

TIME SERIES FORECASTING AND MODELLING OF FOOD DEMAND SUPPLY CHAIN BASED ON REGRESSORS ANALYSIS

POLAGANI NAGA SATEESH

pnsgec677@gmail.com

24NH1D5812

LNV RAO

lankapalli@gmail.com

ASSOCIATE PROFESSOR & ACE-1

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

V.K.R & V.N.B Engineering College

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ABSTRACT

"Time Series Forecasting and Modelling of Food Demand Supply Chain Based on Regressors Analysis" presents an intelligent predictive framework for analyzing and forecasting food demand within supply chain management systems using time series modelling and regression-based analytical techniques. The study focuses on identifying the influence of various regressors such as seasonal variations, population growth, consumer purchasing behavior, climate conditions, transportation costs, and market trends on food demand and supply fluctuations. By applying machine learning algorithms, statistical forecasting models, and regression analysis to historical supply chain data, the proposed system aims to improve demand prediction accuracy, reduce food wastage, optimize inventory management, and enhance distribution efficiency. The framework supports real-time decision-making for suppliers, retailers, and policymakers by providing reliable forecasts that help maintain supply chain stability and ensure food availability. Experimental results demonstrate that integrating regressor analysis with time series forecasting significantly improves prediction performance and contributes to the development of sustainable and efficient food supply chain management systems.

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INTRODUCTION

Food supply chain management plays a vital role in ensuring the availability, accessibility, and distribution of food products to meet the growing demands of the global population. Rapid urbanization, population growth, changing consumer preferences, climate change, and market uncertainties have made food demand forecasting increasingly complex. Inaccurate prediction of food demand can lead to serious problems such as overstocking, food wastage, supply shortages, increased operational costs, and inefficient resource utilization. Therefore, accurate forecasting and modelling techniques are essential for maintaining a stable and sustainable food supply chain system.

Time series forecasting has emerged as an effective approach for analyzing historical demand patterns and predicting future food consumption trends. By studying past sales records, seasonal variations, economic conditions, and consumer behavior, time series models can identify hidden trends and recurring patterns in supply chain data. In addition, regression analysis helps determine the influence

of multiple external factors, known as regressors, such as weather conditions, transportation costs, festivals, inflation rates, and population growth on food demand fluctuations.

The proposed system focuses on developing an intelligent forecasting framework that combines time series modelling with regressor analysis to improve the accuracy of food demand prediction in supply chain management. The framework utilizes statistical methods, machine learning algorithms, and predictive analytics to analyze historical datasets and generate reliable demand forecasts. This approach supports better inventory planning, optimized logistics, reduced food wastage, and efficient decision-making for suppliers, retailers, and policymakers. The system aims to enhance supply chain sustainability, operational efficiency, and overall food distribution management in dynamic market environments.

LITERATURE SURVEY

1. “Time Series Forecasting for Supply Chain Demand Planning”

Author: Rob J. Hyndman and George Athanasopoulos

Description:

This study focused on the application of time series forecasting methods such as ARIMA, exponential smoothing, and seasonal decomposition for demand prediction in supply chain systems. The authors demonstrated how historical sales data and seasonal trends can improve forecasting accuracy and support efficient inventory management.

2. “Machine Learning Techniques for Food Demand Forecasting”

Author: Ahmed Elafif et al.

Description:

The research explored the use of machine learning algorithms including decision trees, random forests, and neural networks for forecasting food demand. The study showed that AI-based forecasting models provide better prediction performance compared to traditional statistical methods by capturing complex demand patterns and market behavior.

3. “Regression Analysis in Supply Chain Management”

Author: Douglas C. Montgomery et al.

Description:

This work presented the importance of regression analysis in identifying relationships between demand and influencing factors such as pricing, transportation, climate conditions, and customer behavior. The authors highlighted how regressors can significantly improve forecasting accuracy in supply chain operations.

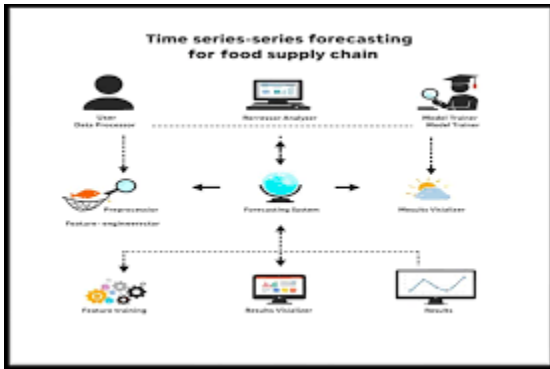
4. “Forecasting Agricultural and Food Product Demand Using Big Data Analytics”

Author: K. R. Kumar and S. Prasad

Description:

The study proposed a big data-driven framework for analyzing food demand trends using consumer purchasing data and environmental factors. The researchers integrated predictive analytics with supply chain management to reduce wastage and optimize product distribution across different regions.

SYSTEM ARCHITECTURE



IMPLEMENTATION SCREEN SHOTS

We have coded this project using JUPYTER notebook and below are the code and output screens with blue colour comments

```

In [41]: #Importing python classes and packages
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import MinMaxScaler
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_absolute_percentage_error
from sklearn.metrics import r2_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import cross_val_score
import logging as log
import os
import random as rd

from keras.models import Sequential, LSTM, LSTM2
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout
import os
from keras.callbacks import ModelCheckpoint
from math import sqrt
from sklearn.metrics import accuracy_score, f1_score
from keras.layers import Conv2D, Conv1D
from keras.layers import Conv2D, Conv1D
    
```

In above screen importing required python classes and packages

```

In [124]: #Read and display meal_sales dataset values
dataset = pd.read_csv('dataset/meal_sales.csv')
dataset.head()

Out[124]:
   id  week  center_id  meal_id  checked_price  base_price  vendor_fin_promotion  homeware_discount  meal_sales
0  1375900    1    35    1005    138.83    152.29             0.00             0.00          1777
1  140884    1    35    1003    138.00    150.00             0.00             0.00          279
2  1348800    1    35    2530    134.00    135.00             0.00             0.00          180
3  1338232    1    35    2739    339.00    427.50             0.00             0.00          54
4  1446400    1    35    2821    260.00    262.00             0.00             0.00          60
...
49554 127130    145    81    1842    488.00    488.00             0.00             0.00          88
49554 160230    145    81    2204    482.00    482.00             0.00             0.00          42
49554 310840    145    81    2094    237.00    221.07             0.00             0.00          501
49554 174732    145    81    2098    220.00    223.34             0.00             0.00          224
49554 136184    145    81    2480    280.00    280.00             0.00             0.00          182

49554 rows x 9 columns
    
```

In above screen reading and displaying meals and its sales dataset

```

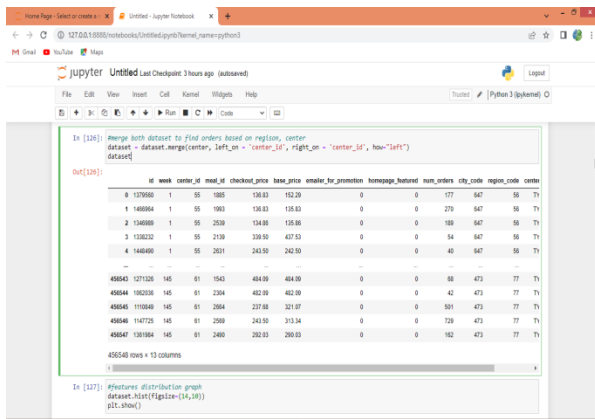
In [125]: #Read and display food_items dataset values
dataset = pd.read_csv('dataset/food_items.csv')
dataset.head()

Out[125]:
   center_id  item_name  region_code  cuisine_type  res_price
0    11    539    36    TFFL_C    2.7
1    12    580    36    TFFL_C    4.7
2    124    600    36    TFFL_C    4.0
3    30    640    34    TFFL_C    4.1
4    34    632    34    TFFL_C    3.6
...
72    81    800    35    TFFL_C    3.8
73    38    800    35    TFFL_C    3.8
74    76    814    35    TFFL_C    3.6
75    60    676    34    TFFL_C    4.1
76    81    830    35    TFFL_C    3.8

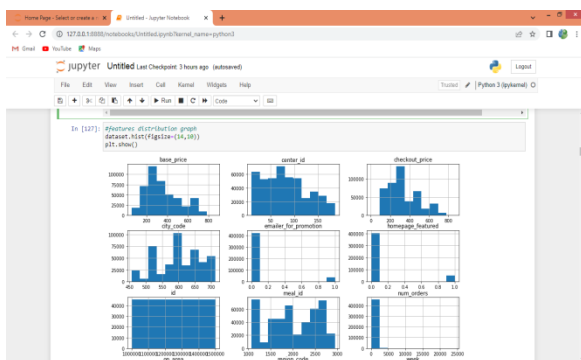
77 rows x 5 columns

In [145]: #Merge both dataset to find sales based on region, center
    
```

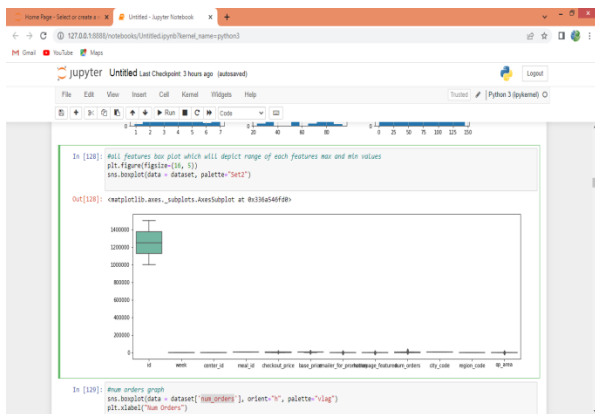
In above screen reading and displaying dataset of different centers which are handling sales and now we will merge both datasets to find sales from different Centers.



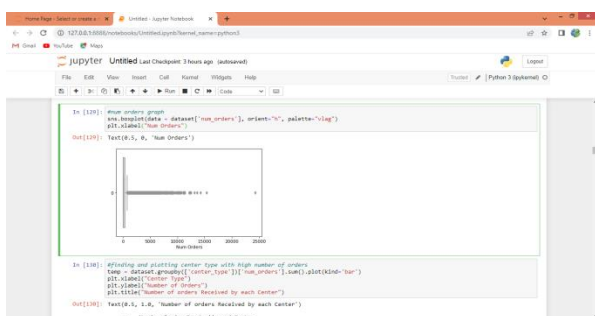
In above screen merging and display both datasets



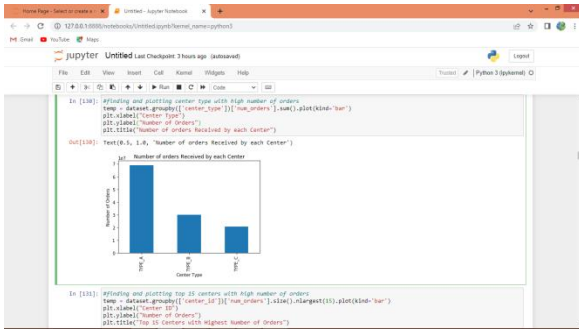
In above graph we are finding distribution of values in each column in the dataset and in graph you can see the high low values of each column in the graph



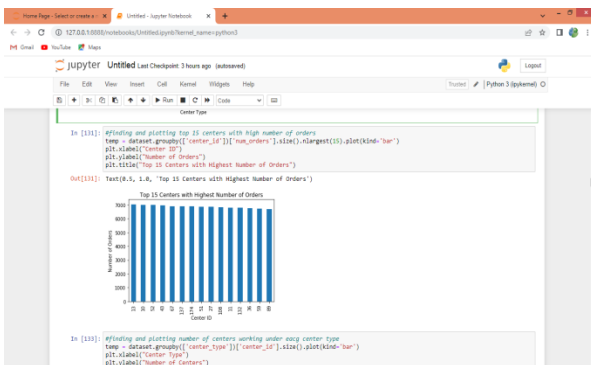
In above graph using box plot we are showing max and min range of each column values



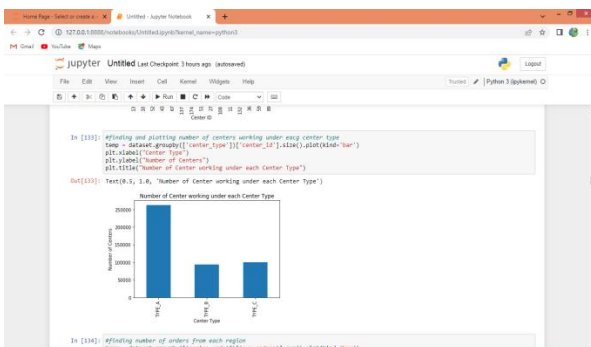
In above graph showing number of orders where x-axis represents number of orders and y-axis refers as order in each week



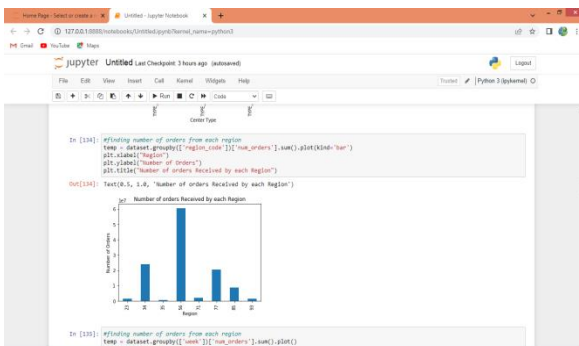
In above graph displaying number of orders from each CENTER



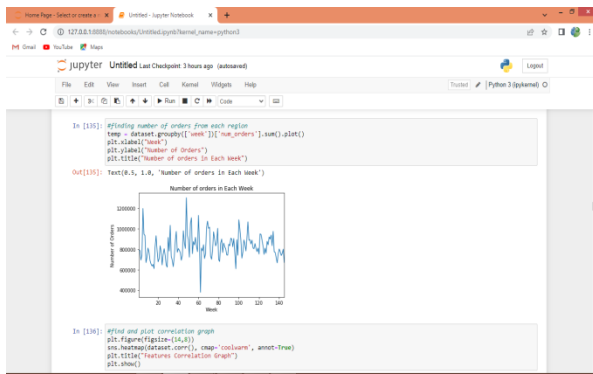
In above graph finding top 15 centers with highest number of orders where x-axis represents center_id and y-axis represents orders



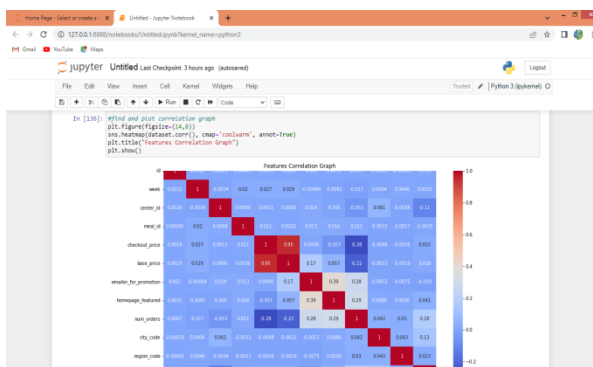
In above screen plotting graph of number center working under each center type where x-axis represents center type and y-axis represents number of centers working under that type



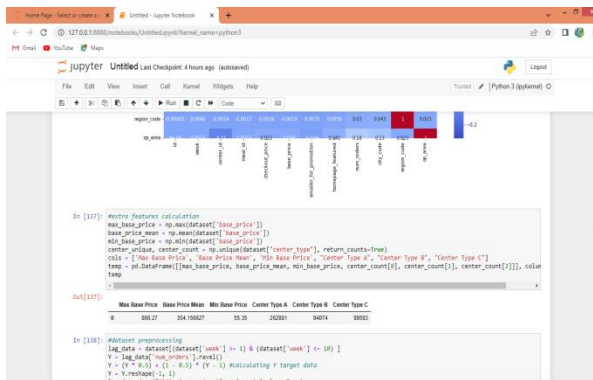
In above graph displaying number of orders received by each region where x-axis represents region code and y-axis represents orders



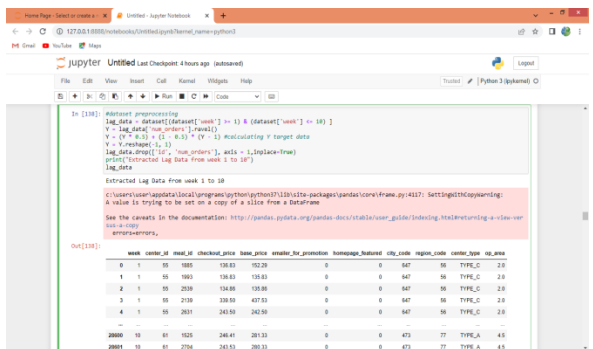
In above graph displaying number of orders received in each week where x-axis represents week and y-axis represents number of orders



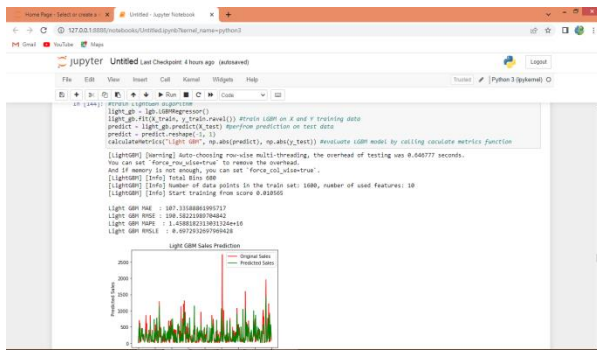
In above screen displaying features correlation graph where red box contains high correlated values which will remove out and remaining boxes contains less correlated values



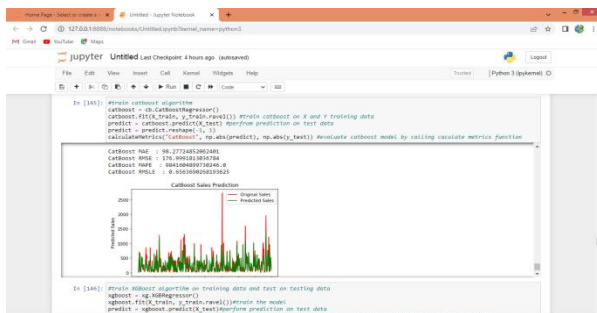
In above screen in tabular format displaying extracted New features



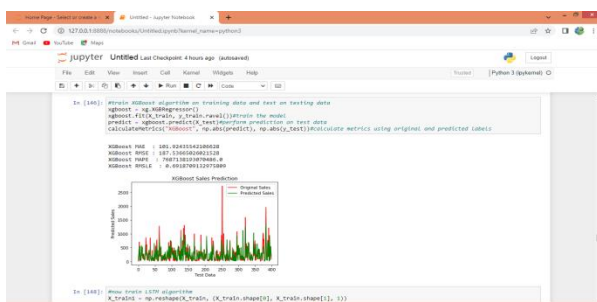
In above screen from dataset extracting LAG features and then calculating Y target using 0.5 alpha value and then displaying extracted dataset



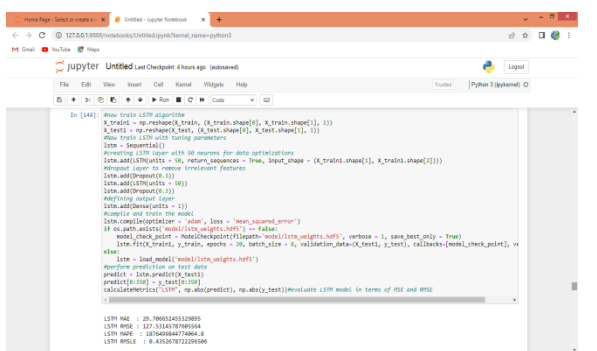
In above screen LIGHTGBM got 107 as MAE



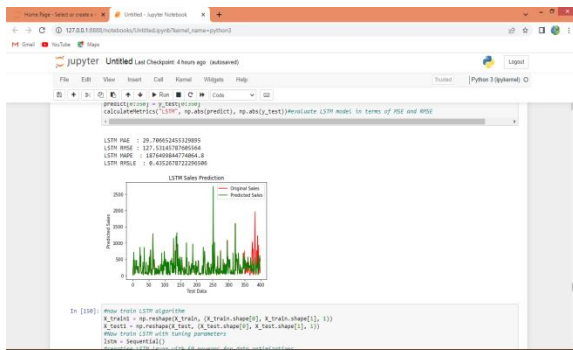
In above screen CATBOOST 98 as MAE



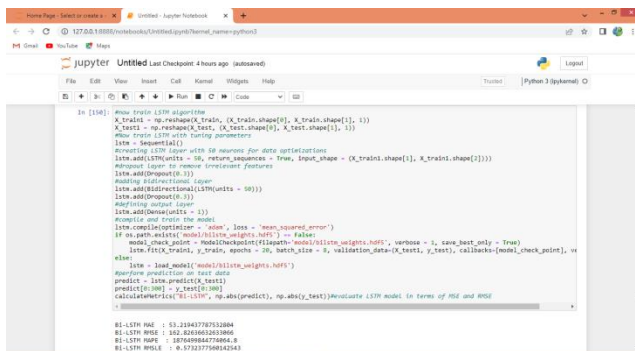
In above screen XGBOOST got 101 as MAE



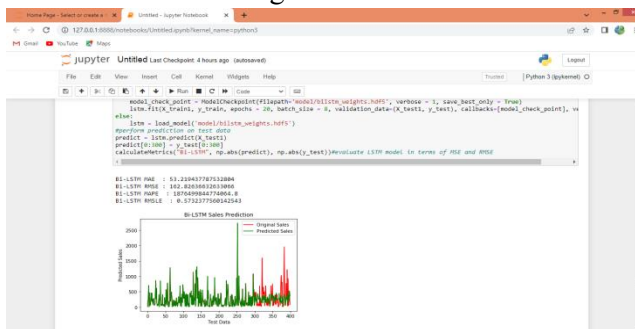
In above screen training LSTM and after executing this block will get below output



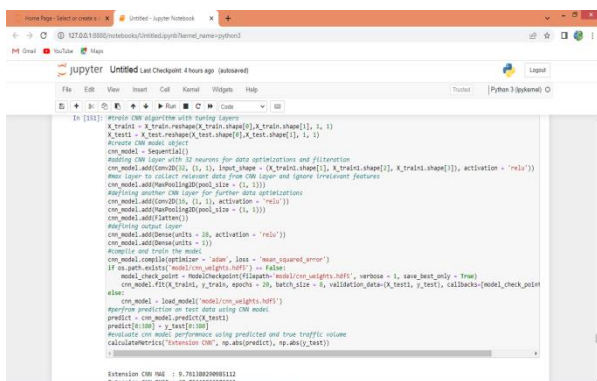
In above screen LSTM got 29 as MAE and both lines are fully overlapping with little gap in end



In above screen training BI-directional LSTM and after executing this block will get below output



In above screen BI-LSTM got 53% MAE



In above screen training extension CNN2d algorithm and after executing above block will get below output

management. By combining time series forecasting techniques with regression analysis, the framework can accurately identify demand patterns, seasonal variations, and the influence of external factors such as weather conditions, market trends, transportation costs, and consumer behavior. This integrated approach enhances forecasting accuracy and supports efficient decision-making in food supply chain operations.

The system helps suppliers, retailers, and policymakers optimize inventory management, reduce operational costs, minimize food wastage, and ensure timely product distribution. The use of machine learning and predictive analytics further improves the adaptability and reliability of the forecasting model in dynamic market environments. Overall, the proposed framework contributes to the development of intelligent, sustainable, and efficient food supply chain systems capable of meeting growing consumer demands while maintaining supply chain stability and resource optimization.

FUTURE WORK

Future improvements to the proposed system can focus on integrating advanced artificial intelligence and deep learning techniques to enhance forecasting accuracy and adaptability in dynamic supply chain environments. Models such as Long Short-Term Memory (LSTM), recurrent neural networks, and transformer-based forecasting algorithms can be implemented to better capture complex temporal patterns and long-term demand dependencies in food supply chains.

The system can also be extended to include real-time data collection from IoT devices, smart sensors, and cloud-based supply chain platforms for continuous monitoring of inventory, transportation, and storage conditions. Incorporating external factors such as climate change, economic fluctuations, social events, and consumer sentiment analysis from online platforms may further improve prediction performance and demand estimation.

Future research may also focus on developing automated decision-support systems for inventory optimization, route planning, and warehouse management using reinforcement learning and optimization algorithms. Additionally, integrating blockchain technology can improve transparency, traceability, and security within the food supply chain network.

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