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Optimizing Food Demand Forecasting in the Supply Chain for Shelf- Life Management

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Abstract

Accurate food demand forecasting plays a critical role in optimizing supply chain operations, reducing waste, and ensuring effective shelf-life management of perishable goods. Its applications span from retail inventory management to large-scale food distribution, enabling businesses to maintain an optimal stock of products such as bread, butter, and other perishables. By anticipating demand fluctuations, organizations can better align production schedules, reduce overstocking and understocking issues, and minimize financial losses. Effective forecasting also supports sustainability by reducing food waste and enhancing consumer satisfaction through improved product availability. Traditional demand forecasting systems often rely on manual approaches or static statistical methods, which are limited by their inability to adapt to dynamic market conditions and complex time-series data. Manual methods, in particular, are prone to human error, delays, and inefficiencies, making them unsuitable for high-stakes decision-making in the supply chain. Furthermore, these approaches struggle to account for multiple influencing factors, such as seasonality, market trends, and external disruptions, resulting in inaccurate demand predictions and poor shelf-life management. To address these limitations, this paper proposes the use of a novel algorithm called the Nonlinear Autoregressive Exogenous Neural Network (NARXNN) for food demand forecasting. NARXNN is a recurrent dynamic network characterized by feedback connections that encompass multiple layers, enabling it to process complex and nonlinear time-series data effectively. Derived from the linear ARX model, NARXNN leverages exogenous inputs to enhance its predictive capabilities. By applying NARXNN to supply chain products such as bread and butter, the model showcases its potential to optimize demand forecasting, improve inventory management, and reduce wastage, thereby setting a new standard for shelf-life management in the food industry.

1. Introduction

The increasing consumer demand and competitive market forces have driven companies to focus on accurate demand forecasting as a means of maintaining profitability. Inaccurate demand forecasts can lead to either surplus inventory, resulting in wastage and high operational costs, or insufficient inventory, which can cause stockouts and push customers to competitors.

The importance of demand forecasting is reflected in its wide application across different company departments. The financial department relies on forecasts to estimate costs, profit margins, and capital requirements. Marketing teams use forecasts to plan strategies and assess the impact of various marketing actions on sales volumes. The purchasing department uses forecasts for investment planning, while the operations department manages the procurement of raw materials, machinery, and labor based on forecasted demand. As a result, the accuracy of demand forecasts can significantly improve logistical management, reduce wastage, and enhance overall efficiency.

2. Literature Survey

Effective demand forecasting is a critical aspect of supply chain management, significantly influencing planning, capacity, and inventory control decisions. Inaccurate demand predictions often lead to higher backlog and holding costs, highlighting the importance of precision in inventory control. [**1**,**2**,**3**]. In the broader context of supply chain management, accurate demand forecasting is essential for informed decision-making, resource allocation, and enhanced operational efficiency. Traditional forecasting methodologies face challenges in capturing the complexities of modern supply chains as global markets become increasingly interconnected and dynamic. Linear models and time-series analyses, though foundational, struggle to predict the nonlinear and intricate relationships that define contemporary business environments. Furthermore, traditional approaches are often inadequate for addressing the challenges posed by intense competition across industries. Companies are now leveraging advanced data science techniques to improve demand forecasting by treating customer demand as a time-series prediction problem. However, forecasting demand for components poses unique challenges, including sporadic demand patterns, limited visibility into downstream processes, and an incomplete understanding of market trends. Addressing these challenges is critical to reducing inventory costs and enabling agile decision-making in supply chains. Despite extensive research in supply chain management, there has been limited focus on the specific challenges of component demand forecasting. Conventional techniques, such as moving averages and the Croston method, are increasingly ineffective in managing the volatility and unpredictability of modern supply chains. Demand patterns in the supply chain industry are continuously evolving due to factors like technological advancements, globalization, and shifting consumer preferences. This dynamic environment poses significant challenges for industries reliant on fast-to-market products and market trends, often leading to inefficient inventory management and resource allocation **[4,5]** Linear models, such as linear regression, oversimplify the relationships between variables and fail to capture the intricate nature of supply chain data. Time-series analysis, while useful for identifying patterns over time, often falls short in accounting for sudden shifts and irregularities in demand, resulting in inaccurate forecasts. Recently, artificial neural networks (ANNs) have garnered attention for their adaptability and robustness in computational intelligence. ANNs excel in decision-making, handling nonlinear systems, adapting to environmental changes, and processing data efficiently. [**7**,**8**,**9**,**10**,**11**,**12**]. Machine learning (ML) techniques have demonstrated significant improvements in demand forecasting accuracy and customer engagement through predictive analytics. ML approaches are particularly adept at capturing complex interdependencies and nonlinear relationships, resulting in improved performance across supply chains. Promising results from ML applications have been observed in large-scale homogeneous product sales data from platforms like [**11**,**18**,**19**]. Amazon, as well as in industries such as foundries and chocolate manufacturing, where time-series data share similar characteristics. However, the complexity of ML methods poses a barrier to their adoption. Beyond technical challenges, the economic benefits of implementing ML-based solutions remain unclear, warranting further research to temper initial enthusiasm and provide clarity on their true organizational value. India's food supply chain exemplifies the pressing need for advanced demand forecasting methods. [**16**,**17**]. Inefficiencies in production, transportation, and delivery result in significant challenges, with approximately 40% of annual food production wasted—leading to economic losses of ₹92,000 crores ($12 billion). As the population is projected to reach 1.6 billion by 2050, coupled with rapid urbanization, the demand for a robust supply chain to ensure food security and sustainability has[**13**,**14**,**15**] become paramount. Traditional methods fail to address issues such as demand-supply mismatches, wastage, and logistical delays effectively. Advanced regressor-based time-series forecasting, powered by AI and ML, offers a transformative solution. These techniques enable precise demand prediction, efficient inventory management, and dynamic pricing, paving the way for a sustainable and resilient food supply chain.

3. Proposed System

Figure 1 shows the proposed system architecture. It includes columns like meal_id (identifying food items) and num_orders (the number of orders for each item). The dataset helps analyze and forecast future food demand using historical trends. The proposed algorithm, NARXNN, uses time-series data to predict demand with high accuracy.

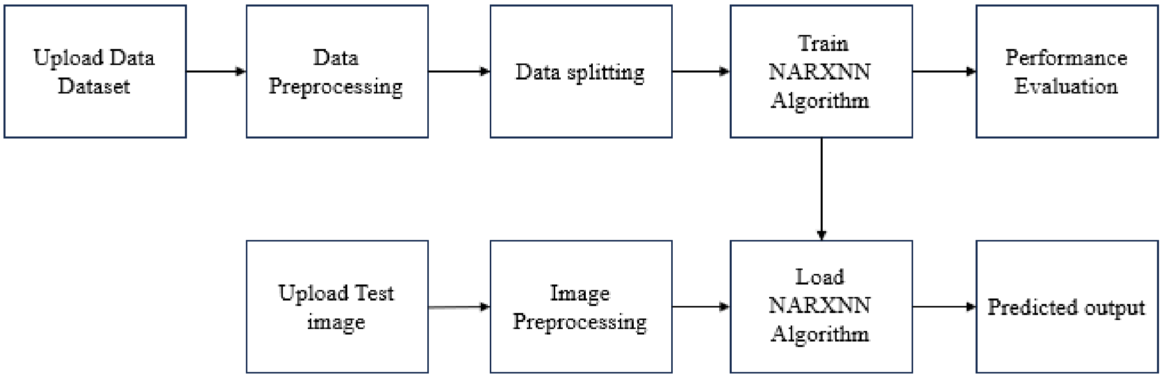

Figure 1 Block Diagram

The Nonlinear Autoregressive Exogenous Neural Network (NARXN) is a model used for time series forecasting, particularly for predicting future values based on past data and external (exogenous) variables. NARXN is a hybrid model that combines the strength of autoregressive neural networks with exogenous inputs to improve forecasting accuracy. The model uses previous values (autoregressive) along with external factors to predict future outcomes, making it highly suitable for dynamic systems with complex dependencies.

NARXN works by leveraging a feedforward neural network architecture where the inputs consist of lagged values from the time series and exogenous features that are expected to influence the output. The model is trained to minimize the prediction error by adjusting the weights of the neural network. The key advantage of NARXN is its ability to model both temporal dependencies (autoregressive) and external influences, providing a more comprehensive understanding of the system being modeled. The model can handle multiple time series inputs and forecast based on the interactions between the system and external variables.

4. Results and Discussion

Figure 3 shows that the dataset consists of a total of 456,548 records, which are divided into a training set and a testing set. The training set contains 365,238 records (approximately 80% of the total dataset), which are used to train the machine learning model by teaching it patterns and relationships in the data.

The remaining 91,310 records (about 20%) form the testing set, which is used to evaluate the model's performance on unseen data, ensuring that it generalizes well and can make accurate predictions on new, unseen instances. This split helps assess the model’s effectiveness and ability to perform in real-

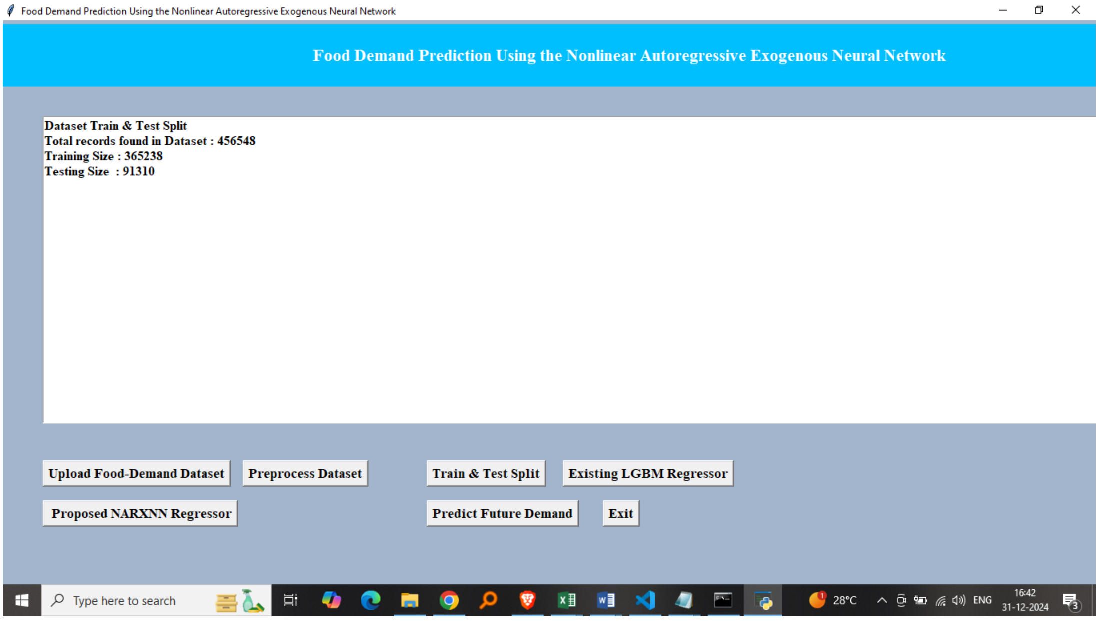

Figure 3: After train-test-split

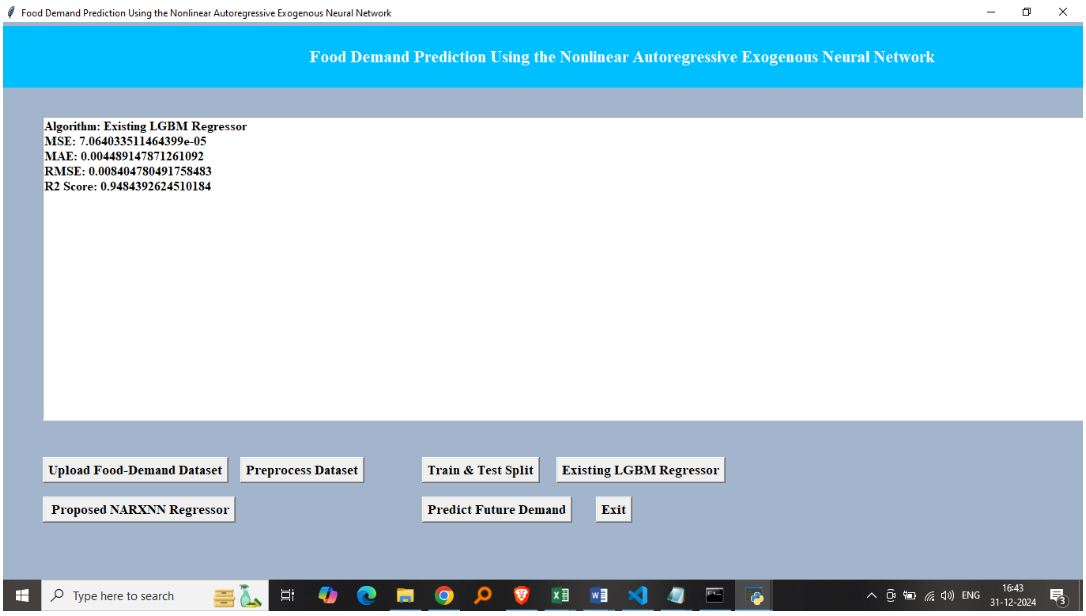

Figure 4: Metrics of the LGBM of Regressor

Figure 4 shows that the The LightGBM Regressor model has demonstrated excellent performance with an MSE of 7.064e-05, indicating a very small average squared difference between predicted and actual values. The MAE of 0.00449 shows that, on average, the model's predictions are very close to the true values, while the RMSE of 0.0084 confirms the model's high accuracy with errors in the same unit as the target variable. The R^2 score of 0.9484 reveals that the model explains about 94.84% of the variance in the data, highlighting its strong predictive ability and effective fit to the data. Overall, the model exhibits outstanding accuracy and generalization.

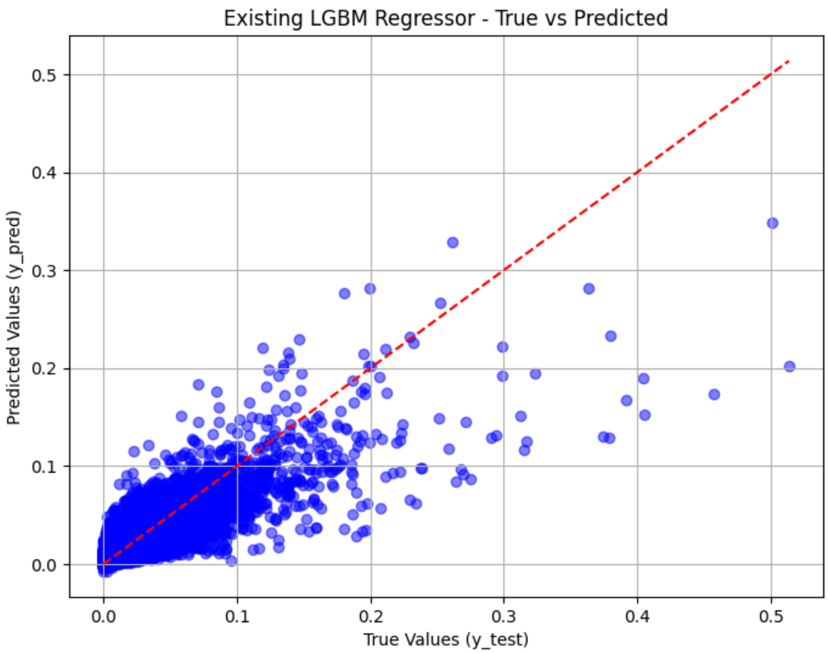

Figure 5: Scatter plot of the LGBM Regressor

Figure 5 shows that Scatter plot of the LGBM Regressor which is not more shaded to the line.

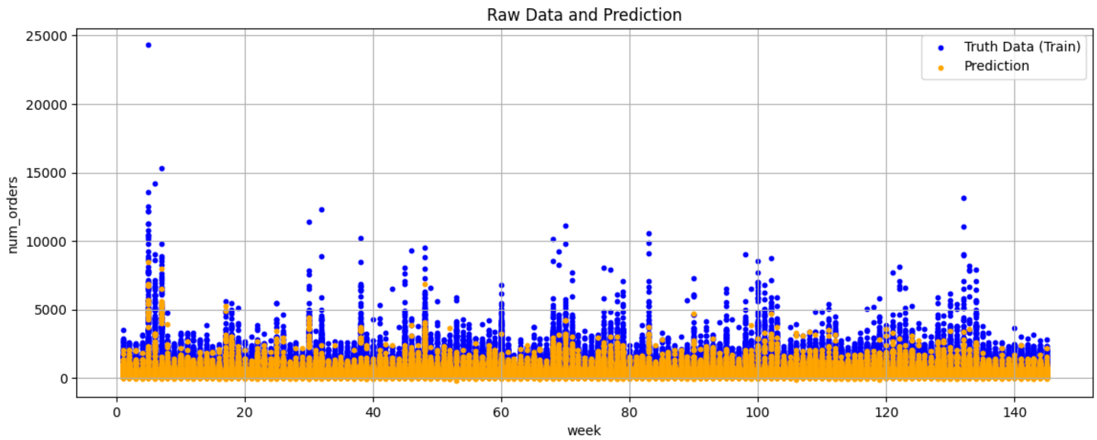

Figure 6: Actual and predicted comparison

Figure 6 shows the displays two sets of data points:

- **Truth Data (Train):** Represented by blue dots. These are likely the actual values from the training dataset.
- **Prediction:** Represented by orange dots. These are the predicted values generated by the model.
- **X-axis:** The x-axis is labeled "week", suggesting that the data represents some quantity (possibly "num_orders") over a period of weeks.
- **Y-axis:** The y-axis is labeled "num_orders", implying that the quantity being plotted is the number of orders

- **Data Distribution:** The blue dots (actual values) exhibit a pattern with peaks and valleys, indicating fluctuations in the number of orders over time. The orange dots (predicted values) also follow a similar pattern but with some deviations from the actual values.

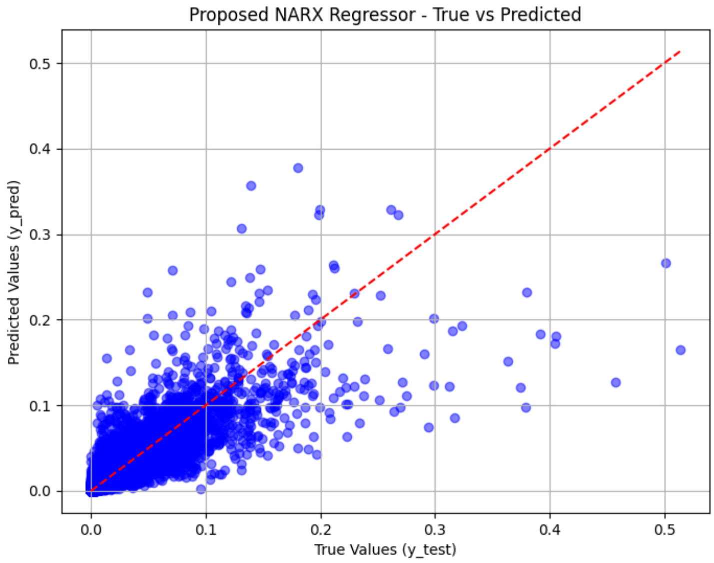

Figure 7: Scatter plot of NARXNN

The above figure 7 shows that scatter plot which is more shaded with the line as compare to existing algorithm.

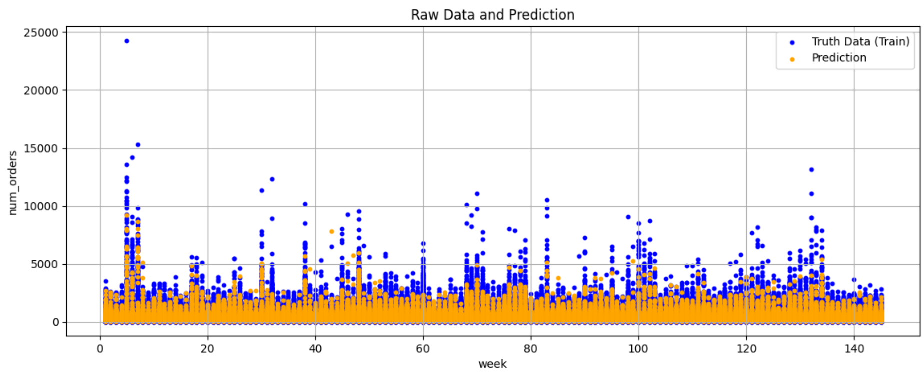

Figure 8: Actual and predicted comparison

Figure 8 shows the **Title:** Raw Data and Prediction

Axes:

- **X-axis:** "week" - This represents the time dimension, likely indicating the week number.
- **Y-axis:** "num_orders" - This represents the number of orders, presumably the target variable being predicted.

Data Points:

- **Blue dots:** "Truth Data (Train)" - These represent the actual number of orders observed in the training data.

- **Orange dots:** "Prediction" - These represent the predicted number of orders generated by the model.

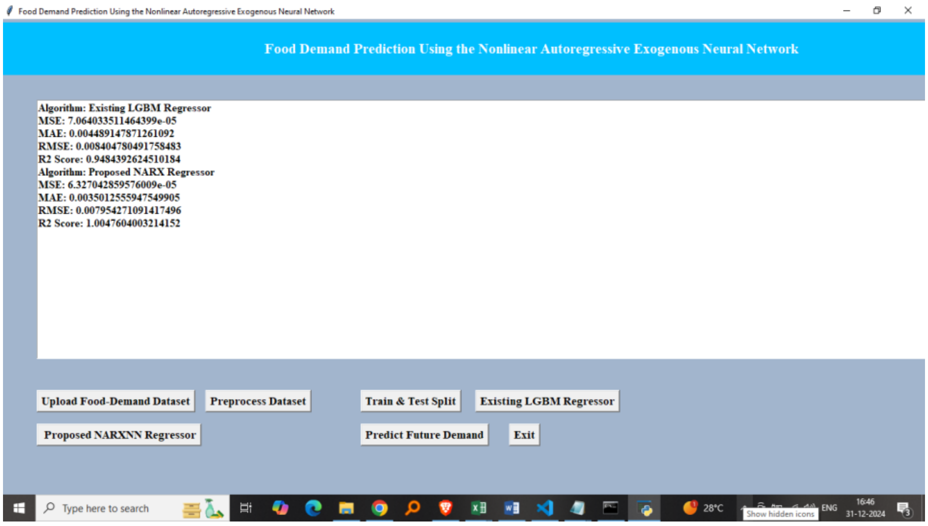

Figure 8: Metrics of the NARX Regressor

Figure show that the proposed NARX (Nonlinear AutoRegressive with eXogenous inputs) Regressor outperforms the existing LGBM Regressor in terms of prediction accuracy. With a Mean Squared Error (MSE) of 6.33e-05, Mean Absolute Error (MAE) of 0.0035, and a Root Mean Squared Error (RMSE) of 0.00795, it demonstrates a more precise prediction model. Additionally, the R2 Score of 1.0047 indicates a near-perfect fit to the data, showcasing its ability to capture underlying patterns with minimal error. In contrast, the existing LGBM Regressor has a higher MSE of 7.06e-05, MAE of 0.0045, and RMSE of 0.0084, along with a slightly lower R2 Score of 0.9484. This makes the NARX Regressor a more effective and reliable model for the given regression task.

5. Conclusion

Accurate food demand forecasting is critical for optimizing supply chain operations, minimizing waste, and ensuring effective shelf-life management of perishable goods. Traditional methods, while foundational, fall short in addressing the complexities of modern supply chains due to their inability to adapt to dynamic market conditions and process nonlinear time-series data. The proposed Nonlinear Autoregressive Exogenous Neural Network (NARXNN) model offers a robust solution by leveraging its recurrent dynamic network structure and the incorporation of exogenous inputs. Through advanced predictive capabilities, NARXNN improves inventory management, reduces overstocking and understocking issues, and aligns production schedules with actual demand. This innovation not only enhances operational efficiency but also promotes sustainability by minimizing food waste and ensuring consistent product availability for consumers. By addressing the limitations of traditional systems, NARXNN sets a new benchmark in food demand forecasting, paving the way for smarter and more sustainable supply chain practices.

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