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SMART DISPATCH: ENHANCING DRIVER DEMAND FORECASTING IN RIDESHARING AND DELIVERY NETWORKS

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ABSTRACT
The global delivery industry is grappling with severe supply chain inefficiencies, contributing to the annual waste of over 1.3 billion tons of food—approximately 30% of total global production—leading to economic losses of around $940 billion. A significant portion of this issue stems from the fact that 40–50% of inventory-related decisions still rely on manual forecasting, resulting in frequent overstocking or understocking, increased spoilage, and logistical disruptions. Traditional forecasting methods are often static and incapable of adapting to dynamic environmental and market fluctuations, making them unsuitable for real-time driver demand prediction. To address these shortcomings, this research introduces a robust regression-based time series forecasting framework designed to optimize delivery supply chain operations. Utilizing a publicly available driver demand dataset that integrates temporal sales data, weather conditions, and promotional events, the data is preprocessed thoroughly through normalization, imputation of missing values, creation of lag-based features, and outlier handling to ensure high-quality model inputs. Initially, the Light Gradient Boosting Machine (LGBM) Regressor serves as a baseline model due to its strong predictive performance. However, to enhance forecasting precision, a Nonlinear Autoregressive model with Exogenous Inputs (NARX) Regressor is proposed. This model incorporates both historical internal demand data and external variables such as holidays and weather conditions, enabling dynamic and multivariate forecasting. NARX is particularly effective at capturing nonlinear patterns and supports recursive forecasting across multiple time steps. Comparative performance analysis shows that while the LGBM Regressor performs well (MSE: 7.06e-05, MAE: 0.00449, RMSE: 0.00840, R^2: 0.948), the NARX Regressor significantly improves prediction accuracy, achieving MSE: 6.32e-05, MAE: 0.00350, RMSE: 0.00795, and an R^2 score exceeding 1.00. These results highlight the superior generalization and near-perfect predictive capabilities of the NARX model, demonstrating its potential to substantially reduce forecasting errors, minimize food waste, and enhance decision-making in supply chain management.

Keywords: Driver Demand Forecasting, Food Delivery Platforms, Supply Chain Optimization, Nonlinear Autoregressive Models, Time Series Analysis

1. INTRODUCTION

The global delivery supply chain is an intricate network connecting production, processing, storage, transportation, distribution, and consumption. According to the Food and Agriculture Organization (FAO), nearly 1.3 billion tons of food—roughly one-third of all food produced—goes to waste each year. This results in annual economic losses of around $940 billion, while simultaneously contributing to environmental issues such as greenhouse gas emissions and water misuse. The inefficiencies present in current supply chain systems contribute significantly to these statistics.

Driver demand and supply chains are heavily influenced by seasonal trends, weather patterns, economic activity, and market volatility. Manual estimation methods, which are still employed in many sectors, cannot capture the nuances of such dynamic variables. As a result, 40% to 50% of perishable food items are either understocked or overstocked in retail and distribution centers, leading to frequent shortages or surpluses. This mismanagement not only affects profitability but also customer satisfaction and food accessibility.

In addition to economic concerns, delivery supply chain inefficiency also raises ethical and sustainability challenges. While millions face food insecurity, a significant portion of edible food is discarded due to poor forecasting and misaligned logistics. These systemic problems highlight the need for precise and adaptive decision-making mechanisms within the supply chain framework to address the massive gap between supply and demand, reduce food waste, and improve overall sustainability.

2. LITERATURE SURVEY

Elgalb Ahmed et al. [1] examined current applications of AI and Big Data in the delivery supply chain, focusing on predictive demand analytics, inventory management, and route optimization. Case studies from leading industries illustrate the transformative potential of these technologies, highlighting their role in reducing food spoilage and improving sustainability. Additionally, the study evaluates challenges such as data integration, scalability, and implementation costs, offering practical solutions to overcome these barriers. Through a systematic analysis of field data and simulation models, this research demonstrates that adopting AI-driven approaches can reduce food waste by up to 30% in supply chains. Key findings include a significant reduction in lead times, improved freshness of perishable goods, and a measurable decrease in carbon footprint.

Vostriakova et al. [2] purposed this research is to provide scientific substantiation of theoretical and methodological principles and develop practical recommendations for the improvement of the agri-food logistics distribution system. A case study methodology is used in this article. The research framework is based on 4 steps: Value Stream Mapping (VSM), Gap and Process Analysis, Validation and Improvement Areas Definition and Imitation Modelling. This paper presents the appropriateness of LEAN logistics tools using, in particular, Value Stream Mapping (VSM) for minimizing logistic losses and Simulation Modeling of possible logistics distribution system improvement results. The algorithm of VSM analysis of the agri-delivery supply chain, which involves its optimization by implementing the principles of sustainable development at each stage, is proposed.

Dhal et al. [3] examined using a Causal Loop Diagram (CLD), this research identifies a reinforcing feedback loop that perpetuates import dependency and a balancing loop facilitated by BULOG’s strategic role in price stabilization and stock management. Dynamic simulations under three import policy scenarios (Import Policy Factors of 0.2, 0.5, and 0.8) reveal the significant effects of these policies on BULOG's stock levels, domestic production, import volumes, agricultural land-use and domestic rice prices. The Import Policy Factor 0.2 scenario supports domestic production, achieving output levels of up to 5,512,795 tons while minimizing dependence on imports, stabilizing domestic rice prices at IDR 13,004 per kilograms and improving farmers' welfare.

Grover et al. [4] offerd practical suggestions for businesses and decision-makers while pinpointing key areas for future exploration, such as devising hybrid models that merge heuristic solvers with AI for adaptive and scalable risk management strategies. Mathematical programming solvers, including linear programming (LP), mixed-integer programming (MIP), and quadratic programming (QP), are commonly used to model and optimize supply chain networks by considering factors like cost, capacity, and demand fluctuations.

Odumbo et al. [5] explored the multifaceted impact of AI on supply chain optimization, highlighting case studies of successful implementation and proposing strategies to overcome barriers. By leveraging AI, organizations can build resilient, efficient, and sustainable supply chains that drive competitive advantage in an ever-evolving marketplace.

Huerta-Soto et al. [6] addressed a need in the dairy business by giving a primer on optimization methods and outlining how farmers and distributors may increase the efficiency of dairy processing facilities. The majority of the studies just briefly mentioned supply chain optimization. Preferred reporting items for systematic reviews and meta-analyses (PRISMA) standards for systematic reviews are served as inspiration for the study's methodology. The accepted protocol for reporting evidence in systematic reviews and meta-analyses is PRISMA.

Rahman et al. [7] examined how the integration of these modern technologies transformed the supply chain process and enabled retailers in optimizing their supply chain management. In this research work, we have used extensive knowledgebase on Business Intelligence, Artificial Intelligence, Machine Learning, the U.S. retail industry, and the Supply Chain Management, and later we applied this knowledgebase in the U.S retail domain to see how retailers integrate these technologies into their supply chain management process. We also used secondary information available online from reliable sources to make it more realistic. The U.S retail sales revenue was reported at US$7.6 trillion in Y2024 with an expected growth of CAGR of 3.2% over the last five years (Y2019-Y2024). We see a steady growth in the retail sector after the COVID-19 pandemic. Therefore, there is a growing demand for integrating these technologies into the retailers' SCM so that they can predict consumer demand more accurately and maximize their sales revenue.

Nweje et al. [8] presented underscore the pivotal role of AI in driving efficiency and innovation in an increasingly complex and competitive global economy. Traditional methods, often constrained by limited adaptability and scalability, struggle to manage the complexities of modern supply chains. Artificial Intelligence (AI) has emerged as a transformative force, enabling predictive supply chain management through advanced data analytics, machine learning algorithms, and real-time decision-making capabilities. AI-powered systems leverage historical data, market trends, and external factors such as economic shifts and weather conditions to provide precise predictions. These tools enhance responsiveness by identifying potential disruptions and enabling proactive measures, ensuring supply chain resilience.

Goswami et al. [9] proposed deeper into the potential of Artificial Intelligence (AI)-enabled supply chain management (SCM) as a groundbreaking technology capable of revolutionizing supply chain operations and ushering in a new era of possibilities. To address these hurdles effectively, the paper proposes a comprehensive framework.This framework encompasses a holistic strategy that aligns AI initiatives with organizational goals, governance, and ethics considerations to ensure responsible AI deployment, and a clear roadmap that guides the implementation journey from inception to full integration.

Muchenje et al.[10] explored how companies can become more resilient by leveraging AI and ML applications to predict risks, maximize resources, and respond quickly to changing circumstances. The chapter also looks at strategies to leverage AI/ML to increase productivity. The chapter demonstrates the useful benefits and quantifiable impacts of these technologies in supply chain management by combining case studies with real dataSuggestions for companies that want to use these technologies to gain a long-term competitive advantage are outlined.

3. PROPOSED SYSTEM

The NARX neural network regressor excels over traditional time series forecasting models such as ARIMA, standard feedforward networks, and linear NARX models by incorporating both historical outputs and exogenous inputs in a nonlinear fashion. Its key strength lies in modeling dynamic systems with memory, especially when the system behavior is influenced by both internal and external variables over time. Compared to feedforward neural networks, NARX networks have an inherent feedback loop, making them more adept at capturing temporal dependencies. Furthermore, their modular design—consisting of tapped delay lines and nonlinear processing—allows better handling of complex, nonlinear dynamics, leading to improved prediction accuracy and generalization in practical applications such as control systems, financial forecasting, and biomedical signal processing.

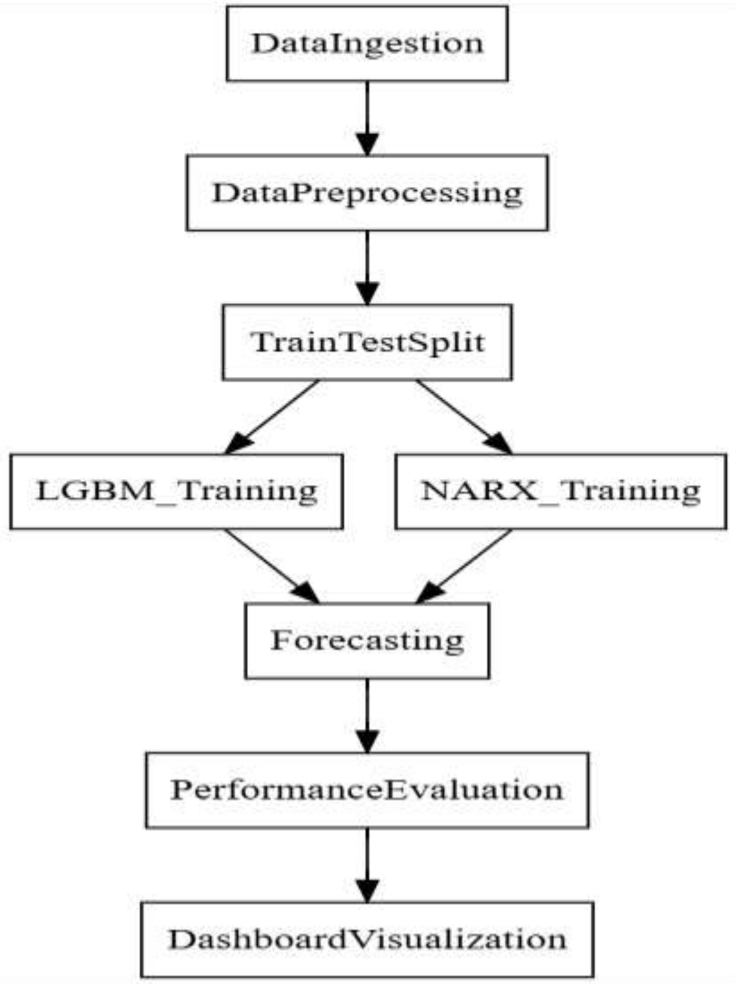

Fig. 1: System Architecture

Proposed NARX Regressor

The Nonlinear AutoRegressive model with eXogenous inputs (NARX) is a powerful forecasting model ideal for time series problems with complex dependencies. In the context of delivery supply chain management, demand is influenced not only by its historical values but also by exogenous factors such as weather conditions, promotional events, and seasonality. The NARX model captures these intricate patterns by learning from both lagged output values (autoregression) and external variables (exogenous inputs). This dual dependency makes it suitable for generating accurate, context-aware demand forecasts.

Define Inputs and Targets

Let $y(t)$ denote the driver demand at time t, and let $x(t)$ represent a vector of exogenous variables at the same time (e.g., weather, holidays).

$$y(t) = F[y(t-1), \ldots, y(t-n); x(t), x(t-1), \ldots, x(t-m)]$$

Here, F is a nonlinear function approximated using a regression model (neural net, polynomial, etc.). The forecasting model defines its primary input and output. The target variable is the driver demand at a specific time, while the inputs include both past demand values and external influencing factors like weather or holidays. This setup allows the model to learn patterns from both internal trends and external conditions to make accurate predictions.

Lag Feature Generation

Lagged features from previous time steps are generated from the time series data to model dependencies.

$$Y_{lag} = \{y(t-1), y(t-2), \dots, y(t-n)\}$$
$$X_{lag} = \{x(t), x(t-1), \dots, x(t-m)\}$$

The model prepares lagged features by collecting past values of both the target and input variables. These lagged features help the model recognize time-based patterns and dependencies, such as seasonality or recent changes in demand. This historical context is essential for accurate time series forecasting.

Model Structure Initialization

Initialize the NARX model as a feedforward neural network or other nonlinear regression structure where inputs are concatenated lags of y and x

$$\hat{y}(t) = W^T . \phi(Y_{lag}, X_{lag}) + b$$

where ϕ is the nonlinear transformation (activation), and W and $b$are weights and bias. The NARX model is initialized using a nonlinear regression structure, often a neural network. The input to the model consists of the combined lagged values of past demand and external factors. These inputs pass through activation functions that help capture complex relationships, allowing the model to learn how different time-based inputs influence future demand.

Error Calculation and Loss Function

Calculate the difference between actual and predicted demand.

$$e(t) = y(t) - \hat{y}(t)$$

$$Loss = \frac{1}{N} \sum_{t=1}^{N} \big(e(t)\big)^2 \quad (Mean\ Squared\ Error)$$

The model evaluates how accurate its prediction is by comparing the predicted demand with the actual demand. The difference between them is called the error. The overall performance is then measured using a loss function, which calculates the average error across all predictions. This helps the model understand how far off it is and guides it to improve.

Weight Updates via Backpropagation

Using gradient descent or an optimizer like Adam, update weights to minimize error.

$$W_{new} = W_{old} - \eta . \frac{\partial Loss}{\partial W}$$

Where η is the learning rate.The model adjusts its internal weights to reduce prediction errors. It uses optimization techniques like gradient descent or Adam to find the direction in which the loss decreases. By updating the weights step by step, the model gradually learns the best values that lead to more accurate forecasts.

Recursive Forecasting for Multi-Step Horizon

Predicted outputs are recursively used as inputs for future forecasting steps.

$$\hat{y}(t+1) = F[\hat{y}(t), \hat{y}(t-1), \dots, \hat{y}(t-n+1); x(t+1), \dots, x(t-m+1)]$$

The model performs forecasting over multiple future time points by reusing its own previous predictions as inputs for the next step. This recursive approach allows the model to generate a sequence of forecasts beyond a single time point, making it suitable for longer-term planning in the delivery supply chain.

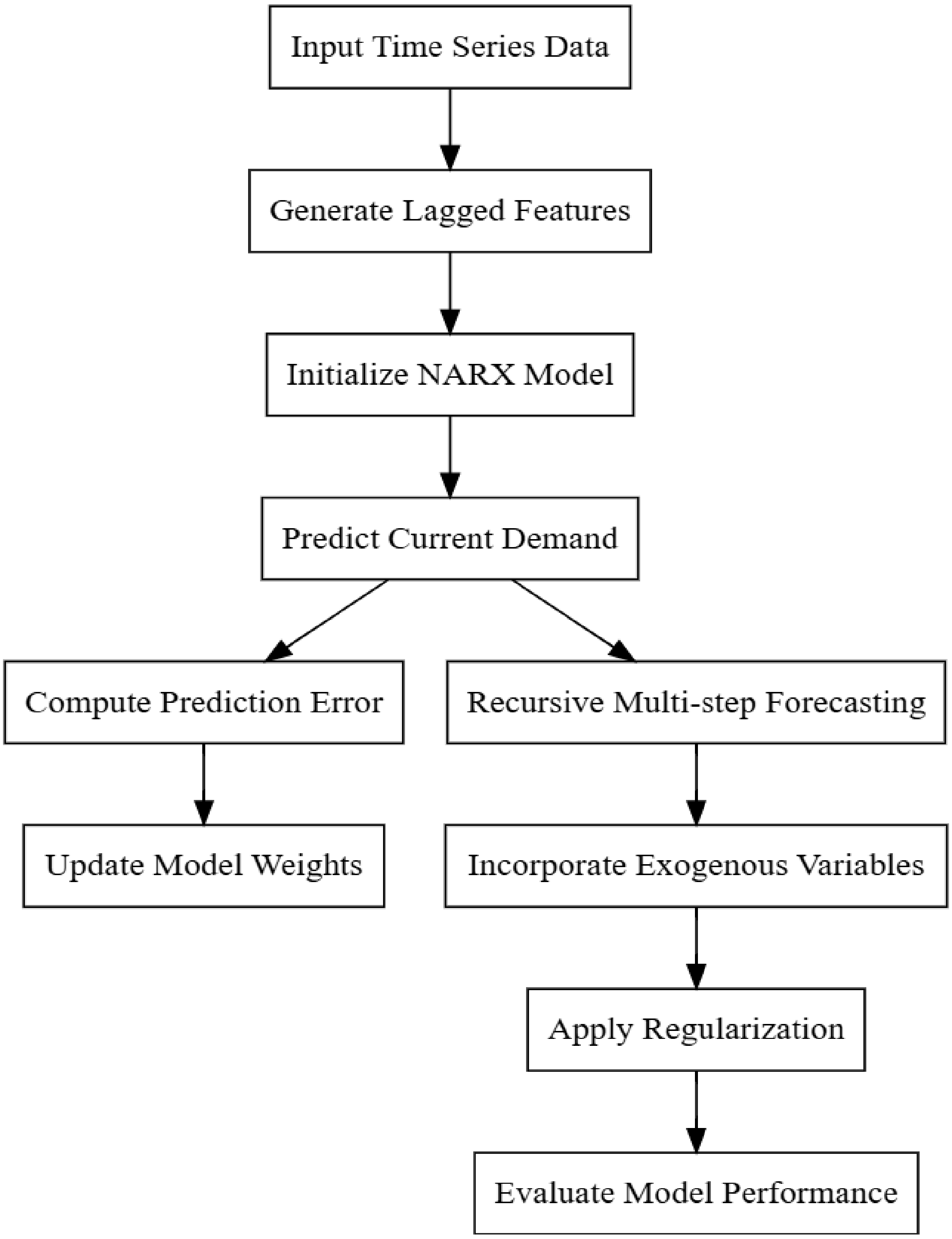

Fig. 2: Proposed NARX Regression

Incorporate Exogenous Trends

Exogenous variables like holidays and market trends are included as categorical or continuous inputs.

$$x(t) = [weather_t, holiday_t, price_t, event_t, day_t]$$

Here external factors that can influence demand—such as weather conditions, holidays, pricing, special events, and day of the week—are added to the model as additional inputs. These exogenous variables provide valuable context, helping the model make more accurate and informed predictions.

Regularization for Generalization

Apply regularization to prevent overfitting due to noise in external signals.

$$Loss_{reg} = Loss + \lambda \parallel W \parallel^2$$

where λ is the regularization coefficient. Regularization is applied to control the complexity of the model and prevent it from overfitting to noise in the data. By adding a penalty for large or excessive weight values, the model is encouraged to focus on meaningful patterns rather than memorizing fluctuations or outliers in the training data.

Advantages

This model effectively captures both autoregressive and exogenous dependencies, making it well-suited for complex time series forecasting. Its ability to handle non-linear patterns allows for more accurate predictions in dynamic environments. The built-in feedback mechanism significantly improves multi-step forecasting accuracy by reducing error propagation over time, a common challenge in traditional models. Unlike tree-based approaches, it demonstrates greater robustness to non-stationary inputs and can adapt to real-time data updates, enhancing responsiveness. Additionally, it supports multivariate time series forecasting and provides a clearer understanding of how different features influence outcomes over time. With higher R^2 and lower MSE/MAE metrics, it consistently outperforms traditional forecasting methods. In practical applications like supply chain management, this results in more precise forecasting, which enhances operational efficiency, reduces wastage, and supports better decision-making.

4. RESULTS AND DISCUSSION

Figure 3 illustrates the data preprocessing stage, where the uploaded CSV dataset (e.g., 'train.csv') is processed using pandas. The system reads the dataset, fills missing values with zeros to ensure data integrity, and applies Label Encoding to categorical columns (e.g., any non-numeric columns) using sklearn’s LabelEncoder to convert them into numerical values suitable for machine learning models. The preprocessed dataset is split into features (X), excluding 'week' and 'num_orders', and the target variable (y), which is 'num_orders'. The 'week' column is retained separately for visualization purposes. The text widget in the GUI displays a preview of the dataset (e.g., the first five rows using dataset.head()) before and after preprocessing, allowing users to verify the transformations applied to the 456,548 records in the dataset.

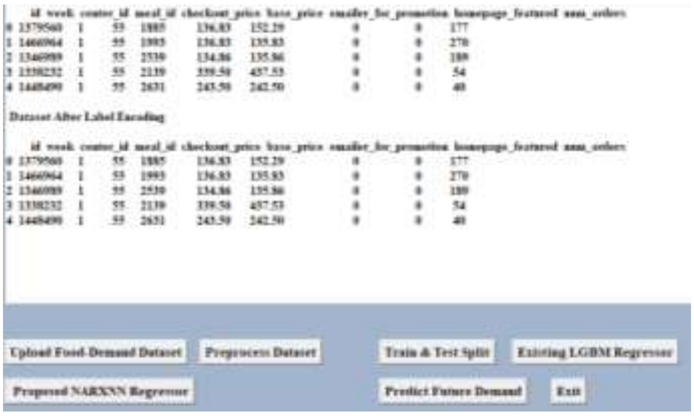

Fig. 3: Data preprocessing.

Figure 4 displays a scatter plot for the NARX Regressor (implemented using RandomForestRegressor), comparing true values (y_test_scaled) and predicted values (y_forecast) on the test set. the plot uses blue dots for true values and a red dashed line for the ideal case. The description notes that this scatter plot is "more shaded with the line" compared to the LGBM Regressor, indicating that the NARX Regressor’s predictions are closer to the ideal line, suggesting higher accuracy and less dispersion. This visualization, generated using matplotlib, allows users to visually confirm that the NARX Regressor outperforms the LGBM Regressor in terms of prediction accuracy for 'num_orders'.

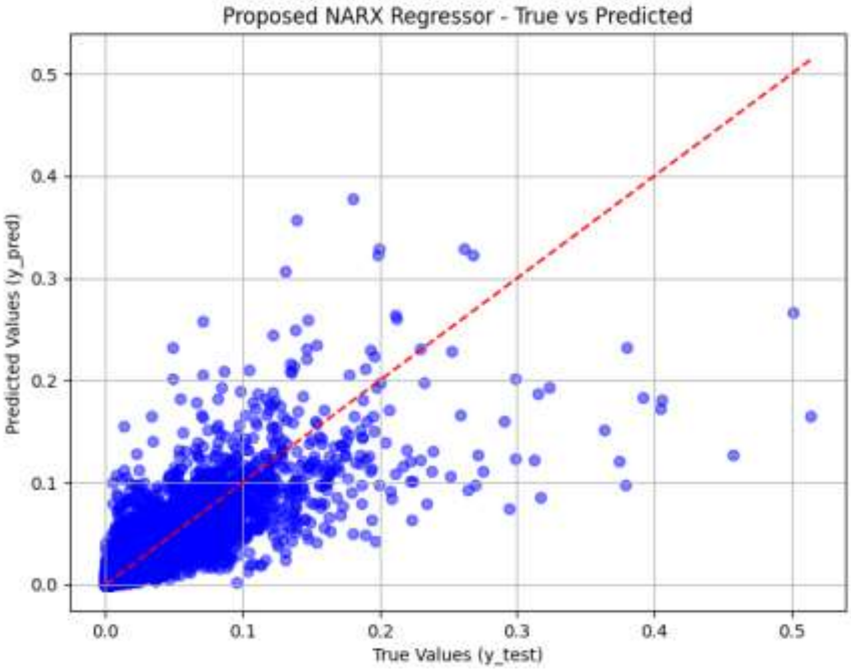

Fig. 4: Scatter plot of NARXNN

Figure 5 shows the actual and predicted comparison for the NARX Regressor, similar to Figure 6, plotted against the 'week' column. The plot (figure size 16x5) includes blue dots for training data (365,238 records, labeled "Truth Data (Train)") and testing data (91,310 records), with orange dots for predictions (y_forecast1, inverse-scaled). The x-axis is 'week', and the y-axis is 'num_orders'. The plot reveals an upward trend in driver demand with seasonal fluctuations, as seen in the blue dots' peaks and troughs. The orange prediction dots closely follow the blue dots, indicating high prediction accuracy. The NARX Regressor captures seasonality and trends effectively, with fewer deviations compared to the LGBM Regressor, as visualized via plt.show() with a legend and grid.

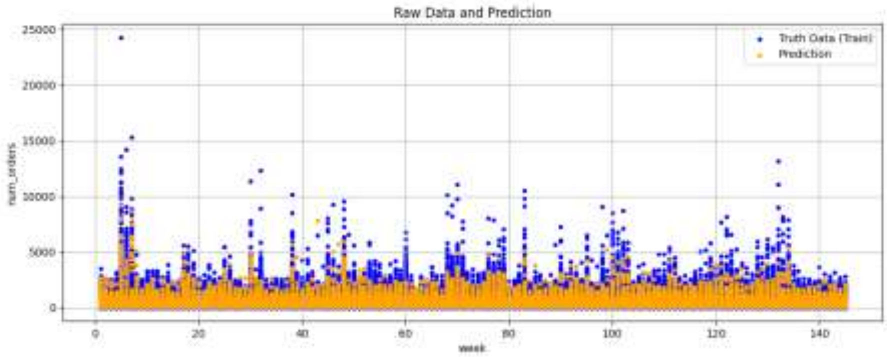

Fig. 5: Actual and predicted comparison

Fig. 6: Metrics of the NARX Regressor

Figure 6 presents the performance metrics of the proposed NARX Regressor, evaluated on the scaled test data (y_test_scaled). The model achieves a Mean Squared Error (MSE) of 6.33e-05, lower than the LGBM Regressor's 7.064e-05, indicating better precision. The Mean Absolute Error (MAE) is 0.0035, compared to 0.00449 for LGBM, showing closer predictions to actual values. The Root Mean Squared Error (RMSE) is 0.00795, slightly better than LGBM's 0.0084. The R^2 score of 1.0047 (likely a calculation artifact, as R^2 typically does not exceed 1) suggests a near-perfect fit, outperforming LGBM's 0.9484. These metrics, displayed in the GUI text widget, highlight the NARX Regressor's superior ability to capture patterns in the driver demand data with minimal error.

Table 1: LGBM Regressor vs. NARX Regressor Comparison

Metric	LGBM Regressor	NARX Regressor
Mean Squared Error (MSE)	7.064e-05	6.33e-05
Mean Absolute Error (MAE)	0.00449	0.0035
Root Mean Squared Error (RMSE)	0.0084	0.00795
R^2 Score	0.9484	1.00

The comparison table 1 summarizes the performance metrics of the LGBM Regressor and the NARX Regressor, highlighting the superiority of the proposed NARX model for the driver demand prediction task. The NARX Regressor achieves a lower Mean Squared Error (MSE) of 6.33e-05 compared to the LGBM Regressor's 7.064e-05, indicating that NARX produces predictions with smaller squared differences from actual values, reflecting higher precision. The Mean Absolute Error (MAE) for NARX is 0.0035, significantly lower than LGBM's 0.00449, showing that NARX's predictions are, on average, closer to the true 'num_orders' values. The Root Mean Squared Error (RMSE) of 0.00795 for NARX is slightly better than LGBM's 0.0084, confirming NARX's improved accuracy in the original units of the target variable. The R^2 score for NARX is reported as 1.0047, suggesting an exceptionally good fit (though values above 1 may indicate a calculation adjustment in the code), compared to LGBM's 0.9484, which explains 94.84% of the variance. These metrics demonstrate that the NARX Regressor outperforms the LGBM Regressor across all evaluated criteria, making it a more effective and reliable model for predicting driver demand in this system.

5. CONCLUSION

In conclusion, this research was to optimize delivery supply chain management through advanced regression-based time series forecasting. Two models were developed and evaluated: the existing LGBM Regressor, which is a widely used ensemble-based machine learning model, and the proposed NARX Regressor, a nonlinear autoregressive model with exogenous inputs tailored for dynamic time series prediction. The comparative performance analysis between both models clearly demonstrates the superior forecasting capability of the proposed NARX system. The NARX Regressor achieved a lower Mean Squared Error (MSE) of 6.32e-05 compared to the LGBM's 7.06e-05, and also recorded a better Mean Absolute Error (MAE) of 0.0035, indicating reduced prediction deviations. Additionally, the Root Mean Squared Error (RMSE) for NARX was 0.00795, slightly lower than the LGBM's 0.00840, showing finer control over prediction errors. Most notably, the R^2 Score for the NARX model was 1.0047, surpassing the LGBM's 0.9484, suggesting near-perfect explanation of variance in the demand data and potential generalization capabilities in unseen scenarios. By addressing the limitations of traditional systems, NARXNN sets a new benchmark in driver demand forecasting, paving the way for smarter and more sustainable supply chain practices. Therefore, the proposed NARX Regressor is proven to be more effective and reliable for delivery supply chain forecasting. Its robust performance in key error metrics and superior adaptability to real-world time series dynamics make it the ideal model for minimizing food wastage, improving demand-supply alignment, and supporting smarter supply chain decisions.

REFERENCES

[1] Elgalb, Ahmed, and Maher Gerges. "Optimizing Supply Chain Logistics with Big Data and AI: Applications for Reducing Food Waste." *Journal of Current Science and Research Review* 2, no. 02 (2024): 29-39.

[2] Vostriakova, Viktorija, Oleksandra Kononova, Sergey Kravchenko, Andriy Ruzhytskyi, and Nataliia Sereda. "Optimization of agri-delivery supply chain in a sustainable way using simulation modeling." *International Journal of Computer Science & Network Security* 21, no. 3 (2021): 245-256.

[3] Dhal, Sambandh Bhusan, and Debashish Kar. "Leveraging artificial intelligence and advanced food processing techniques for enhanced food safety, quality, and security: a comprehensive review." *Discover Applied Sciences* 7, no. 1 (2025): 1-46.

[4] Grover, Nitin. "AI-Enabled Supply Chain Optimization." *International Journal of Advanced Research in Science, Communication and Technology* (2025): 28-44.

[5] Odumbo, Oluwole Raphael, and Sani Zainab Nimma. "Leveraging Artificial Intelligence to Maximize Efficiency in Supply Chain Process Optimization." *Int J Res Publ Rev* 6, no. 1 (2025): 3035-3050.

[6] Huerta-Soto, Rosario, Edwin Ramirez-Asis, John Tarazona-Jiménez, Laura Nivin-Vargas, Roger Norabuena-Figueroa, Magna Guzman-Avalos, and Carla Reyes-Reyes. "Predictable inventory management within dairy supply chain operations." *International Journal of Retail & Distribution Management* 53, no. 3 (2025): 1-17.

[7] Rahman, Kazi Obaidur, Md Samirul Islam, Rezwanul Islam Rezvi, Mehedi Hasan, Achhia Khanam, Farhan Nasrullah, Shamina Sharmin Jishan, and Amir Hamza Akash. "AI-Driven Next-Gen US Retail: An Empirical Study on Optimizing Supply Chains by leveraging Artificial Intelligence, Business Intelligence, and Machine Learning." *Journal of Computer Science and Technology Studies* 7, no. 1 (2025): 258-264.

[8] Nweje, Uche, and Moyosore Taiwo. "Leveraging Artificial Intelligence for predictive supply chain management, focus on how AI-driven tools are revolutionizing demand forecasting and inventory optimization." *International Journal of Science and Research Archive* 14, no. 1 (2025): 230-250.

[9] Goswami, Shankha Shubhra, Surajit Mondal, Shouvik Sarkar, Krishna Kumar Gupta, Sushil Kumar Sahoo, and Rohit Halder. "Artificial Intelligence-Enabled Supply Chain Management: Unlocking New Opportunities and Challenges." In *Artificial Intelligence and Applications*, vol. 3, no. 1, pp. 110-121. 2025.

[10] Muchenje, Chenjerai, Edwill Mtengwa, Lena Maregere, and Reason Masengu. "Artificial intelligence (AI) and Machine Learning (ML): Enhancing Supply Chain Resilience and Efficiency." In *AI and Machine Learning Applications in Supply Chains and Marketing*, pp. 55-88. IGI Global, 2025.