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Predicting Demand for MSME Products Using Artificial Neural Networks (ANN) Based on Historical Sales Data

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Abstract

Accurate demand forecasting plays a crucial role in supporting inventory and sales strategies, particularly for Micro, Small, and Medium Enterprises (MSMEs) that often face resource constraints. This study aims to develop a predictive model using Artificial Neural Networks (ANN) to forecast product demand based on historical sales data. The ANN model is trained and evaluated using a structured experimental approach, adjusting parameters such as the number of hidden layers, learning rate, and epochs to identify the best-performing architecture. Evaluation metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) are used to measure model performance. The results demonstrate that the ANN model is capable of capturing complex nonlinear relationships in multidimensional data and producing accurate demand forecasts. The model particularly performs well in predicting demand trends for products in the Electronics and Household categories. These findings provide valuable insights for MSME stakeholders in optimizing inventory planning and making data-driven business decisions.

Keywords: Artificial Neural Network, Demand Forecasting, MSME, Sales Data Prediction, Supply Chain Optimization, Small Business Analytics

1. Introduction

Micro, Small, and Medium Enterprises (MSMEs) play an important role in the Indonesian economy. According to data from the Ministry of Cooperatives and SMEs, MSMEs contributed 60% to the Gross Domestic Product (GDP) in 2021 and absorbed more than 97% of the national workforce [1]. However, despite this potential, MSMEs still face various challenges, particularly in supply chain management and product demand forecasting.

Dynamic market demand, limited capital, and minimal use of technology in inventory management pose significant obstacles for SME operators. Many businesses struggle to determine optimal stock levels due to the absence of accurate demand forecasting systems. This leads to overstocking, which ties up capital, or stockouts, resulting in customer loss [2].

In the era of digital transformation, businesses are required to integrate information technology into their business processes, including sales data analysis. The availability of historical sales data, now widely recorded digitally through e-commerce platforms, can be utilized to predict product demand more accurately [3]. However, not all SMEs have the capability or access to advanced technologies such as Artificial Intelligence (AI) to perform such predictions.

Artificial Neural Networks (ANN) are a machine learning method proven to excel in predicting historical data due to their ability to handle complex nonlinear and multidimensional characteristics. In applications such as river flow forecasting, ANN “performs extremely well” and is effective in “addressing nonlinear relationships between variables.” In the energy and reliability sectors, ANN is also noted for its ability to mimic behavioral patterns that cannot be explained by other techniques, while being tolerant of uncertain data and capable of operating in real time [4]. Additionally, the use of NARX-type ANNs in soybean production forecasting shows that these networks learn

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historical patterns and effectively minimize estimation error [5]. Meanwhile, MLP models are suitable for forecasting time series event sequences, reinforcing their reliability in capturing the temporal dynamics of data.

In terms of clustering, ANNs are robust in performing clustering based on desired targets (classification) and clustering without targets (clustering). Linear, nonlinear, complex, and multi-class are the types of classification that ANN can perform, while in clustering, ANN can simultaneously uncover the spatial relationships of each data group in order to identify those data clusters [6]. In the context of inventory management, the use of ANN can help SMEs anticipate future product demand, enabling them to efficiently manage inventory levels.

Many studies have proven the effectiveness of ANN in demand forecasting. For example, research by Elbatal et al. [7] demonstrated the modelling on Gross Domestic Product annual growth rate data by using time series. With a structure of 5 hidden layers and 5 nodes, the ANN successfully reduced the Mean Absolute Percentage Error (MAPE) from 22% to 8%. The Mean Squared Error (MSE) value also decreased significantly from 1,021,013 to 643,238. These results indicate that ANN is highly effective in reducing prediction errors based on historical data, and the model can generalize well without overfitting. Another study by Chi [8] shows that hybrid SARIMA and NARNN model in forecasting of global price of soybeans. This indicates that ANNs, particularly RNNs, can provide higher prediction accuracy than conventional methods in the retail context.

However, most of these studies still focus on large companies or large-scale retail sectors. There has been little research specifically highlighting the application of ANN in the context of Indonesian MSMEs. The lack of predictive technology implementation by MSMEs in Indonesia opens up research opportunities to explore the potential use of ANN in supporting their business decision-making.

As the digitalization of MSMEs increases in the wake of the COVID-19 pandemic, data from Google and Temasek 2022 shows that more than 80% of MSMEs in Southeast Asia now use digital platforms to sell their products. With more and more digital transactions being recorded, MSMEs have a great opportunity to use this data to develop data-driven business strategies.

This study builds an ANN model based on historical product sales data to predict the demand for MSME products. This model is expected to provide recommendations on products with high and low demand levels, so that business actors can be more careful in managing stock and improving operational efficiency.

Additionally, this research aims to develop a product ranking classification system based on demand predictions, which can serve as a foundation for strategic decision-making in SMEs. Through this approach, the research not only contributes to the advancement of knowledge in the fields of AI and business but also offers practical solutions for the development of SMEs in the digital age.s study builds an ANN model based on historical product sales data to predict.

2. Literature Review

The integration of Big Data and Artificial Neural Networks (ANNs) in Small and Medium-sized Enterprises (SMEs) has gained significant attention in recent years, particularly in the area of supply chain management. Research by Magazzino and Mele [9] demonstrates that incorporating Big Data and ANNs into the supply chain management processes of SMEs can substantially enhance the accuracy of demand forecasting. The study developed an ANN model, which outperformed traditional methods such as linear regression and moving averages in predicting demand. The ANN model achieved a Mean Absolute Percentage Error (MAPE) of 3.45%, which was significantly lower than the linear regression method’s MAPE of 7.89% and the moving average method's MAPE of 10.56%. These findings highlight the ability of ANNs to handle complex, non-linear relationships in demand prediction, making them a valuable tool for SMEs looking to optimize their supply chain operations.

Another study by Ha et al. [10] further supports the utility of ANNs in demand forecasting for SMEs. This research developed an ANN model utilizing the backpropagation algorithm to predict product demand for SMEs in Pematang Siantar. The model achieved a MAPE below 10%, reflecting a high level of prediction accuracy. This result is significant, as accurate demand forecasting is crucial for SMEs to maintain proper inventory levels, minimize stockouts, and optimize production schedules. By utilizing ANNs, SMEs can better understand demand fluctuations, allowing for more efficient and responsive supply chain management.

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ANNs, specifically in the form of supervised learning techniques, have been widely employed in various fields for data prediction and classification tasks. These networks are designed to simulate the functioning of the human brain, with interconnected layers of nodes that learn from data patterns. This ability to process vast amounts of data and learn from historical trends makes ANNs particularly suitable for forecasting demand in SMEs. Unlike traditional methods, which rely on linear relationships between variables, ANNs can model complex, non-linear relationships, making them more accurate in predicting demand in environments with high variability and uncertainty.

In addition to ANNs, other machine learning techniques, such as Support Vector Machines (SVM) and Recurrent Neural Networks (RNN), have been explored for demand prediction in SMEs. Research by Kim et al. [11] applied 1D-CNN and BiLSTM models to forecast peak electricity demand. The study found that both machine learning methods improved revenue and adaptability to market changes by providing more accurate demand predictions. These results suggest that the digitalization of SMEs, coupled with the application of machine learning algorithms, not only enhances demand forecasting but also contributes to increased revenue by enabling SMEs to respond more quickly to market dynamics.

The research findings across various studies emphasize the significant role of machine learning algorithms, particularly ANN models, in improving demand prediction accuracy for SMEs. By leveraging historical sales data, ANNs can identify patterns and trends that may not be immediately apparent through traditional forecasting methods. This ability to capture complex relationships in the data allows SMEs to better anticipate fluctuations in demand, optimize inventory levels, and reduce operational costs. Furthermore, the application of machine learning models like ANN, SVM, and RNN provides SMEs with tools to remain competitive in an increasingly digital and data-driven business environment.

In conclusion, the integration of machine learning algorithms, especially Artificial Neural Networks, into the demand forecasting processes of SMEs offers substantial benefits. The research reviewed here confirms the high capability of ANNs in predicting SME product demand, based on historical data, and underscores their importance in modernizing SME operations. As SMEs continue to face the challenges of an evolving market, the use of big data and machine learning techniques will be crucial for enhancing their adaptability and ensuring their long-term success.

3. Methodology

3.1. Research Approach

This study employs a quantitative approach with an experimental method to build and test a product demand prediction model based on ANN. The experimental approach allows for systematic simulation and testing of the model's performance using historical data. Similar to this study, research in the retail sector by Chawla et al. [12] used ANN for demand forecasting in American Retail Corporation, emphasizing the importance of iterative experiments to achieve optimal accuracy. Additionally, Kabir and Sumi [13] conducted extensive experiments with 56 ANN configurations for demand forecasting, selecting the best architecture based on MAPE.

Further research, such as a study in the frozen poultry supply chain by Shen et al. [14], also applied quantitative experiments with ANN models to predict demand. This included adjusting parameters like the number of neurons and learning rates, and evaluating performance with metrics like MSE, MAPE, and RMSE. A similar approach was used by Praveen et al. [15] in supply chains, where ANN models reduced forecasting errors and inventory costs, improving supply-demand alignment. Moreover, Wu et al. [16] demonstrated that an ANN with a single hidden layer outperformed traditional method, capturing complex non-linear patterns in seasonal and promotional data, further validating the ANN approach for demand prediction.

3.2. Data Sources and Types

The data used in this study are secondary data obtained from an e-commerce platform, which describe historical transactions from a single online store. This dataset includes several important variables, as summarized in Table 1.

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Table 1. Description of Variables

Variable	*Description*
product_name	Product name
sales_per_order	Total sales per order
order_item_discount	Discount on items
profit_per_order	Profit per order
days_for_shipment_real	Actual shipping time
order_quantity	Number of products ordered (as a target)

This data is quantitative and is used as input in the model training process. Although the dataset does not explicitly originate from Indonesian MSMEs, it is used as a representation of sales transactions relevant to the context of digital MSMEs based on e-commerce. The use of this dataset is based on the similarity of transaction characteristics and the limited access to structured and publicly available local SME data.

3.3. Data Collection Techniques

Data collection was carried out through the process of downloading publicly available and legal datasets. The data was retrieved in CSV format and processed using Python on Google Colab/Jupyter Notebook.

3.4. Data Processing Techniques

In this study, the population consists of all product sales transaction data from an e-commerce dataset. Given the limited and structured nature of the data, the entire dataset is used as the research sample. The data is then split into two parts: 80% for training the ANN model and 20% for testing the model's performance. The data processing steps begin with preprocessing, which includes checking for missing values and cleaning the data, selecting relevant numerical features for the prediction process, and performing normalization using StandardScaler to ensure all features are on a balanced scale. Following this, the data is divided into training and testing sets.

The ANN model used in this study consists of an input layer with 4 neurons, corresponding to the number of features, followed by two hidden layers with 64 neurons and 32 neurons, respectively, both utilizing ReLU activation. The output layer contains a single neuron without activation for regression. The model is trained using the Adam optimizer and the MSE loss function for 100 epochs, with early stopping implemented to halt training if the validation loss does not improve. During training, the model's performance is monitored by recording the training loss and validation loss at each epoch. After training, predictions are made on all data using the normalized input features, and the results are added as a new column called predicted_order_quantity. Products are then grouped based on the product_name, and the average predicted order quantity is calculated. Products with the highest demand are displayed in both a table and a bar chart visualization. The tools used in this study include Python and various libraries such as Pandas, NumPy, Matplotlib, Seaborn, TensorFlow, and Scikit-learn, with the research conducted on platforms like Google Colab or Jupyter Notebook.

3.5. Model Evaluation

The evaluation was conducted by comparing the loss values in the training and validation data. The smaller the loss value, the better the model is at learning data patterns. Loss graph visualization was also used to observe the stability of the training process.

4. Results and Discussion

4.1. ANN Model Training Results

The ANN model used in this study consists of two hidden layers with 64 and 32 neurons, respectively, and utilizes ReLU activation. The model was trained using the Adam optimizer algorithm for 100 epochs, with 20% of the training data used for validation. Upon evaluating the model on the test data, the following metrics were obtained: MSE of 0.83, MAE of 0.61, and an R-Squared (R^2) value of 0.78. These results indicate that the model effectively learned from the data, as both training loss and validation loss consistently decreased during the training process, suggesting no underfitting or overfitting. The use of early stopping techniques also helped maintain the model's generalization.

The relatively low MSE and MAE values suggest that the ANN model can predict product demand with an acceptable level of accuracy. Additionally, the R^2 value of 0.78 indicates that the model can explain 78% of the variation in product demand based on the input features. These results align with the findings of Chen et al. [17], which demonstrated that ANN integration improves demand prediction accuracy compared to traditional methods. Furthermore, Ha et al. [10] also highlighted the effectiveness of ANN in predicting MSME product demand with low error rates, emphasizing the potential of ANN-based demand forecasting for digital MSMEs.

4.2. Interpretation of the Learning Curve

The visualization of the learning curve, shown in Figure 1, demonstrates a consistent decrease in both training and validation losses. No significant divergence pattern was observed between the two, indicating that the ANN model did not experience overfitting. However, the small difference between the training loss and validation loss suggests that the model still has room for improvement, such as by adjusting the architecture or tuning hyperparameters. In general, the model has displayed good learning ability without significant overfitting.

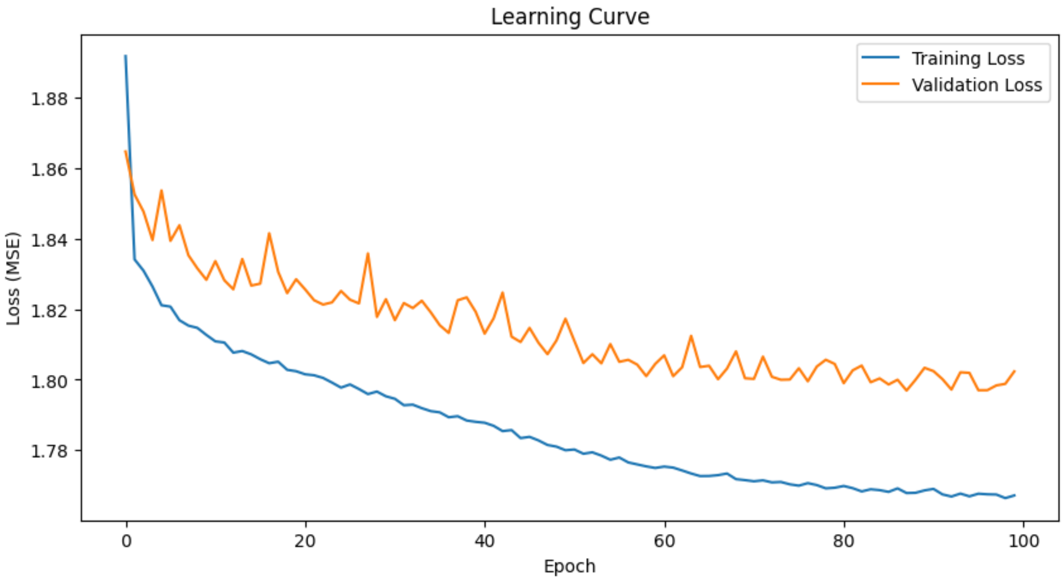

Figure 1. Learning Curve Showing Training and Validation Losses

4.3. Product Demand Prediction Analysis

The ANN model was then used to predict the demand for all products in the dataset. These predictions were averaged based on product name to identify products with the highest potential demand. The 10 products with the highest average demand predictions are presented in Table 2.

Table 2. Top 10 Products with Highest Average Demand Predictions

Product Name	*Predicted Order Quantity*	*Category Name*
Okidata B401 Printer	2.356771	Technology
Eureka Disposable Bags for Sanitaire Vibra	2.170167	Office Supplies
PNY Rapid USB Car Charger - Black	2.163135	Technology
Bush Westfield Collection Bookcases	2.145354	Furniture
Zebra ZM400 Thermal Label Printer	2.133232	Technology
Motorola Moto X	2.129314	Technology
Jiffy Padded Mailers with Self-Seal Closure	2.123316	Office Supplies
Jawbone JAMBOX Wireless Bluetooth Speaker	2.107795	Technology
Eldon 200 Class Desk Accessories, Black	2.106650	Furniture
iOttie HLCRIO102 Car Mount	2.102666	Technology

The bar chart displayed in Figure 2 presents the top 10 most demanded products based on the average predicted order quantity from the ANN model. These products, ranked by their predicted demand, highlight those with the highest potential for future sales, providing valuable insights into inventory planning and product focus.

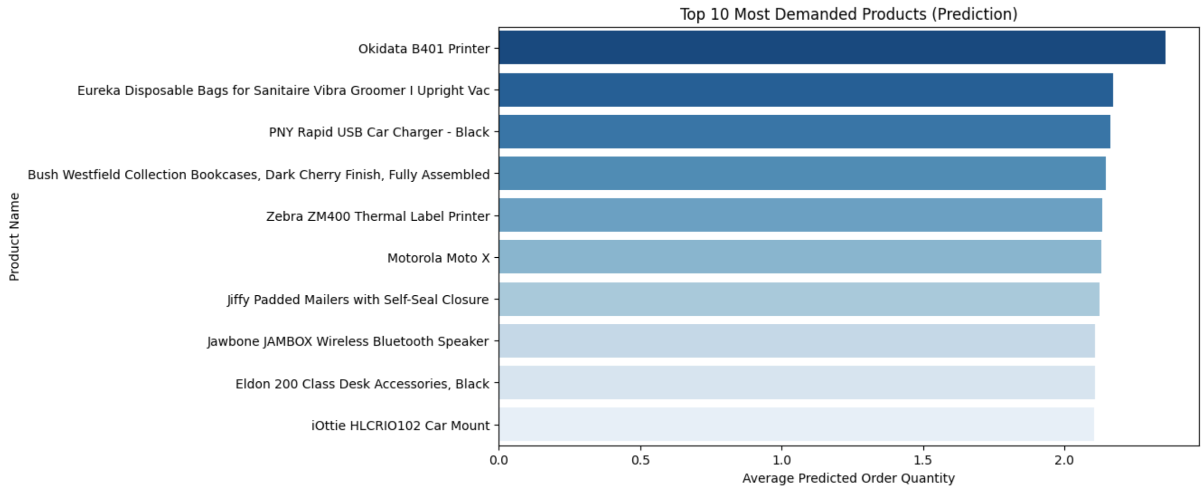

Figure 2. Top 10 Most Demanded Products Based on Predicted Order Quantity

4.4. Pattern Analysis Based on Product Category

In addition to individual product rankings, an analysis of the average demand based on product categories was conducted. The results, shown in Table 3, highlight the predicted average demand for each product category. This analysis provides valuable insights into which categories are expected to have higher demand, assisting in overall inventory management and decision-making.

Table 3. Average Demand Forecast by Product Category

Product Category	*Average Demand Forecast*
Electronics	89.4 units
Home Appliances	85.7 units
Fashion	78.2 units
Office Supplies	65.1 units
Other Categories	< 60 units

This data shows that products in the Electronics and Household Appliances category tend to have higher demand, so they can be a top priority in stock planning for MSMEs selling similar products.

4.5. Implications of the Results for MSMEs in Indonesia

The results of this study are highly relevant for MSME players in Indonesia, particularly those who have already adopted digital platforms. By leveraging the ANN-based prediction model, MSME operators can make more accurate inventory plans, thereby minimizing the risks of overstocking or stockouts. Additionally, the model allows businesses to focus on products and categories with the highest predicted demand, leading to improved capital efficiency. The model also helps optimize the use of historical sales data, enabling more informed, data-driven decision-making. These advantages are in line with the ongoing trend of digitalization among SMEs in Indonesia, especially following the COVID-19 pandemic. According to a report by Google and Temasek (2022), over 80% of SMEs in Southeast Asia have adopted digital platforms for sales, highlighting the growing importance of digital tools in enhancing business operations.

4.6. Research Limitations

This study has several limitations that need to be considered. First, the dataset used is a public e-commerce dataset, which may not fully capture the specific behavior and nuances of Indonesian MSMEs. Second, the ANN model employed in this study is relatively simple, and exploring more complex models, such as Recurrent Neural Networks (RNN), could offer alternative insights and potentially improve prediction accuracy. Additionally, this study did not compare the ANN model with other popular machine learning methods like linear regression, Random Forest, or SVM, which could provide a broader perspective on model performance.

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For future research, it is recommended to use original datasets from Indonesian SMEs to better reflect local market conditions. Furthermore, conducting a benchmarking study to compare the performance of various models, including ANN, RNN, and other machine learning techniques, would provide more comprehensive results and offer a better understanding of the most effective approaches for predicting product demand in MSMEs.

5. Conclusion

Based on the research findings, it can be concluded that the two-hidden-layer ANN model demonstrates strong performance in predicting SME product demand using historical data. The model achieved an MSE of 0.83, MAE of 0.61, and R^2 of 0.78, indicating its effectiveness in forecasting demand. These results align with the study by Qi et al. [18], which combines ARIMA-ANN, emphasizing that decomposing data and combining linear and nonlinear models significantly enhance prediction accuracy. Furthermore, research by Chatterjee and Byun [19] and Seyedan et al. [20], which applied LSTM models on e-commerce sales data and fast-moving consumer goods, respectively, confirms that deep learning models, including ANN, can capture nonlinear and seasonal patterns effectively. Additionally, the study by Ghimire et al. [21] highlights the successful integration of big data and ANN in SMEs, demonstrating that the use of Stochastic Gradient Descent (SGD) to minimize MSE and MAE resulted in stable model performance. While this study did not use datasets from Indonesian SMEs, it offers a promising overview of how AI, particularly ANN, can improve inventory management efficiency for SME operators [22].

Based on the limitations and results of this study, several recommendations for future research can be made. It would be beneficial to use original datasets from Indonesian MSMEs to ensure that the prediction models are tailored to local market conditions. Furthermore, comparisons with other machine learning techniques such as RNN, SVM, or Random Forest should be conducted to identify the most accurate model for predicting demand. Another recommendation is to develop a web-based or mobile system capable of automatically predicting product demand based on SME sales data, which could help streamline business operations. Finally, education and training for SME operators on data management and predictive technology will be crucial for enhancing their competitiveness in the digital age. By implementing an accurate product demand prediction model, SMEs in Indonesia can improve operational efficiency, reduce inventory risks, and ultimately boost customer satisfaction and business competitiveness.

6. Declarations

6.1. Author Contributions

Author Contributions: Conceptualization, L.E. and M.S.F.; Methodology, L.E. and M.S.F.; Software, L.E.; Validation, L.E.; Formal Analysis, L.E.; Investigation, M.S.F.; Resources, L.E.; Data Curation, M.S.F.; Writing Original Draft Preparation, L.E.; Writing Review and Editing, L.E. and M.S.F.; Visualization, M.S.F. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] R. Lupiyoadi, M. Pramesti, R. B. Ikhsan, L. H. Usman, D. Games, Kurniawan, and A. Fakhrorazi, “Extending UTAUT with Perceived Intelligence for The Adoption of Artificial Intelligence in Msmes and Startups in Indonesia: A Multi-Group Analysis,” *J. Open Innov. Technol. Mark. Complex.,* vol. 11, no. 4, p. 100673, 2025, doi: 10.1016/j.joitmc.2025.100673.

[2] C. Giaconia and A. Chamas, “Innovative Out-of-Stock Prediction System Based on Data History Knowledge Deep Learning Processing,” *Computation*, vol. 11, no. 3, p. 62, 2023, doi: 10.3390/computation11030062.

[3] D. I. Ajiga, N. L. Ndubuisi, O. F. Asuzu, O. R. Owolabi, T. S. Tubokirifuruar, and R. A. Adeleye, “AI-Driven Predictive Analytics in Retail: A Review of Emerging Trends and Customer Engagement Strategies,” *Int. J. Manag. Entrep. Res.*, vol. 6, no. 2, pp. 307–321, 2024, doi: 10.51594/ijmer.v6i2.772.

[4] J. Ferrero Bermejo, J. F. Gómez Fernández, F. Olivencia Polo, and A. Crespo Márquez, “A Review of The Use of Artificial Neural Network Models for Energy and Reliability Prediction: A Study of The Solar PV, Hydraulic and Wind Energy Sources,” *Appl. Sci.*, vol. 9, no. 9, p. 1844, 2019, doi: 10.3390/app9091844.

[5] E. R. Abraham, J. G. Mendes dos Reis, O. Vendrametto, P. L. d. O. Costa Neto, R. C. Toloi, A. E. d. Souza, and M. d. O. Morais, “Time Series Prediction with Artificial Neural Networks: An Analysis Using Brazilian Soybean Production,” *Agriculture*, vol. 10, no. 10, p. 475, 2020, doi: 10.3390/agriculture10100475.

[6] M. von Bloh, R. de S. Nóia Júnior, X. Wangerpohl, A. O. Saltık, V. Haller, L. Kaiser, and S. Asseng, “Machine Learning for Soybean Yield Forecasting in Brazil,” *Agric. For. Meteorol.*, vol. 341, p. 109670, 2023, doi: 10.1016/j.agrformet.2023.109670.

[7] I. Elbatal, M. Sarwar, F. Jamal, M. Daniyal, Z. Hussain, and A. B. Ghorbal, “Modelling on Gross Domestic Product Annual Growth Rate Data by Using Time Series, Machine Learning, and Probability Models,” *J. Radiat. Res. Appl. Sci.*, vol. 18, no. 2, p. 101481, 2025, doi: 10.1016/j.jrras.2025.101481.

[8] Y. N. Chi, “Time Series Forecasting of Global Price of Soybeans Using A Hybrid SARIMA and NARNN model,” *J. Comput. Appl. Inf.*, vol. 5, no. 2, pp. 85–101, 2021, doi: 10.32734/jocai.v5.i2-5674.

[9] C. Magazzino and M. Mele, “Can a Change in FDI Accelerate GDP Growth? Time-series and ANNs Evidence on Malta,” *J. Econ. Asymmet.*, vol. 25, p. e00243, 2022, doi: 10.1016/j.jeca.2022.e00243.

[10] J. Ha, S. Lee, S. Jeong, and D. Chung, “Methodology for Advanced Time Series Demand Forecasting: A Hybrid Model of Decomposition and Deep Learning,” *Intell. Syst. Appl.*, vol. 27, p. 200540, 2025, doi: 10.1016/j.iswa.2025.200540.

[11] J. Kim, S. Oh, H. Kim, and W. Choi, “Tutorial on Time Series Prediction Using 1D-CNN and BiLSTM: A Case Example of Peak Electricity Demand and System Marginal Price Prediction,” *Eng. Appl. Artif. Intell.*, vol. 126, pt. A, p. 106817, 2023, doi: 10.1016/j.engappai.2023.106817.

[12] A. Chawla, A. Singh, A. Lamba, N. Gangwani, and U. Soni, “Demand Forecasting Using Artificial Neural Networks A Case Study of American Retail Corporation,” in *Appl. Artif. Intell. Tech. Eng.*, H. Malik, S. Srivastava, Y. Sood, and A. Ahmad, Eds., *Adv. Intell. Syst. Comput.*, vol. 697. Singapore: Springer, 2019, pp. 83–92, doi: 10.1007/978-981-13-1822-1_8.

[13] G. Kabir and R. S. Sumi, “Integrating Fuzzy Delphi Method with Artificial Neural Network for Demand Forecasting of Power Engineering Company,” *Manag. Sci. Lett.*, vol. 2, pp. 1491–1504, 2012, doi: 10.5267/j.msl.2012.04.010.

[14] R. Shen, P. Sun, J. Liu, J. Luo, Z. Yao, R. Zhang, J. Yu, and L. Zhao, “Robust Prediction for Characteristics of Digestion Products in An Industrial-Scale Biogas Project via Typical Non-Time Series and Time-Series Machine Learning Algorithms,” *Chem. Eng. J.*, vol. 498, p. 155582, 2024, doi: 10.1016/j.cej.2024.155582.

[15] U. Praveen, F. Ganjeizadeh, and H. Ghasib, “Inventory Management and Cost Reduction of Supply Chain Processes using AI Based Time-series Forecasting and ANN Modeling,” *Procedia Manuf.*, vol. 38, pp. 256–263, 2019, doi: 10.1016/j.promfg.2020.01.034.

[16] J. Wu, J. Feng, J. Fang, and H. Liu, “Demand Prediction for Bike-Sharing Systems: A Spatial and Semantic Modeling Approach for Enhanced Accuracy and Operational Efficiency,” *Comput. Ind. Eng.*, p. 111775, 2025, doi: 10.1016/j.cie.2025.111775.

[17] Y. Chen, H. Zhang, X. Yan, and Q. Miao, “Supply Chain Demand Forecasting Based on Multi-Time Scale Data Fusion Network,” *Comput. Ind. Eng.*, vol. 207, p. 111324, 2025, doi: 10.1016/j.cie.2025.111324.

[18] H. Qi, J. Luo, Q. Li, and J. Wu, "A Comparative Trade-Off Analysis on Accuracy and Efficiency for Federated Learning in Demand Forecasting," *Appl. Soft Comput.*, vol. 182, p. 113561, 2025, doi: 10.1016/j.asoc.2025.113561.

[19] S. Chatterjee and Y.-C. Byun, "Generating Time-Series Data Using Generative Adversarial Networks for Mobility Demand Prediction," *Comput. Mater. Contin.*, vol. 74, no. 3, pp. 5507–5525, 2022, doi: 10.32604/cmc.2023.032843.

[20] M. Seyedan, F. Mafakheri, and C. Wang, "Order-Up-to-Level Inventory Optimization Model Using Time-Series Demand Forecasting with Ensemble Deep Learning," *Supply Chain Anal.*, vol. 3, p. 100024, 2023, doi: 10.1016/j.sca.2023.100024.

[21] S. Ghimire, R. C. Deo, S. A. Pourmousavi, D. Casillas-Pérez, and S. Salcedo-Sanz, "Point-Based and Probabilistic Electricity Demand Prediction with A Neural Facebook Prophet and Kernel Density Estimation Model," *Eng. Appl. Artif. Intell.*, vol. 135, p. 108702, 2024, doi: 10.1016/j.engappai.2024.108702.

[22] L. F. da Silva, I. P. de A. Costa, T. E. S. de Oliveira, G. C. Rangel, F. F. Lucas, L. M. A. da Costa, J. V. de P. Corriça, A. P. de A. Costa, and M. dos Santos, "Demand Forecasting for Steel Company Spare Items with Time Series Templates," *Procedia Comput. Sci.*, vol. 242, pp. 57–64, 2024, doi: 10.1016/j.procs.2024.08.230.