OPTIMIZING FOOD SUPPLY CHAIN MANAGEMENT THROUGH ADVANCED REGRESSOR-BASED TIME SERIES FORECASTING

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ABSTRACT

Food supply chain management is a critical domain in agriculture and retail industries, aiming to ensure the efficient production, transportation, and delivery of food products to consumers. In India, the food supply chain faces challenges such as excessive wastage, demand-supply mismatches, and delays in logistics. Reports suggest that 40% of food produced in India is wasted annually due to inefficiencies, costing the economy around ₹92,000 crores ($12 billion). With rising demand due to population growth (expected to reach 1.6 billion by 2050), addressing inefficiencies is vital for food security and economic sustainability. To develop a machine learning-driven solution for optimizing food supply chain management by accurately forecasting demand using historical data and contextual features, minimizing food wastage, and improving resource allocation. Tradition system like Historical Averages predicting demand based on previous years' average sales. Rule-Based Systems like using static rules for inventory management and procurement. Human Intuition Manual forecasting by managers based on experience, often prone to errors and biases. Problems statement like fail to account for dynamic market conditions such as price fluctuations, seasonality, and promotional activities. These systems result in overproduction, underutilization, and wastage of resources, leading to significant economic losses. Motivation is the growing complexity of food supply chains, driven by urbanization, changing consumer preferences, and climate variability, necessitates the adoption of smarter forecasting techniques. The proposed system leverages a CNN regressor to revolutionize food supply chain management by extracting spatial and temporal features from historical and contextual data for precise demand forecasting. Convolutional layers capture patterns such as seasonality, promotions, and regional dynamics, enabling accurate weekly demand predictions for various meals. This enhances inventory optimization by aligning stock levels with forecasted demand, minimizing wastage. Additionally, the system facilitates dynamic pricing by accounting for pricing trends and promotional activities, while optimizing logistics by predicting demand patterns across supply chain nodes. By integrating CNN regressors, the system ensures accurate demand forecasts, reduced food wastage, and improved resource allocation, fostering efficient decision-making in pricing and inventory management.

KEYWORDS : Food supply chain management, Demand-supply mismatches, Economic sustainability

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

[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.

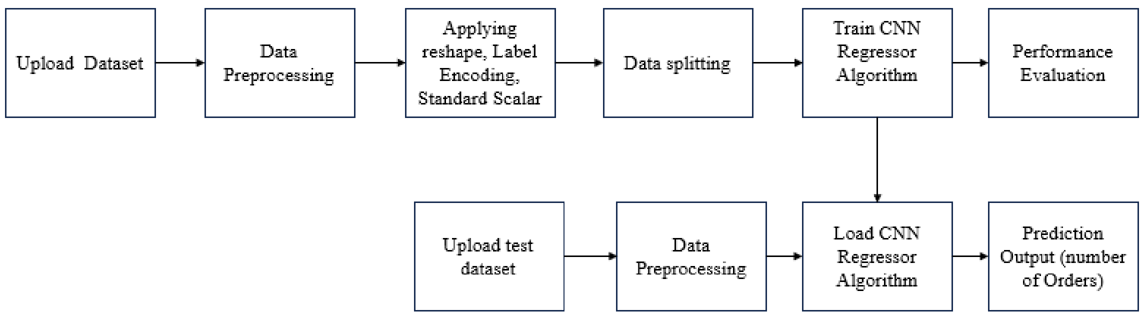

Figure 1; Proposed Block diagram

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

Figure 2: Home Page

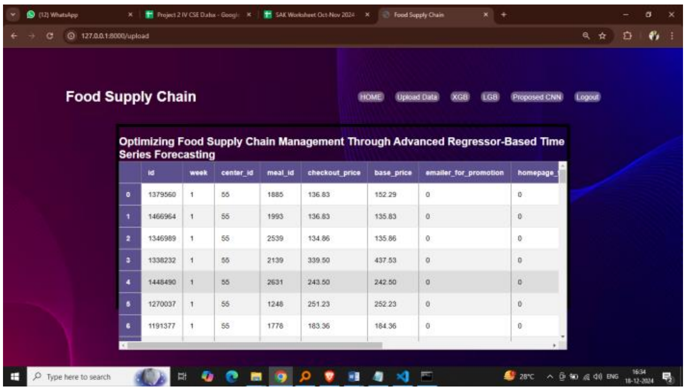

Figure 3: Uploaded Dataset

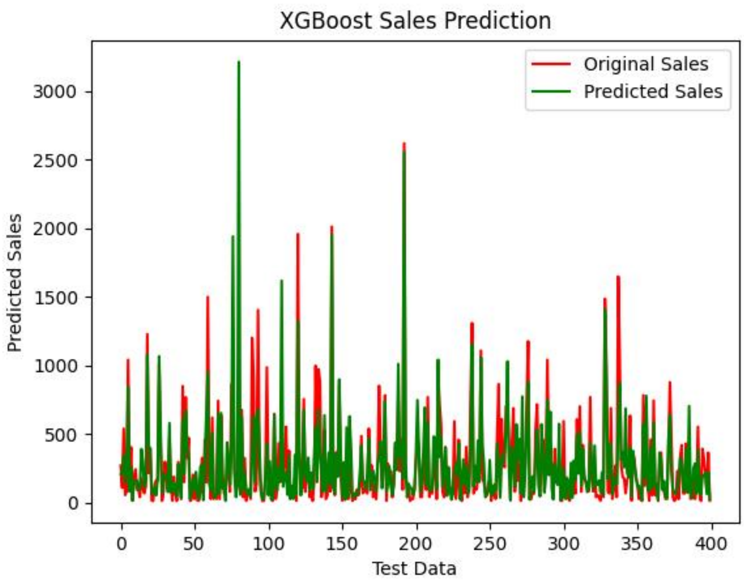

Figure 4: Line plot.

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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