors, with ARIMA trailing slightly behind. Notably, LSTM regained its leading performance for Product 13. Across this group of products, XGBoost continued to record the highest errors consistently. Overall, the results indicate that LSTM, ARIMA, and Prophet outperform XGBoost across all products, albeit with performance variations among them. The findings highlight the potential of deep learning (LSTM) and statistical models (ARIMA and Prophet) in effectively capturing demand patterns in the food manufacturing context.

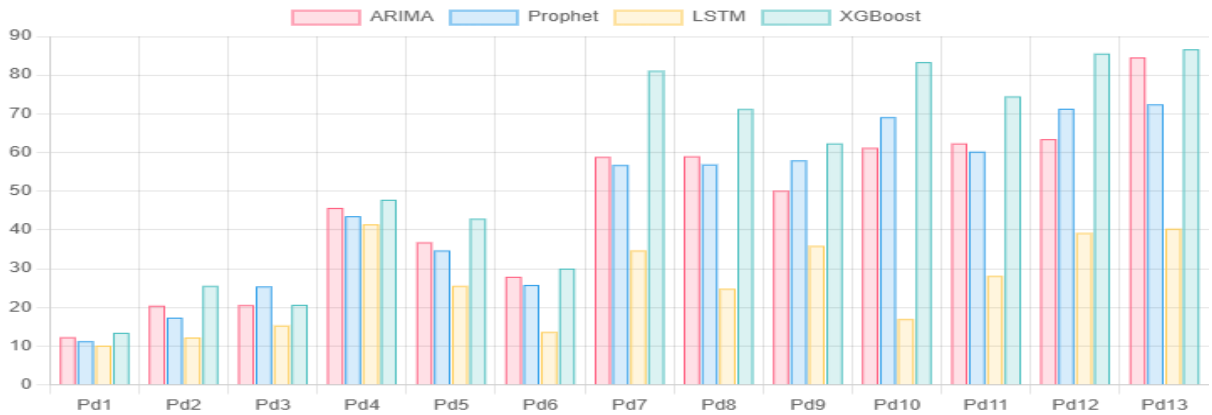


Fig 1.2 Mean Absolute Error

Figure 1.3 presents the R-squared values for the four forecasting models LSTM, ARIMA, Prophet, and XGBoost across thirteen products. The results highlight notable differences in model fit and predictive accuracy. Across all products, LSTM consistently achieved the highest R-squared values, indicating superior goodness-of-fit and predictive capability. ARIMA and Prophet exhibited competitive performance, often yielding similar R-squared scores, though slightly lower than LSTM. Conversely, XGBoost frequently recorded the lowest R-squared values, suggesting poor model fit and limited forecasting effectiveness in this context. For Products 1 to 3, LSTM maintained the highest R-squared in all cases, followed by ARIMA and Prophet, while XGBoost remained the least accurate. This trend persisted for Products 4 to 6, where LSTM continued to outperform the other models, with ARIMA and Prophet showing moderate fit and XGBoost lagging behind.

A similar pattern was observed for Products 7 to 9 and Products 10 to 13, where LSTM sustained its leading position in all instances. ARIMA and Prophet maintained their relative ranking with comparable R-squared values, and XGBoost consistently performed the poorest.

Overall, these findings reinforce the effectiveness of LSTM in capturing complex demand patterns and variability in inventory forecasting for food manufacturing SMEs, while underscoring the limitations of XGBoost for this application.

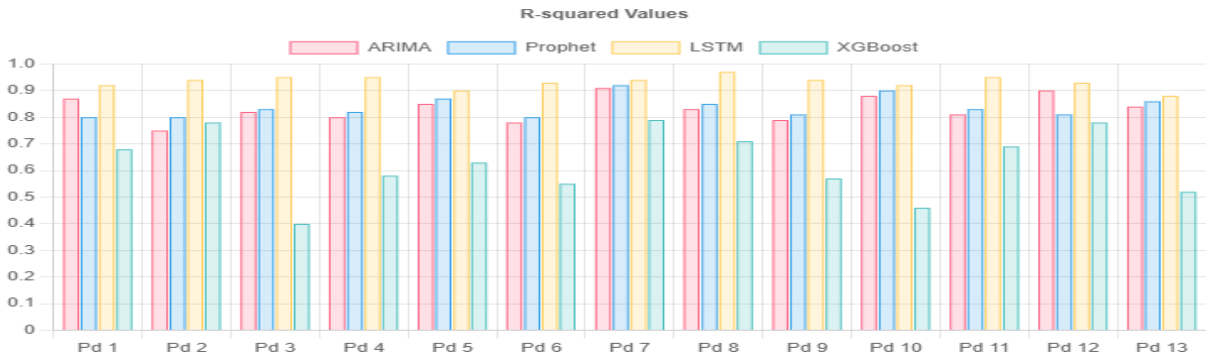



Fig 1.4: R-Squared Evaluation

In summary, LSTM generally performs the best across most periods, as indicated by the highest R-squared values, suggesting it fits the data well. ARIMA and Prophet exhibit competitive performance, often yielding similar R-squared values, though slightly lower than LSTM. XGBoost frequently has the lowest R-squared values, indicating it has the poorest fit to the data among the four models. Based on the performance metrics provided, the LSTM (Long Short-Term Memory) model emerges as the best overall model for the given set of products. The LSTM model consistently outperforms the other models, including XGBoost, ARIMA, and Prophet, across all three-evaluation metrics (MAE and $R^2$). The LSTM model's superior performance can be attributed to its ability to effectively capture complex non-linear relationships and handle time series data, which are crucial for accurate predictions in this application. The LSTM's low MAE values along with its high $R^2$ scores demonstrate its effectiveness in minimizing both small and large errors, as well as its strong explanatory power in accounting for the variation in the demand data. In contrast, the XGBoost model underperforms across all metrics, while the ARIMA and Prophet models fall somewhere in between the LSTM and XGBoost models, with the Prophet model generally outperforming the ARIMA model. Therefore, the LSTM model is the recommended choice for inventory demand forecasting application in the case study.

## CONCLUSION

This study conducted a comparative analysis of four machine learning models Long Short-Term Memory (LSTM), Facebook Prophet, XGBoost, and Gradient Boosting Regressor for inventory demand forecasting in a food manufacturing small and medium enterprise (SME). The results revealed significant differences in model performance across multiple evaluation metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared ($R^2$). Among the models evaluated, the LSTM model consistently outperformed others, demonstrating superior predictive accuracy and robustness across diverse product categories. Its ability to capture temporal dependencies and complex non-linear demand patterns underscores its suitability for inventory forecasting in SMEs with dynamic and seasonal demand profiles. Conversely, XGBoost recorded the lowest

performance in terms of accuracy and model fit, indicating its limited effectiveness in univariate time series forecasting for inventory management. Facebook Prophet and Gradient Boosting showed moderate performance, with Prophet excelling in ease of implementation and interpretability, which may be advantageous in resource-constrained SME environments. The study's findings reinforce the critical role of advanced machine learning techniques in improving demand forecasting accuracy. Accurate forecasts enable SMEs to optimize inventory levels, reduce holding costs, minimize stockouts and overstock situations, and ultimately enhance customer satisfaction. For SMEs operating in volatile and competitive markets like food manufacturing, leveraging data-driven forecasting solutions can contribute significantly to operational efficiency and strategic decision-making. SMEs in the food manufacturing sector are encouraged to adopt LSTM models for demand forecasting tasks, especially when dealing with large datasets and complex temporal patterns. While LSTM requires higher computational resources, its predictive accuracy offers long-term benefits that outweigh initial setup costs. Future studies and practical applications should explore hybrid approaches that combine the strengths of LSTM with interpretable models like Prophet to achieve a balance between accuracy and operational simplicity. Given the computational demands of deep learning models, SMEs with limited resources may consider cloud-based forecasting solutions or lightweight architectures of LSTM to ensure feasibility and scalability. In conclusion, this study demonstrates that the thoughtful application of machine learning techniques can significantly transform inventory demand forecasting practices in SMEs. Implementing these findings can position food manufacturing SMEs for improved competitiveness and sustainable growth in an increasingly data-driven business environment.

REFERENCES

Abbasimehr, H., Shabani, M., & Mohsen Yousefi. (2020). An optimized model using LSTM network for demand forecasting. Computers & Industrial Engineering, 163.

Al-karkhi, M. I., & Rza, G. (2025). Innovative machine learning approaches for complexity in economic forecasting and SME growth_ A comprehensive review. Journal of

Economy and Technology, 3(December 2024), 109–122. https://doi.org/10.1016/j.ject.2025.01.001

Charles Chikwendu, O., Nkemakonam Chidiebube, I., & Constance Obiuto, N. (2023). Revolutionizing Manufacturing: Harnessing the Power of Artificial Intelligence for Enhanced Efficiency and Innovation. International Journal of Engineering Research and Development, 19(6), 18–25. www.ijerd.com

Chidiebube, I. N., Martinjoe, U. C., Chukwuma, O., & Chukwuemeka, G. H. (2024). Bi-Model-Based Multi-Criteria Optimization Decision Support System for Strategic Maintenance Scheduling in Food Manufacturing Industries. Unizik Journal of Engineering and Applied Sciences, 3(3), 1066–1080.

Chidiebube, I. N., Nwamekwe, C. O., Harold, G., & Wilfred, M. (2025). Optimization of Overall Equipment Effectiveness Factors in a Food Manufacturing Small and Medium Enterprise. Journal of Research in Engineering and Applied Science, 10(01), 836–845.

Chidiebube, I. N., Uzochukwu, M. G., Nwamekwe, O., & Sunday, A. P. (2025). Evaluating Machine Learning Models for Optimizing Overall Equipment Effectiveness in Food Manufacturing Smes. Jurnal Inovasi Teknologi Dan Edukasi Teknik, 5(2). https://doi.org/10.17977/um068.v5.i2.2025.5

Chukwutoo, C. I., & Nkemakonam, C. I. (2018). Total Productive Maintenance (TPM) as a Business Strategy in Manufacturing Small and Medium Enterprises in Nigeria. Advances in Research, 15(5), 1–9. https://doi.org/10.9734/AIR/2018/41330

Douaioui, K., Oucheikh, R., Benmoussa, O., & Mabrouki, C. (2024). Machine Learning and Deep Learning Models for Demand Forecasting in Supply Chain Management: A Critical Review. Applied System Innovation, 7(5). https://doi.org/10.3390/asi7050093

Godwin, H., Umeonwujiaku, I., Aguh, P., & Igbokwe, N. (2022). Development of the best optimal policy for Inventory control in a Small and Medium Enterprise. International Journal of Engineering Science and Computing, 12(11), 29829–29833.

Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: Principles and Practice.

Igbokwe, N. C., & Godwin, H. C. (2021). Maintenance Performance Evaluation and Downtime Analysis of Manufacturing Equipment in a Food Manufacturing Company.

Journal of Engineering Research and Reports, 20(11), 100–107. https://doi.org/10.9734/jerr/2021/v20i1117413

Igbokwe, N., & Godwin, H. (2022). Cost Effective Maintenance and Machine Reliability for Food Manufacturing Industries using Optimal Maintenance Strategy. Archives of Current Research International, 22(8), 27–34. https://doi.org/10.9734/ACRI/2022/v22i8543

Igbokwe, N., & Mba, W. (2019). Assessing the Nature of Risk Management Implementation in Manufacturing Small Medium Enterprises in Nigeria. Archives of Current Research International, 16(4), 1–11. https://doi.org/10.9734/ACRI/2019/v16i430098

Igbokwe, N., Chukwuemeka, G. H., & Constance, N. (2021). A GANetXL Approach to an Optimal Maintenance Strategy in Food Manufacturing. International Journal of Engineering Science and Computing.

Kolková, A., & Ključnikov, A. (2022). Demand Forecasting: Ai-Based, Statistical and Hybrid Models Vs Practice-Based Models-the Case of Smes and Large Enterprises. Economics and Sociology, 15(4), 39–62. https://doi.org/10.14254/2071-789X.2022/15-4/2

Le Dinh, T., Vu, M. C., & Tran, G. T. C. (2025). Artificial Intelligence in SMEs: Enhancing Business Functions Through Technologies and Applications. Information (Switzerland), 16(5), 1–22. https://doi.org/10.3390/info16050415

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and Machine Learning forecasting methods: Concerns and ways forward. PLoS ONE, 13(3), 1–26. https://doi.org/10.1371/journal.pone.0194889

Nwamekwe C. O., and Nwabunwanne E. C. (2025). Circular Economy and Zero-Energy Factories: A Synergistic Approach to Sustainable Manufacturing. Journal of Research in Engineering and Applied Sciences (JREAS), 10(1), 829-835. https://qtanalytics.in/journals/index.php/JREAS/article/view/4567

Nwamekwe C. O., Ewuzie Nnamdi Vitalis, Igbokwe Nkemakonam Chidiebube, & Nwabueze Chibuzo Victoria. (2025). Evaluating Advances in Machine Learning Algorithms for Predicting and Preventing Maternal and Foetal Mortality in Nigerian Healthcare: A

Systematic Approach. (2025). International Journal of Industrial and Production Engineering, 3(1), 1-15. https://journals.unizik.edu.ng/ijipe/article/view/5161

Nwamekwe C. O., Ezeanyim O. C., and Igbokwe N. C. (2025). Resilient Supply Chain Engineering in the Era of Disruption: An Appraisal. International Journal of Innovative Engineering, Technology and Science (IJIETS), 9(1), 11-23. https://hal.science/hal-05061524/

Nwamekwe, C. O., and Igbokwe, N. C. (2024). Supply Chain Risk Management: Leveraging AI for Risk Identification, Mitigation, and Resilience Planning. International Journal of Industrial Engineering, Technology & Operations Management, 2(2), 41–51. https://doi.org/10.62157/ijietom.v2i2.38

Nwamekwe, C. O., and Okpala, C. C. (2025). Circular economy strategies in industrial engineering: From theory to practice. International Journal of Multidisciplinary Research and Growth Evaluation, 6(1):1773-1782.

https://www.allmultidisciplinaryjournal.com/uploads/archives/20250212103754_MGE-2025-1-288.1.pdf

Nwamekwe, C. O., and Okpala, C. C. (2025). Machine learning-augmented digital twin systems for predictive maintenance in highspeed rail networks. International Journal of Multidisciplinary Research and Growth Evaluation, 6(1), 1783-1795. https://www.allmultidisciplinaryjournal.com/uploads/archives/20250212104201_MGE-2025-1-306.1.pdf

Nwamekwe, C. O., Chinwuko, C. E. & Mgbemena, C. E. (2020). Development and Implementation of a Computerised Production Planning and Control System. UNIZIK Journal of Engineering and Applied Sciences, 17(1), 168-187

Nwamekwe, C. O., Ewuzie, N. V., Igbokwe, N. C., Okpala, C. C., andamp; U-Dominic, C. M. (2024). Sustainable Manufacturing Practices in Nigeria: Optimization and Implementation Appraisal. Journal of Research in Engineering and Applied Sciences, 9(3). https://qtanalytics.in/journals/index.php/JREAS/article/view/3967

Nwamekwe, C. O., Ewuzie, N. V., Igbokwe, N. C., U-Dominic, C. M., andamp; Nwabueze, C. V. (2024). Adoption of Smart Factories in Nigeria: Problems, Obstacles, Remedies and

Opportunities. International Journal of Industrial and Production Engineering, 2(2). Retrieved from https://journals.unizik.edu.ng/ijipe/article/view/4167

Nwamekwe, C. O., Ewuzie, N. V., Okpala, C. C., Ezeanyim, C., Nwabueze, C. V., Nwabunwanne, E. C. (2025). Optimizing Machine Learning Models for Soil Fertility Analysis: Insights from Feature Engineering and Data Localization. Gazi University Journal of Science Part A: Engineering and Innovation, 12(1), 36-60. https://dergipark.org.tr/en/pub/gujsa/issue/90827/1605587

Nwamekwe, C. O., Ewuzie, N.V., Igbokwe, N. C., Nwabunwanne, E. C., & Ono, C. G. (2025). Digital Twin-Driven Lean Manufacturing: Optimizing Value Stream Flow. Letters in Information Technology Education (LITE), 8(1), pp.1-13. https://hal.science/hal-05127340/

Nwamekwe, C. O., Okpala, C. C., and Okpala, S. C., (2024). Machine Learning-Based Prediction Algorithms for the Mitigation of Maternal and Fetal Mortality in the Nigerian Tertiary Hospitals. International Journal of Engineering Inventions, 13(7), PP: 132-138. https://www.ijeijournal.com/papers/Vol13-Issue7/1307132138.pdf

Oldemeyer, L., Jede, A., & Teuteberg, F. (2024). Investigation of artificial intelligence in SMEs: a systematic review of the state of the art and the main implementation challenges. In Management Review Quarterly (Vol. 75, Issue 2). Springer International Publishing. https://doi.org/10.1007/s11301-024-00405-4

Peretz-Andersson, E., Tabares, S., Mikalef, P., & Parida, V. (2024). Artificial intelligence implementation in manufacturing SMEs: A resource orchestration approach. International Journal of Information Management, 77(April). https://doi.org/10.1016/j.ijinfomgt.2024.102781

Phir, R., & Mbale, J. (2024). Leveraging Machine Learning and Artificial Intelligence for Innovation and Sustainability in Small and Medium Sized Enterprises (SMEs): A Case Study of Kalumbila, Zambia. Sixth International Conference in Information and Communication Technologies, Lusaka, Zambia, October, 56–62.

Vitalis, E. N., Nwamekwe, C. O., Nkemakonam, I., Victoria, N. C., Nwabunwanne, E. C., & Ono, C. G. (2024). Application of Machine-Learning-Based Hybrid Algorithm for

Production Forecast in Textile Company. Jurnal Inovasi Teknologi Dan Edukasi Teknik, 4(12), 1–9. https://doi.org/10.17977/um068.v4.i12.2024.2

Vitalis, E. N., Onyeka, N. C., Chikwendu, O. C., Chidiebube, N., U-dominic, C. M., & Victoria, N. C. (2024). Machine Learning Models Application for Maintenance Operations Enhancement in a Petrochemical Industry. Faculty of Engineering International (Hybrid) Conference 2024, 66–76.