



International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 21 No. 3 (1) 2025



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Research Paper**ENHANCING FOOD SUPPLY CHAIN EFFICIENCY USING AI-BASED DEMAND FORECASTING**Md. Nusrath Begum¹, N. Bhoomika², K. Parameshwar², K. Udaykiran², K. Rahul²¹Assistant Professor, ²UG Student, ^{1,2}Department of Computer Science and Engineering (Data Science)^{1,2}Sree Dattha Group of Institutions, Sheriguda, Ibrahimpatnam, 501510, Telangana.**ABSTRACT**

Food supply chain management is a crucial component of the agriculture and retail sectors, aimed at ensuring the efficient production, transportation, and distribution of food products to end consumers. In India, this supply chain faces significant challenges, including excessive food wastage, demand-supply mismatches, and delays in logistics. According to reports, nearly 40% of the food produced in India is wasted annually due to systemic inefficiencies, resulting in economic losses of approximately ₹92,000 crores (around \$12 billion). With the country's population projected to reach 1.6 billion by 2050, it is imperative to address these inefficiencies to ensure long-term food security and economic resilience. Traditional methods for demand forecasting—such as historical averages, static rule-based systems, and manual forecasting based on human intuition—often fall short. These approaches fail to capture dynamic market variables such as seasonal variations, pricing changes, and promotional activities, leading to overproduction, underutilization, and significant resource wastage. The increasing complexity of food supply chains, driven by urbanization, shifting consumer behavior, and climate variability, underscores the need for more intelligent forecasting solutions. This project proposes a machine learning-based approach using Convolutional Neural Network (CNN) regressors to enhance food supply chain efficiency. The model extracts both spatial and temporal features from historical sales and contextual data, allowing for precise weekly demand predictions across different food categories and regions. Convolutional layers are particularly adept at identifying patterns such as seasonal trends, promotional influences, and regional consumption dynamics. These insights enable improved inventory management by aligning stock levels with actual demand, thereby reducing spoilage and overstocking. Additionally, the system supports dynamic pricing strategies by incorporating real-time pricing trends and promotional data. It also enhances logistics planning by forecasting demand at various nodes within the supply chain. By leveraging CNN-based regression models, the proposed system delivers accurate demand forecasting, minimizes food wastage, optimizes resource allocation, and supports data-driven decision-making in pricing and inventory control. This intelligent forecasting approach paves the way for a more sustainable and efficient food supply chain in India.

Keywords: Food Supply Chain Management, Demand Forecasting, Inventory Optimization, Dynamic Pricing, Food Wastage Reduction, Machine Learning, Spatial-Temporal Analysis, Supply Chain Efficiency, Agricultural Logistics

Received: 14-7-2025

Accepted: 21-8-2025

Published: 28-8-2025

1. INTRODUCTION

Forecasting demand is an essential part of managing the supply chain and has a considerable influence on planning, capacity, and inventory control choices. The significance of precise demand prediction becomes apparent in inventory control when incorrect forecasts lead to higher backlog and holding expenses. The uncertainty of demand has a significant impact on order amplification, which affects all participants in the supply chain. In the broader field of supply chain management, accurate demand

forecasting is crucial for making decisions, allocating resources, and improving operational efficiency. However, traditional methodologies face challenges in capturing the complex dynamics of modern supply chains as global markets evolve and become more interconnected. Linear models and time series analyses, though foundational, struggle to predict the nonlinear and intricate relationships that characterize contemporary business environments. Traditional methods of demand forecasting are no longer effective in accurately predicting customer demands due to intense competition in various industries. In order to address this problem, companies are currently implementing advanced data science methods to predict customer demand. By treating customer demand as a series of data points over a period of time, the issue of demand forecasting can be seen as a challenge of predicting values in a time series. However, predicting the demand for components presents its own difficulties, such as a lack of adequate information about downstream processes, sporadic occurrences of demand, and a limited comprehension of market trends. It is crucial to address these challenges in order to reduce inventory costs and make flexible decisions in agile supply chains. While there have been several studies on supply chain management, limited research has specifically focused on the issues related to forecasting demand for components. Conventional approaches like moving averages and the Croston method, which is commonly used, may not be effective in dealing with the growing volatility of the supply chain. The demand patterns in the supply chain industry are constantly changing due to technological advancements, globalization, and changing consumer preferences. Traditional forecasting models struggle to keep up with these nonlinear and unpredictable patterns. Industries that rely on quick-to-market products and are heavily influenced by market trends face particular challenges in accurately predicting future demand. This leads to inefficient inventory management and resource allocation. Linear models like linear regression oversimplify the relationships between input variables and demand, making it difficult to capture the complex nature of supply chain data. The proposed system leverages machine learning techniques, including advanced regression models such as CNN regressors to improve demand forecasting accuracy. CNNs capture spatial and temporal features like seasonality, promotions, and regional dynamics from historical and contextual data. These predictions enable precise inventory optimization, dynamic pricing, and efficient logistics planning.

2. LITERATURE SURVEY

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3. PROPOSED SYSTEM

Begin by gathering a comprehensive dataset relevant to your time-series problem. Ensure it includes clear timestamps and associated features, such as numerical, categorical, or textual data points. Examples of such datasets include stock price data, weather data, or sensor readings. Understand the dataset's attributes, format, and structure, ensuring it has no missing timestamps or incomplete records.

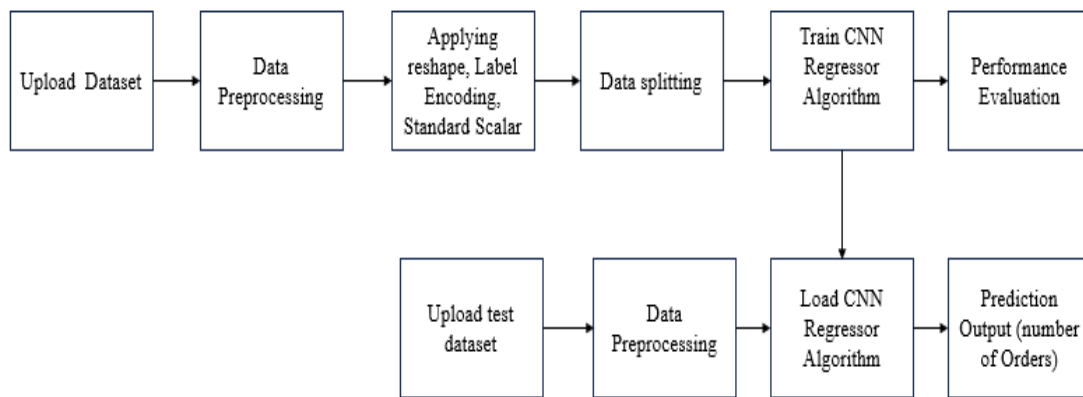


Figure 1; Proposed Block diagram

Preprocess the dataset by handling missing values, smoothing noisy data, and ensuring all timestamps are uniformly spaced. Convert the data into a time-series format by indexing with timestamps. Normalize or standardize the features to improve the convergence of algorithms. Split the dataset into training, validation, and testing sets, ensuring no data leakage between sets due to overlapping time periods. The dataset is divided into training, validation, and testing sets to ensure unbiased model evaluation. Typically, 70% of the data is allocated for training, 15% for validation, and 15% for testing. Time-series data preprocessing includes handling missing values, smoothing noisy data, and ensuring consistent time intervals. Features are normalized or standardized to improve model convergence. Temporal order is preserved to prevent data leakage. Additionally, lag features or rolling statistics may be created to capture trends. The processed data is reshaped into a format compatible with the model, such as sequences for time-step-based learning in CNNs or other algorithms.

4. RESULTS AND DISCUSSION



Figure 2: Home Page

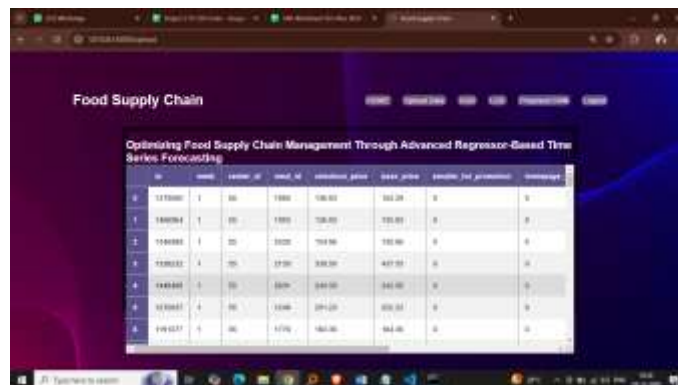


Figure 3: Uploaded Dataset

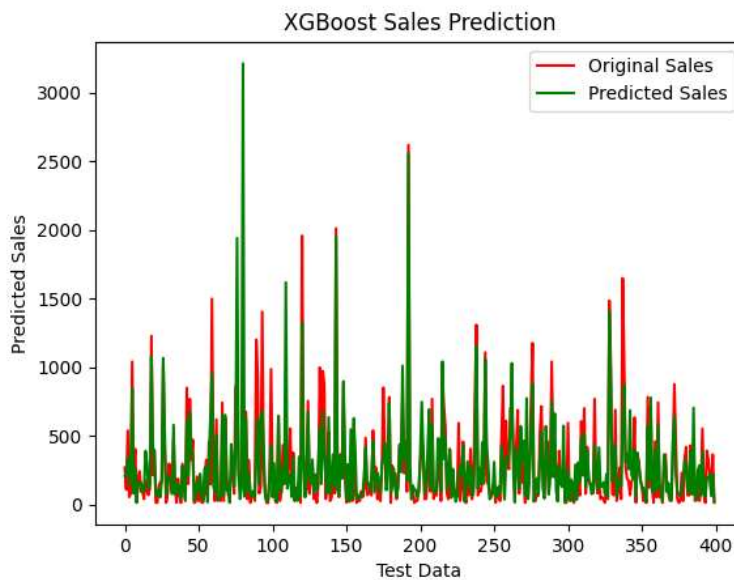


Figure 4: Line plot.

5. CONCLUSION

Optimizing food supply chain management through advanced regressor-based time series forecasting offers significant improvements over traditional methods. By utilizing machine learning techniques like CNNs, LSTMs, and other advanced regressors, the system can predict demand more accurately and in real-time, leading to better resource allocation and inventory management. Traditional

methods, such as rule-based forecasting and human intuition, often lead to inefficiencies like food wastage, stockouts, and excessive production costs. In contrast, AI-driven models help reduce these issues by considering dynamic factors like promotions, seasonality, and regional demand patterns. This system provides substantial economic benefits, especially in countries like India, where food wastage is a major issue. By aligning supply with actual demand, this approach contributes to sustainability, economic efficiency, and improved decision-making for food supply chain stakeholders. The future of food supply chain optimization lies in further integrating AI and emerging technologies. IoT sensors could provide real-time data, enabling even more accurate forecasting by tracking product conditions throughout the supply chain. Blockchain could improve traceability and reduce fraud, enhancing food safety. Additionally, incorporating sustainability metrics into AI models can optimize not only for cost and efficiency but also for environmental factors like carbon footprints. As global supply chains become more interconnected, AI models could adapt to integrate cross-border data and optimize international food distribution. Further advancements could also involve incorporating reinforcement learning for more adaptable models capable of responding to unexpected disruptions, such as natural disasters or pandemics. Moreover, using personalized demand forecasting could lead to hyper-localized supply chain models, reducing waste and improving customer satisfaction. These developments will allow for more resilient, efficient, and sustainable food supply chains.

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