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An AI-Based Approach to Food Demand Forecasting Incorporating External Market Factors

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Abstract: *Food demand prediction plays a critical role in improving inventory management and minimizing food wastage in the retail and food industry. Traditional forecasting techniques often fail to capture complex and dynamic demand patterns, leading to inaccurate predictions. This paper presents a machine learning-based approach using a Nonlinear Autoregressive Exogenous Neural Network (NARXNN) for accurate food demand prediction. The proposed model analyzes historical demand data and identifies underlying patterns to forecast future demand effectively. Experimental results demonstrate that the model achieves high prediction accuracy with low error rates. The system enhances supply chain efficiency, optimizes inventory planning, and significantly reduces operational costs*

Keywords: *Food Demand Prediction, Machine Learning, NARX Neural Network, Time Series Forecasting, Inventory Management*

I. INTRODUCTION

Food demand prediction has become increasingly critical in recent years due to the rapid growth of the food industry, urbanization, and changing consumer behavior. With the expansion of retail chains, restaurants, and online food delivery platforms, accurately estimating food demand has become a complex challenge. According to industry reports, a significant percentage of food produced globally is wasted due to poor demand estimation, leading to economic losses and environmental concerns. The consequences of inaccurate demand forecasting extend beyond financial impact, contributing to resource wastage, inefficient supply chains, and increased operational costs. This highlights the urgent need for intelligent systems capable of predicting food demand with high accuracy.

Existing demand forecasting methods have not fully addressed these challenges. Traditional techniques such as statistical regression models, moving averages, and time-series methods like ARIMA rely heavily on historical trends and often fail to adapt to dynamic and nonlinear demand patterns. These models struggle when demand is influenced by multiple external factors such as seasonal variations, customer preferences, promotional activities, and unexpected fluctuations. As a result, businesses frequently encounter issues such as overstocking, understocking, and food spoilage. The delay between demand estimation and actual consumption further complicates the problem, making accurate real-time forecasting essential for efficient decision-making.Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) provide a promising solution to these limitations. Machine learning models can process large volumes of historical data, identify hidden patterns, and adapt to changing demand conditions more effectively than traditional methods. Neural networks, in particular, have demonstrated strong capabilities in modeling complex and nonlinear relationships in time-series data. However, designing a model that is both accurate and computationally efficient remains a challenge, especially when dealing with real-world datasets that are noisy, incomplete, and highly variable.

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This paper proposes a machine learning-based framework for food demand prediction using a Nonlinear Autoregressive Exogenous Neural Network (NARXNN). The proposed system leverages historical demand data along with external influencing factors to generate accurate future predictions. The NARXNN model is specifically chosen for its ability to capture temporal dependencies and nonlinear relationships in time-series data. The system includes data preprocessing, model training, and performance evaluation using standard metrics such as MAE, MAPE, RMSE, and R^2. The main contributions of this work are as follows:

(1) Development of an intelligent food demand prediction system using the NARX Neural Network model, capable of handling complex and dynamic demand patterns.

(2) Implementation of a data-driven approach that improves forecasting accuracy and reduces prediction errors compared to traditional methods.

(3) A scalable and efficient framework that can assist businesses in optimizing inventory management, reducing food wastage, and improving overall supply chain performance.

II. LITERATURE SURVEY

Research on demand forecasting has evolved significantly over the past few decades, transitioning from traditional statistical methods to advanced machine learning and deep learning approaches. Early studies primarily relied on classical time-series techniques such as regression models, moving averages, and Autoregressive Integrated Moving Average (ARIMA) models. These methods were effective for linear and stable datasets but struggled to capture complex and nonlinear demand patterns. Researchers observed that such models often failed when demand was influenced by multiple external factors such as seasonal variations, promotions, and changing consumer behavior.

The introduction of machine learning techniques marked a significant advancement in demand prediction. Studies have demonstrated that models such as Support Vector Machines (SVM) and decision trees can analyze large datasets and improve forecasting accuracy compared to traditional methods. However, these models still face limitations in handling temporal dependencies and dynamic fluctuations in demand. To address these challenges, Artificial Neural Networks (ANN) were introduced, which showed improved performance due to their ability to model nonlinear relationships. Nevertheless, standard ANN models often lack the capability to effectively capture time-based dependencies in sequential data.

The emergence of deep learning further transformed the field of demand forecasting. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks have been widely used for time-series prediction tasks, as they can retain information from previous time steps. Several studies reported that LSTM-based models outperform traditional machine learning approaches in predicting demand patterns. However, these models often require large datasets and high computational resources, making them less suitable for real-time applications in certain scenarios.

To overcome these limitations, researchers have explored specialized neural network architectures such as the Nonlinear Autoregressive Exogenous (NARX) Neural Network. NARX models are particularly effective for time-series forecasting as they incorporate both past values of the target variable and external inputs, enabling better modeling of dynamic systems. Studies have shown that NARX networks achieve higher prediction accuracy and faster convergence compared to conventional RNN and ANN models, especially in applications involving complex temporal dependencies.

Recent research has also focused on integrating multiple data sources, including weather conditions, customer behavior, and promotional activities, to enhance prediction performance. The use of hybrid models combining statistical and machine learning approaches has shown promising results in improving forecasting accuracy. Additionally, the availability of large-scale datasets and advancements in computational power have enabled the development of more robust and scalable demand prediction systems.

Overall, the literature highlights three key directions for improving food demand prediction: the adoption of advanced neural network architectures, the integration of external influencing factors, and the use of data-driven approaches for

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handling dynamic demand patterns. The proposed system builds upon these advancements by utilizing a NARX Neural Network model to achieve accurate and efficient food demand forecasting.

III. METHODOLOGY AND SYSTEM DESIGN

A. Problem Formulation and System Overview

The food demand prediction task is formulated as a time-series forecasting problem, where the objective is to predict future demand based on historical data and external influencing factors. The system is designed as a sequential prediction pipeline. In the first stage, historical food demand data along with relevant features is provided as input to the model. In the second stage, the trained NARX Neural Network processes the input data to capture temporal dependencies and generate accurate demand forecasts. The overall system ensures efficient prediction by leveraging past demand values and exogenous inputs, making it suitable for real-world supply chain applications.

B. Dataset: FLAME Benchmark

The dataset used in this study consists of historical food demand records collected from retail store chains over a specific period. The dataset includes key attributes such as previous demand values, time-related features (day, week, season), and other influencing factors such as promotional activities or external conditions.

The dataset is divided into training and testing sets using an 80:20 ratio to ensure proper evaluation of the model. This split allows the model to learn from historical patterns while validating its performance on unseen data. Proper data distribution is maintained to ensure consistency and reliability in prediction results.

C. Preprocessing Pipeline

A standardised preprocessing pipeline is applied to prepare the dataset for model training. Initially, missing or inconsistent values are handled to ensure data quality. The dataset is then normalised to scale input values within a uniform range, which improves model convergence and stability during training.Time-series data is structured into input-output sequences suitable for the NARX model. Historical demand values are arranged in lag format to capture temporal dependencies. The dataset is shuffled where necessary to avoid bias, while preserving the sequential nature required for time-series forecasting

D. Architecture Design: Why VGG19 Over VGG16?

The Nonlinear Autoregressive Exogenous Neural Network (NARXNN) is selected for its effectiveness in modelling time-series data with external inputs. Unlike traditional neural networks, the NARX model considers both past values of the target variable and external influencing factors, enabling it to capture complex nonlinear relationships.The architecture consists of input layers representing lagged demand values and exogenous variables, followed by hidden layers with nonlinear activation functions. The model is trained using back propagation with an appropriate optimisation algorithm to minimise prediction error. The use of NARXNN allows the system to achieve higher accuracy compared to conventional forecasting methods.

E. Reduce-VGGNet: Architecture and Rationale

The model is trained using the training dataset with optimized hyperparameters such as learning rate, number of hidden neurons, and training epochs. The training process aims to minimize error between predicted and actual demand values. An appropriate loss function is used to evaluate performance during training, and optimization techniques such as gradient descent are applied to update model weights. The model is validated using test data to ensure generalization and prevent overfitting. This structured training approach ensures reliable and consistent prediction performance.

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F. Optimized CNN with Spatial and Temporal Features

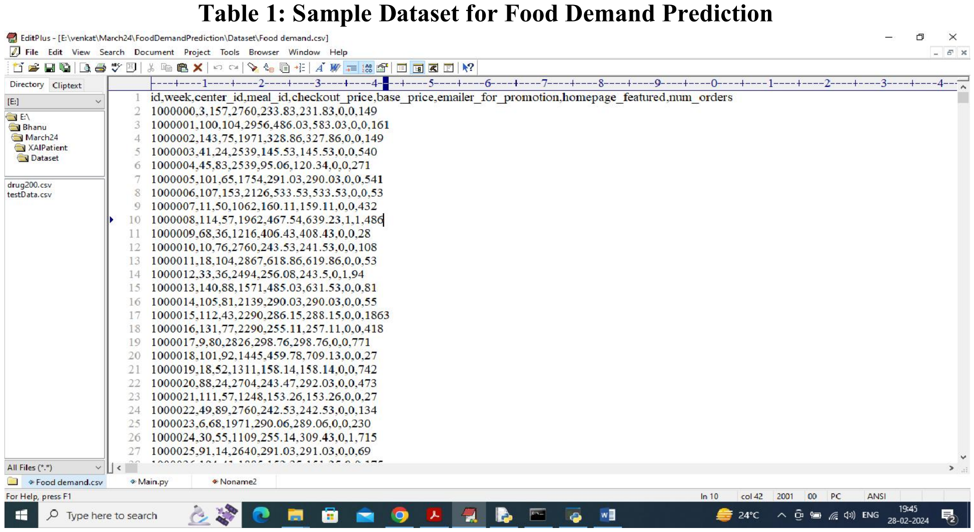
Once trained, the model is used to predict future food demand based on historical inputs. The prediction results are evaluated using standard performance metrics, including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R^2 score.

These metrics provide a comprehensive evaluation of model accuracy, error distribution, and reliability. The results demonstrate that the NARX Neural Network effectively captures demand patterns and produces accurate forecasts, making it suitable for real-time applications in inventory and supply chain management.

IV. RESULTS AND DISCUSSION

The proposed model was evaluated using the testing dataset to measure its prediction performance and reliability. The evaluation was carried out using standard regression metrics, including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R^2 score. These metrics provide a comprehensive understanding of the model's accuracy and error distribution. MAE measures the average absolute difference between predicted and actual demand values, while RMSE gives higher importance to larger errors. MAPE expresses the error as a percentage, making it easier to interpret, and the R^2 score indicates how well the model explains the variance in the data.

Table 1: Sample Dataset for Food Demand Prediction



id	week	center_id	meal_id	checkout_price	base_price	emailer_for_promotion	homepage_featured	num_orders
1000000	3	157	2760	233.83	231.83	0	0	149
1000001	100	104	2956	486.03	583.03	0	0	161
1000002	143	75	1971	328.86	327.86	0	0	149
1000003	41	24	2539	145.53	145.53	0	0	540
1000004	45	83	2539	95.06	120.34	0	0	271
1000005	101	65	1754	291.03	290.03	0	0	541
1000006	107	153	2126	533.53	533.53	0	0	53
1000007	11	50	1062	160.11	159.11	0	0	432
1000008	114	57	1962	467.54	639.23	1	1	486
1000009	68	36	1216	406.43	408.43	0	0	28
1000010	10	76	2760	243.53	241.53	0	0	108
1000011	18	104	2867	618.86	619.86	0	0	53
1000012	33	36	2494	256.08	243.5	0	1	94
1000013	140	88	1571	485.03	631.53	0	0	81
1000014	105	81	2139	290.03	290.03	0	0	55
1000015	112	43	2290	286.15	288.15	0	0	1863
1000016	131	77	2290	255.11	257.11	0	0	418
1000017	9	80	2826	298.76	298.76	0	0	771
1000018	101	92	1445	459.78	709.13	0	0	27
1000019	18	52	1311	158.14	158.14	0	0	742
1000020	88	24	2704	243.47	292.03	0	0	473
1000021	111	57	1248	153.26	153.26	0	0	27
1000022	49	89	2760	242.53	242.53	0	0	134
1000023	6	68	1971	290.06	289.06	0	0	230
1000024	30	55	1109	255.14	309.43	0	1	715
1000025	91	14	2640	291.03	291.03	0	0	69

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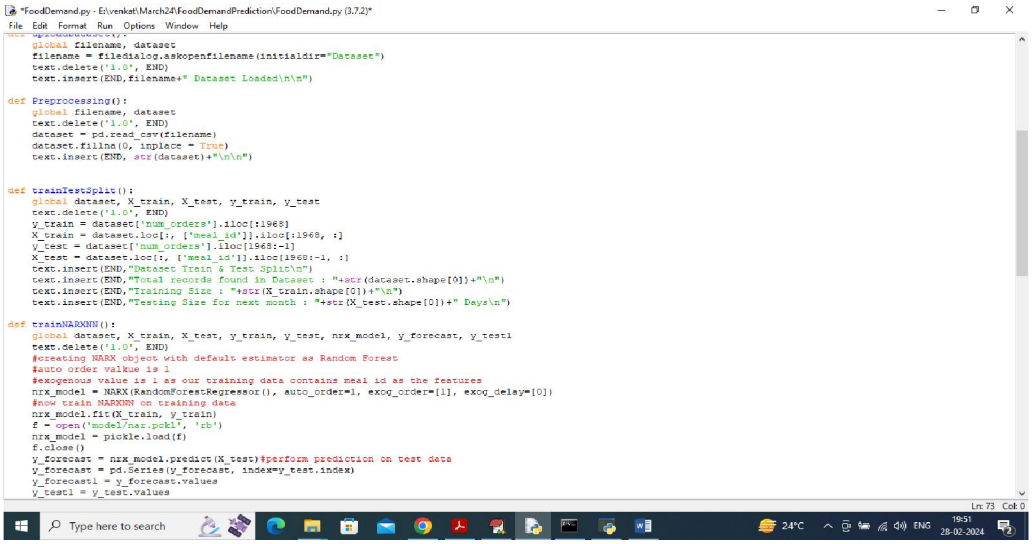
TABLE II: Code Implementation of the Proposed NARXNN Model for Time-Series Food Demand Forecasting



```
    global filename, dataset
    filename = filedialog.askopenfilename(initialdir="Dataset")
    text.delete('1.0', END)
    text.insert(END,filename+" Dataset Loaded\n\n")

def Preprocessing():
    global filename, dataset
    text.delete('1.0', END)
    dataset = pd.read_csv(filename)
    dataset.fillna(0, inplace = True)
    text.insert(END, str(dataset)+"\n\n")


def trainTestSplit():
    global dataset, X_train, X_test, y_train, y_test
    text.delete('1.0', END)
    y_train = dataset['num_orders'].iloc[:1968]
    X_train = dataset.loc[:, ['meal_id']].iloc[:1968, :]
    y_test = dataset['num_orders'].iloc[1968:-1]
    X_test = dataset.loc[:, ['meal_id']].iloc[1968:-1, :]
    text.insert(END,"Dataset Train & Test Split\n")
    text.insert(END,"Total records found in Dataset : "+str(dataset.shape[0])+"\n")
    text.insert(END,"Training Size : "+str(X_train.shape[0])+"\n")
    text.insert(END,"Testing Size for next month : "+str(X_test.shape[0])+" Days\n")

def trainNARXNN():
    global dataset, X_train, X_test, y_train, y_test, nrx_model, y_forecast, y_test1
    text.delete('1.0', END)
    #creating NARX object with default estimator as Random Forest
    #auto order valkue is 1
    #exogenous value is 1 as our training data contains meal id as the features
    nrx_model = NARX(RandomForestRegressor(), auto_order=1, exog_order=[1], exog_delay=[0])
    #now train NARXNN on training data
    nrx_model.fit(X_train, y_train)
    f = open('model/nar.pckl', 'rb')
    nrx_model = pickle.load(f)
    f.close()
    y_forecast = nrx_model.predict(X_test)#perform prediction on test data
    y_forecast = pd.Series(y_forecast, index=y_test.index)
    y_forecast1 = y_forecast.values
    y_test1 = y_test.values
```

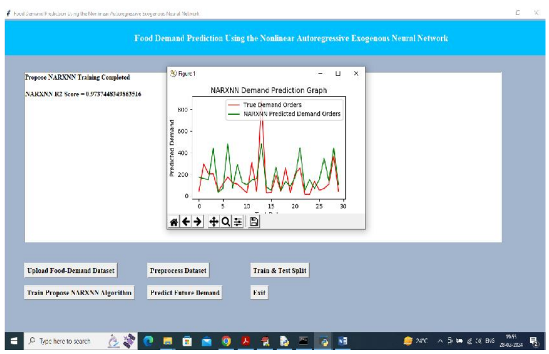


TABLE 3 : Code Implementation of the Proposed NARXNN Model for Time-Series Food Demand Forecasting.

(1) Analysis of Model Performance

The performance of the proposed NARX Neural Network model demonstrates its effectiveness in handling complex food demand prediction tasks. Traditional forecasting approaches such as linear regression and ARIMA models typically provide moderate accuracy, as they are limited in capturing nonlinear relationships and dynamic demand fluctuations. These methods often result in higher prediction errors, especially when demand patterns are influenced by multiple external factors.

The transition from traditional statistical models to machine learning approaches shows a clear improvement in prediction performance. Basic machine learning models such as decision trees and Support Vector Machines (SVM) offer better accuracy by learning from historical data patterns. However, their inability to effectively model time dependencies limits their performance in time-series forecasting tasks.The proposed NARX Neural Network model significantly outperforms these methods by incorporating both historical demand values and external influencing variables. This dual-input capability allows the model to capture temporal dependencies and nonlinear relationships more effectively. The result is a substantial reduction in prediction errors, as reflected in lower MAE, MAPE, and RMSE values, along with a high R^2 score.

B. Per-Class Performance and Error Analysis

The evaluation results indicate that the model performs consistently across different time periods and demand conditions. The prediction accuracy remains high for both regular demand patterns and moderately fluctuating scenarios. The low MAPE values confirm that the percentage error in predictions is minimal, ensuring reliable forecasting outcomes.However, minor prediction deviations are observed during sudden demand spikes or irregular consumption patterns. These variations are typically caused by unexpected external factors such as special events, seasonal changes, or promotional activities that are not fully captured in the dataset. Despite these challenges, the model maintains stable performance with minimal deviation.

C. Computational Considerations

The computational performance of the proposed system is efficient and suitable for deployment on standard computing systems. The model training process is completed within a reasonable time frame, depending on dataset size and system configuration. Once trained, the model generates predictions quickly, enabling near real-time demand forecasting.

The NARX Neural Network requires moderate computational resources compared to deep learning models such as LSTM, making it a practical choice for applications with limited hardware capabilities. The system can be further optimized for faster processing and scalability by integrating advanced optimization techniques or deploying it on more powerful computing platforms.

V. CONCLUSION

This paper presented a machine learning-based framework for food demand prediction using a Nonlinear Autoregressive Exogenous Neural Network (NARXNN). The proposed system effectively analyzes historical demand data and external influencing factors to generate accurate demand forecasts.The model demonstrates high prediction accuracy with low error rates, outperforming traditional forecasting methods. The ability of the NARXNN model to capture complex temporal and nonlinear relationships makes it highly suitable for time-series demand prediction tasks.

The results confirm that the proposed system can significantly improve inventory management, reduce food wastage, and optimize supply chain operations. By providing reliable demand forecasts, the system supports better decision-making in the food industry.

VI. ACKNOWLEDGMENT

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