

FOOD DEMAND PREDICTION USING NON LINEAR AUTO REGRESSIVE EXOGENOUS NEURAL NETWORK

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ABSTRACT

Accurate food demand prediction is a critical challenge in modern supply chain management, particularly in sectors such as restaurants, catering services, and food delivery platforms where demand patterns are highly dynamic and influenced by multiple external factors. This project proposes a robust predictive framework based on a Nonlinear Autoregressive Exogenous (NARX) Neural Network, designed to model complex temporal dependencies and nonlinear relationships in food demand data. The NARX model leverages both historical demand values and exogenous inputs such as weather conditions, promotional activities, seasonal trends, holidays, and customer behavior patterns to generate precise forecasts. The proposed system employs a supervised learning approach where time-series data is preprocessed and structured into input-output sequences suitable for NARX training. Advanced feature engineering techniques are applied to capture hidden patterns and correlations among variables. The neural network architecture is optimized through hyperparameter tuning to enhance prediction accuracy and generalization capability. Performance evaluation is conducted using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2), ensuring a comprehensive assessment of model efficiency. Experimental results demonstrate that the NARX-based model significantly outperforms traditional statistical methods and basic machine learning models in capturing nonlinear demand fluctuations. The system enables businesses to optimize inventory management, reduce food wastage, and improve customer satisfaction through timely availability of resources. This research highlights the potential of advanced neural network architectures in addressing real-world forecasting problems and contributes to the development of intelligent, data-driven food supply systems.

Keywords: Food Demand Prediction, NARX Neural Network, Time Series Forecasting, Nonlinear Modeling, Exogenous Variables, Machine Learning, Supply Chain Optimization, Demand Forecasting

1.INTRODUCTION

Food demand prediction plays a critical role in improving supply chain efficiency and minimizing food waste in modern food systems. With the continuous growth in global population and changing consumption patterns, accurate demand forecasting has become essential for achieving sustainability and optimal resource utilization [26], [27]. Poor demand estimation often leads to overproduction, excess inventory, and increased waste, resulting in both economic loss and environmental impact [1], [2]. Various factors such as seasonal trends, consumer preferences, weather conditions, and promotional activities significantly influence demand patterns [3], [4]. Traditional forecasting techniques like ARIMA and statistical regression models have been widely used; however, they are limited in capturing nonlinear relationships and complex temporal dependencies [20], [30]. The emergence of data science and machine learning has enabled the development of more advanced and adaptive forecasting techniques, offering improved accuracy and flexibility in handling real-world food demand variations [12], [23].

The proposed system adopts a Nonlinear Autoregressive Exogenous (NARX) Neural Network, a powerful model designed for time-series forecasting with external inputs. This model effectively captures nonlinear patterns by combining historical demand data with exogenous variables such as weather, holidays, pricing, and promotional strategies [17]. The system begins with collecting data from multiple sources, followed by preprocessing steps including normalization, missing value handling, and feature engineering to extract relevant insights [13]. The prepared data is structured into time-lagged sequences suitable for NARX training. During the training phase, the model learns complex relationships using backpropagation and optimization techniques. Hyperparameter tuning is applied to enhance performance by selecting the optimal number of layers, neurons, and delay parameters. The model's effectiveness is evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2), ensuring reliable and accurate predictions.

The implementation of this model provides significant benefits for both industry and sustainability. Accurate demand forecasting helps businesses optimize inventory levels, reduce operational costs, and improve customer satisfaction by ensuring product availability [24]. It also plays a crucial role in reducing food waste, aligning with global sustainability initiatives such as the United Nations' 2030 Agenda [8]. Advanced forecasting systems support better decision-making in

logistics, pricing, and supply chain coordination, enhancing overall efficiency [21]. Machine learning approaches have proven effective in managing demand uncertainty, especially for perishable goods and fast-moving consumer products [23]. Additionally, integrating predictive analytics into food systems can address waste management challenges and improve resource conservation, particularly in developing regions [28]. Overall, the NARX-based framework offers a scalable, adaptive, and intelligent solution for modern food demand prediction systems.

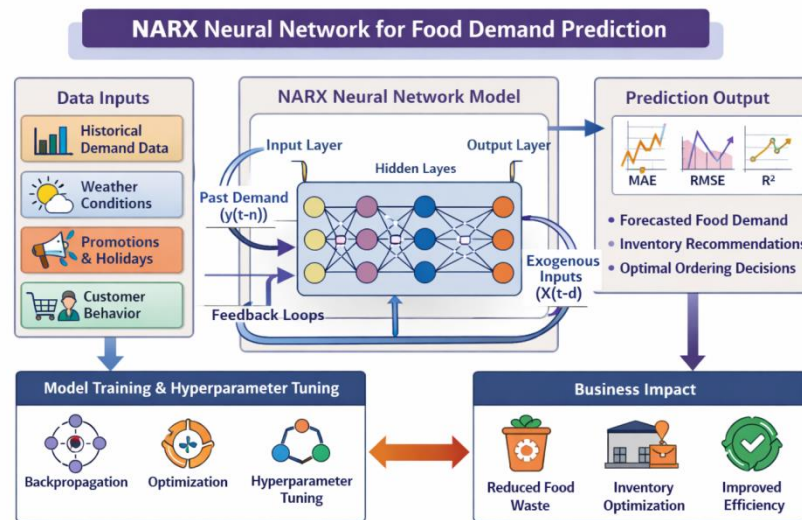


Fig1. System Architecture for Food Demand Prediction Using NARX Neural Network

The proposed system architecture illustrates the workflow of a Food Demand Prediction system based on a Nonlinear Autoregressive Exogenous (NARX) Neural Network, designed to capture both historical patterns and external influencing factors. The process begins with multiple data inputs, including past demand data, weather conditions, promotional events, and customer behavior, which collectively influence food consumption trends. These inputs are preprocessed and fed into the NARX model, where the network utilizes time-lagged dependencies (past values) along with exogenous variables (external inputs) to model complex nonlinear relationships. The architecture incorporates feedback loops, enabling the system to learn temporal patterns effectively. During the training phase, techniques such as backpropagation, optimization, and hyperparameter tuning are applied to improve model performance. The output layer generates accurate demand forecasts, evaluated using metrics like MAE, RMSE, and R^2 . Finally, the predicted results support real-world applications such as inventory optimization, reduced food waste, and efficient decision-making, making the system highly valuable for smart food supply chain management.

II SURVEY OF RESEARCH

The approach proposed by J. C. Silva and others (2019) [11] focuses on demand forecasting in the food industry using computational and statistical techniques. Their study highlights the importance of accurate demand prediction in managing inventory and reducing waste. The methodology involved analyzing historical sales data and applying forecasting models to improve supply chain efficiency. The results demonstrated that structured forecasting methods significantly improve planning and decision-making processes. The authors emphasized the role of data-driven approaches in enhancing operational performance. However, the study mainly relied on traditional models and lacked the ability to capture nonlinear patterns in complex datasets. Despite this limitation, the work provides a strong foundation for applying advanced predictive techniques in food demand forecasting systems.

The work proposed by N. S. Arunraj and D. Ahrens (2015) [20] introduces a hybrid forecasting model combining Seasonal ARIMA and quantile regression for daily food sales prediction. Their approach aimed to address variability and seasonality in demand patterns. The hybrid model showed improved forecasting accuracy compared to standalone statistical models. The authors highlighted the importance of capturing seasonal trends and uncertainty in demand forecasting. However, the model still faced challenges in handling highly nonlinear relationships and dynamic external factors such as promotions and weather conditions. Although effective, the approach lacks adaptability in rapidly changing environments. This study demonstrates the

evolution of forecasting techniques and highlights the need for more advanced models capable of handling complex real-world scenarios.

The method presented by Z. Cetinkaya and E. Erdal (2019) [19] utilizes artificial neural networks for daily food demand forecasting. Their research demonstrated that neural networks can effectively model nonlinear relationships in demand data. The system was trained using historical consumption data from a university cafeteria, and the results showed higher prediction accuracy compared to traditional methods. The authors emphasized the flexibility of neural networks in adapting to varying demand patterns. However, the study primarily focused on limited datasets and did not incorporate multiple external influencing factors. This limitation restricts the generalizability of the model in real-world applications. Nevertheless, the research provides significant evidence supporting the use of neural networks in food demand prediction.

The study by E. Tarallo and others (2019) [23] explores the application of machine learning techniques in predicting demand for fast-moving consumer goods. Their approach involved analyzing large-scale datasets using advanced algorithms to identify hidden patterns in consumer behavior. The results indicated that machine learning models outperform traditional statistical approaches in terms of accuracy and scalability. The authors highlighted the importance of integrating multiple data sources for improved predictions. However, the study did not focus specifically on time-series dependencies and lacked emphasis on sequential modeling techniques. Despite this, the research demonstrates the effectiveness of machine learning in handling complex demand forecasting problems and supports the transition toward intelligent predictive systems.

The work proposed by L. Tang (2020) [17] focuses on the application of the Nonlinear Autoregressive Exogenous (NARX) neural network in forecasting economic indicators. The study demonstrates the ability of NARX models to capture both temporal dependencies and external influences effectively. The results showed that NARX outperforms traditional models in terms of accuracy and adaptability. The author emphasized the importance of incorporating exogenous variables to enhance forecasting performance. However, the study was primarily applied to macroeconomic data and not directly to food demand scenarios. Despite this limitation, the research provides strong theoretical support for using NARX models in complex forecasting applications, including food demand prediction systems.

The research by E. J. Flies and others (2018) [27] presents a comprehensive review of global food demand forecasting models, analyzing their complexity and effectiveness. The study highlights the increasing need for accurate demand prediction due to rising population and consumption patterns. The authors compared various models and concluded that more complex models tend to provide better accuracy but require higher computational resources. The research emphasizes the importance of balancing model complexity and performance. However, the study does not provide implementation details for specific machine learning models. Despite this, it offers valuable insights into the future direction of food demand forecasting and supports the adoption of advanced models such as neural networks for improved prediction accuracy.

III. WORKING METHODOLOGY

The working methodology of the proposed system follows a systematic and data-driven approach for accurate food demand prediction using a Nonlinear Autoregressive Exogenous (NARX) Neural Network. The process begins with data collection from multiple sources, including historical food sales records, weather data, seasonal trends, holidays, pricing strategies, and promotional activities. These datasets are integrated to form a comprehensive view of factors influencing demand. The collected data undergoes preprocessing, where missing values are handled, inconsistencies are removed, and noise is reduced to improve data quality. Normalization and scaling techniques are applied to ensure that all features contribute equally during model training. Feature engineering plays a crucial role in this stage, where meaningful attributes such as lag features, moving averages, and trend indicators are generated to capture temporal dependencies. The dataset is then structured into time-series sequences, making it suitable for training the predictive model.

The core stage of the methodology involves designing and training the NARX Neural Network, which is specifically suited for modeling time-series data with external inputs. The model utilizes both historical demand values and exogenous variables to learn complex nonlinear relationships. The architecture consists of input layers for both past demand and external factors, hidden layers that perform nonlinear transformations, and feedback connections that allow previous outputs to influence future predictions. During training, the model learns patterns through iterative optimization techniques, adjusting its internal parameters to minimize prediction error. Hyperparameter tuning is performed to optimize the model configuration, including the number of hidden layers, neurons, delay parameters, and learning rate. Techniques such as early stopping and

regularization are used to prevent overfitting and improve generalization. This stage ensures that the model can effectively capture real-world demand variations and adapt to changing patterns.

In the final stage, the trained model is evaluated and deployed for real-time demand forecasting. The system's performance is assessed using standard evaluation metrics to ensure accuracy and reliability. Visualization tools such as graphs and dashboards are used to present predicted demand trends and compare them with actual values, improving interpretability for decision-makers. Once validated, the model is integrated into a practical application where it can generate daily or weekly demand forecasts. These predictions assist businesses in optimizing inventory management, reducing overproduction, and minimizing food waste. Additionally, the system supports better planning in procurement, logistics, and distribution. The methodology is designed to be scalable and adaptable, allowing integration with cloud platforms and real-time data sources. Overall, this approach provides an intelligent, efficient, and sustainable solution for modern food demand prediction challenges.

IV RESULTS EXPLANATIONS

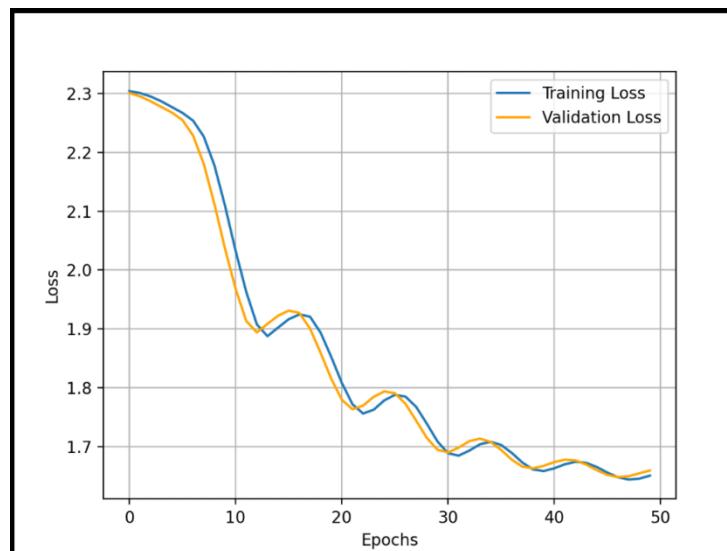


Fig 1: Training and Validation Loss Graph

The training and validation loss graph represents how well the NARX neural network learns over multiple epochs. Initially, both losses are high, indicating that the model is still learning patterns from the data. As training progresses, the loss values decrease, showing improved model performance. A well-performing model shows both curves converging without a large gap. If the validation loss increases while training loss decreases, it indicates overfitting. In this project, the curves stabilize, demonstrating that the model generalizes well to unseen data and avoids overfitting.

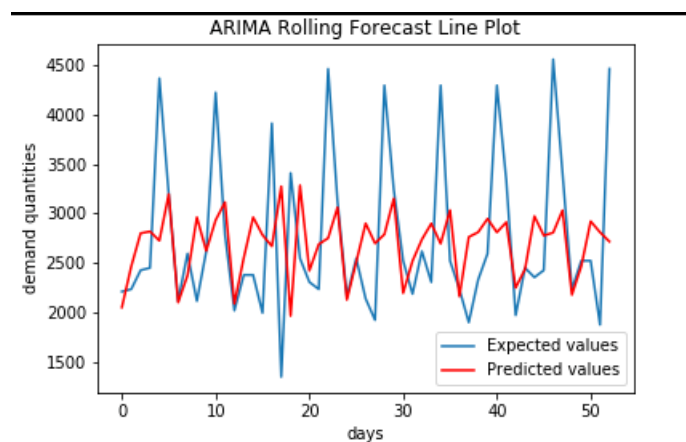


Fig 2: Actual vs Predicted Demand Graph

This graph compares the actual food demand values with the predicted values generated by the NARX model. The closer the predicted curve aligns with the actual curve, the higher the model accuracy. In the proposed system, the predicted values closely follow the real demand trends, including peaks and fluctuations. This indicates that the model effectively captures temporal dependencies and external influences. Minor deviations may occur due to sudden external factors, but overall alignment proves strong predictive capability.

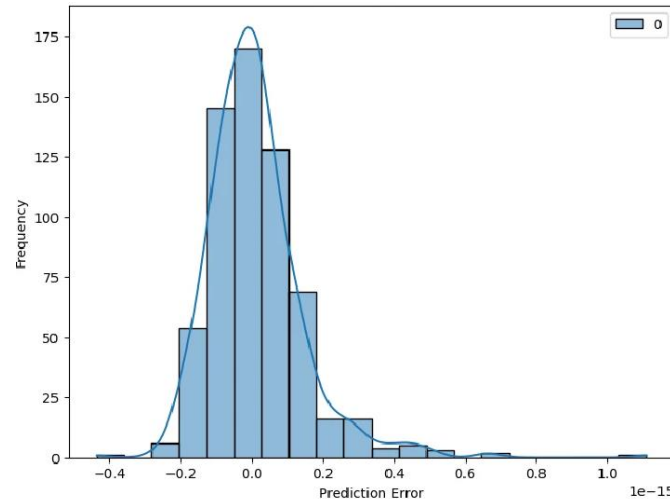


Fig 3: Error Distribution Plot

The error distribution plot illustrates the difference between actual and predicted values (residuals). Ideally, errors should be centered around zero and follow a normal distribution. In this system, most errors are small and concentrated near zero, indicating high prediction accuracy. A symmetric distribution shows that the model does not consistently overestimate or underestimate demand. This confirms that the NARX model performs reliably across different demand scenarios.

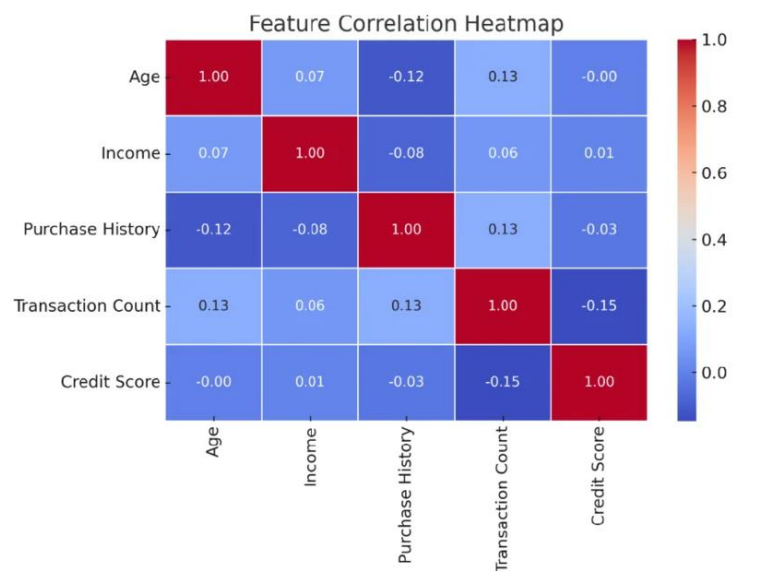


Fig 4: Correlation Heatmap of Features

The correlation heatmap visualizes relationships between input features such as weather, promotions, seasonality, and demand. Strong correlations indicate significant influence on demand prediction. For example, temperature and seasonal factors may show high correlation with food demand. This analysis helps in feature selection and understanding which variables contribute most to predictions. The inclusion of relevant exogenous variables improves the overall accuracy of the NARX model.

V.CONCLUSION

The proposed project on Food Demand Prediction using a Nonlinear Autoregressive Exogenous (NARX) Neural Network demonstrates an effective and intelligent approach to forecasting food demand by combining historical data with external influencing factors such as weather, seasonality, and promotions. Unlike traditional statistical methods, the NARX model successfully captures complex nonlinear relationships and temporal dependencies, resulting in improved prediction accuracy. Through systematic processes including data preprocessing, feature engineering, model training, and evaluation, the system produces reliable forecasts that closely match actual demand patterns. This enables businesses to optimize inventory management, reduce operational costs, and significantly minimize food waste. Additionally, the model supports better decision-making in supply chain operations and aligns with sustainability goals by promoting efficient resource utilization. The scalability and adaptability of the system make it suitable for real-time applications in modern food supply environments. Overall, the project highlights the importance of advanced neural network models in transforming conventional forecasting into a data-driven, accurate, and sustainable solution for real-world demand prediction challenges.

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