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Research Paper

ENHANCING FOOD SUPPLY CHAIN EFFICIENCY USING AI-BASED DEMAND FORECASTING

K. Manohar Rao[1], Renukuntla Sukumar[2], Banoth Swarupa[2], G Surya Kiran[2]
[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering,
Kommuri Pratap Reddy Institute of Technology, Hyderabad, Telangana, India.
Email: manoharkat@gmail.com

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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

1. INTRODUCTION

Due to the consumer’s varying needs and increasing levels of competitiveness among companies, most companies in today’s market are shifting their focus to demand forecasting for the effective demand-supply chain management. Demand forecasts are beyond the scope of any planning decisions, as they directly impact a company’s profitability. Inaccurate ap- proximation of demand can either cause too much inventory, which eventually results in a high risk of wastage and high costs to pay or too little inventory, leading to out-of-stocks which ultimately pushes the company's customers to seek services from its competitors. For these very reasons, the use of demand forecasting methods is one of the most fundamen- tal components of the strategic planning and administration of a company's logistics. Its importance becomes evident as its outcome is used by many subdivisions in the company: the financial department uses it to estimate costs, profit levels, and the required capital; the marketing department uses it to plan its course of action and analyze the impact of diverse marketing strategies on the volume of sales; the purchasing department may devise their plans of short- and long-term investments; and finally, the operations department can manage their plan of purchasing the necessary raw materials, machinery, and labor well in advance. It is, therefore, concordant that forecasts are beneficial, and their high accuracy has the potential to prove lucrative, improve demand-supply chain management, and reduce wastage Due to the consumer's varying needs and increasing levels of competitiveness among companies, most companies in today's market are shifting their focus to demand forecasting for the effective demand-supply chain management. 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[13] have suggested many methods to predict the electricity demands and prices for various times, i.e., short term, medium-term, and long-term as well. But, electricity demands may vary largely in restaurants or meal delivery centers as it, in turn, depends on the order of their meals/products. The same is the case of a factory producing preprocessed food products. Once the meal/product demand is known, it can increase the accuracy of the prediction of electricity demands and let the farmers estimate how much of the crop must be grown to meet the required demands. Hence, forecasting in the domain of meal demand prediction is of utmost importance. Statistical techniques like exponential smoothing [14], the Holt-Winters method [15], moving average, and the Auto- Regressive Integrated Moving Average (ARIMA) model [16] have traditionally been used in forecasting. Ramos et al. [17] used ARIMA and state-space models to predict the volume of upcoming commodity sales. 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Forecasting demand plays a critical role in supply chain management, directly influencing decisions related to planning, capacity utilization, and inventory control. Inaccurate forecasts can lead to significant consequences, including increased holding costs, backlogs, and disrupted operations. The uncertainty in demand often leads to order amplification, impacting all levels of the supply chain and creating inefficiencies. Accurate demand forecasting is, therefore, essential for informed decision-making, effective resource allocation, and overall operational efficiency. However, traditional forecasting approaches—such as linear models and basic time series analyses—struggle to capture the complex, nonlinear, and dynamic nature of modern supply chains, which are increasingly shaped by globalization, technological advancements, and evolving consumer behavior. These conventional methods, including moving averages and the Croston method, often fall short in managing volatile and sporadic demand, especially in industries with fast-changing trends and fragmented data. Component-level demand forecasting is particularly challenging due to limited visibility into downstream processes, irregular demand occurrences, and insufficient understanding of market shifts. To address these limitations, organizations are adopting advanced data science and machine learning techniques, treating customer demand as a time-series prediction problem. Among these, Convolutional Neural Networks (CNNs) offer a promising solution by capturing both spatial and temporal features—such as seasonal variations, promotional impacts, and regional factors—from historical and contextual datasets. The integration of CNN-based regression models enhances forecasting accuracy, enabling businesses to optimize inventory, implement dynamic pricing strategies, and plan logistics more efficiently, thereby ensuring a more responsive and agile supply chain.

2. LITERATURE SURVEY

[1]Chen F Drezner Z Ryan JK Simchi-Levi D Quantifying the bullwhip effect in a simple supply chain The impact of forecasting lead times and information Manag Sci 2000 46 436–443.**[2]**Gonçalves JN Cortez P Carvalho MS Frazao NM A multivariate approach for multi-step demand forecasting in assembly industries Empirical evidence from an automotive supply chain Decis Support Syst 2021 142 113452.**[3]**Kerkkänen A Korpela J Huiskonen J Demand forecasting errors in industrial context Measurement and impacts Int J Prod Econ 2009 118 43–48.**[4]**Babai MZ Boylan JE Rostami-Tabar B Demand forecasting in supply chains A review of aggregation and hierarchical approaches Int J Prod Res 2022 60 324–348.**[5]**Kilimci ZH Akyuz AO Uysal M Akyokus S Uysal MO Bulbul BA Ekmis MA An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain Complexity Wiley Hoboken NJ USA 2019.**[6]**Bahram M Hubmann C Lawitzky A Aeberhard M Wollherr D A combined model-and learning-based framework for interaction-aware maneuver prediction IEEE Trans Intell Transp Syst 2016 17 1538–1550.**[7]**Dua D Graff C UCI Machine Learning Repository University of California Irvine Available online https archive ics uci edu ml index php accessed on 6 February 2024.**[8]**Fanoodi B Malmir B Jahantigh FF Reducing demand uncertainty in the platelet supply chain through artificial neural networks and ARIMA models Comput Biol Med 2019 113 103415.**[9]**Fausett LV Fundamentals of neural networks Architectures algorithms and applications Pearson Education India Prentice Hall Upper Saddle River NJ USA 2006.**[10]**Feizabadi J Machine learning demand forecasting and supply chain performance Int J Logist Res Appl 2022 25 119–142.**[11]**Fu W Chien CF UNISON data-driven intermittent demand forecast framework to empower supply chain resilience and an empirical study in electronics distribution Comput Ind Eng 2019 135 940–950.**[12]**Ghosh PK Manna AK Dey JK Kar S Optimal production run in an imperfect production process with maintenance under warranty and product insurance Opsearch 2023 60 720–752.**[13]**Abbasimehr H Shabani M Yousefi M An optimized model using the LSTM network for demand forecasting Comput Ind Eng 2020 143 106435.**[14]**Guo F Diao J Zhao Q Wang D Sun Q A double-level combination approach for demand forecasting of repairable airplane spare parts based on turnover data Comput Ind Eng 2017 110 92–108.**[15]**Villegas MA Pedregal DJ Trapero JR A support vector machine for model selection in demand forecasting applications Comput Ind Eng 2018 121 1–17.**[16]**Islam S Amin SH Prediction of probable backorder scenarios in the supply chain using Distributed Random Forest and Gradient Boosting Machine learning techniques J Big Data 2020 7 65.

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

The process begins with gathering a well-structured dataset containing timestamps and relevant features, such as numerical, categorical, or textual data, ensuring completeness and consistency. Preprocessing follows, involving handling missing values, smoothing noise, converting data into time-indexed format, normalizing features, and splitting the data into training, validation, and test sets without time overlap. Initially, the XGBoost algorithm is applied as a baseline model, leveraging its ensemble learning approach to enhance prediction accuracy, followed by the implementation of a tailored Convolutional Neural Network (CNN) using 1D convolutional layers to extract deep temporal patterns in the data. The performance of both models is then compared using metrics like accuracy, MAE, and RMSE, with visual tools such as confusion matrices and error plots to highlight CNN's superiority. Dataset preprocessing is particularly fine-tuned for bakery demand forecasting by integrating transactional sales data with center-level metadata, normalizing and transforming the target variable, and engineering features such as center type and base price. Key steps include reading and merging data, computing descriptive statistics, filtering relevant time windows (weeks 1–10), transforming the target variable (num_orders) with a weight factor for variance stabilization, and cleaning features by removing identifiers and redundant columns

Figure 2: Home Page

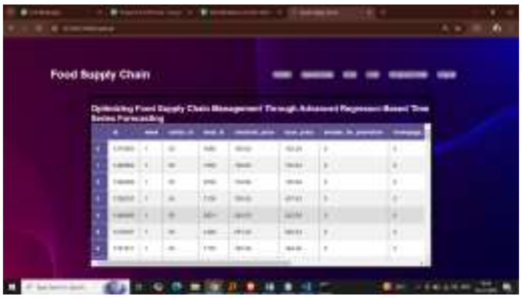

Figure 3: Uploaded Dataset

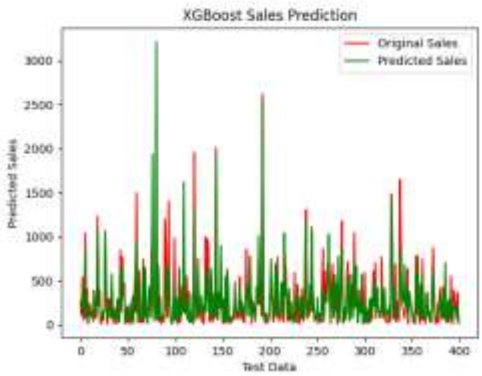

Figure 4: Line plot.

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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