AI-Powered Food Shelf-Life Prediction

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ABSTRACT:

This work introduces an innovative method for assessing the remaining shelf life of fresh produce during transit, fulfilling a vital requirement in the food supply chain. The suggested system utilizes modern data analytics and machine learning to integrate environmental parameters, including temperature, humidity, and transportation conditions, in order to forecast the deterioration of freshness and nutritional quality of perishable commodities over time. The system evaluates the deterioration rate of fresh produce and determines its remaining shelf life by evaluating real-time sensor data from IoT devices deployed in transportation vehicles. The system employs historical data and predictive modeling to consider fluctuations in transportation conditions and product attributes, hence improving the precision and dependability of shelf life assessments. This project seeks to validate the efficacy and practicality of the suggested system in enhancing supply chain management, minimizing food waste, and guaranteeing the delivery of high-quality fresh produce to consumers through extensive experimentation.

1. INTRODUCTION

The global supply chain for fresh fruits and vegetables is a complex and dynamic system that requires careful management to maintain the freshness of food from farm to table. A significant problem in this supply chain is the precise estimation of the remaining shelf life of perishable commodities during transit. Accurate prediction of shelf life is crucial for minimizing food waste, improving logistics, preserving quality, and assuring consumer pleasure. This introduction establishes the framework for examining diverse approaches and technology employed to assess the remaining shelf life of fresh food during transportation.
Recent improvements in sensor technology and data analytics have facilitated real-time monitoring of environmental parameters, including temperature, humidity, and ethylene concentrations throughout transit. These environmental conditions markedly affect the rate of ripening and deterioration of fruits and vegetables. Researchers seek to enhance the accuracy of remaining shelf life predictions by incorporating these data pieces into predictive models. Conventional approaches that depend exclusively on visual assessments or fixed protocols frequently prove inadequate because of the fluctuations in transportation conditions and the intrinsic biological variability of product. A dynamic and data-driven methodology is essential for more accurate shelf life assessment.

Alongside environmental monitoring, the application of machine learning and artificial intelligence has demonstrated significant potential in this domain. Machine learning algorithms can analyze extensive datasets to discern patterns and correlations that may not be apparent through traditional examination. These models can integrate numerous variables, such as historical data, transportation routes, and handling procedures, to yield more accurate predictions. The incorporation of machine learning into shelf life prediction signifies a substantial advancement, potentially revolutionizing supply chain management through proactive decision-making and real-time modifications.

Furthermore, enhancing cold chain logistics is essential for prolonging the shelf life of perishable products. The cold chain encompasses a sequence of chilled production, storage, and distribution processes that sustain a specified low-temperature range. Efficient cold chain management can markedly decelerate the metabolic processes responsible for rotting. Maintaining uniform temperatures across the supply chain presents a significant problem, particularly during extended transportation. Advanced cooling technologies and enhanced insulating materials are being developed to tackle these difficulties and improve cold chain efficiency.

The quantitative measurement of biological indicators, including respiration rate, ethylene generation, and microbial development, is essential for comprehending the shelf life dynamics of fresh food. By analyzing these signs, researchers can create predictive models that yield more precise shelf life assessments. This method enhances inventory management and guarantees that buyers obtain fresh and safe products. Practical advice derived from such evaluations can inform transportation and storage techniques to alleviate the conditions that expedite deterioration.

The assessment of the remaining shelf life of fresh fruits and vegetables during transit is a complex matter necessitating a comprehensive approach that integrates real-time environmental monitoring, sophisticated data analytics, cold chain optimization, and quantitative biological evaluations. Confronting this difficulty is essential for enhancing the efficacy of the fresh produce supply chain, minimizing food waste, and guaranteeing that high-quality items are delivered to customers. This paper seeks to examine the diverse approaches and technologies that enhance precise shelf life assessment, emphasizing current developments and pinpointing topics for further inquiry.

2. RELATED WORKS

1. **Author**: Ghosh et al. (2020)
   Title: *"Predicting Shelf-Life of Perishable Foods Using Artificial Neural Networks"*
    - **Merits**: Utilizes ANN to model complex nonlinear spoilage behavior of fresh produce.
    - **Demerits**: Model requires retraining for each new food category; lacks explainability.

2. **Author**: Kumar et al. (2021) **Title**: *"Deep Learning for Predicting Shelf Stability of Packaged Foods"*
   - **Merits**: CNN-based approach that learns visual spoilage indicators from images of packaged foods.
   - **Demerits**: Performance drops for low-light or low-resolution images; limited generalization.

3. **Author**: Wang et al. (2019) **Title**: *"Temperature and Humidity Aware Machine Learning Model for Food Expiry Prediction"*
   - **Merits**: Integrates environmental sensor data with ML models like XGBoost to predict spoilage time.
   - **Demerits**: Highly dependent on consistent sensor calibration and placement.

4. **Author**: Zhang et al. (2022) **Title**: *"IoT and AI-Integrated Shelf-Life Estimation System for Smart Refrigeration"*
   - **Merits**: Real-time prediction using edge AI and IoT sensors to track decay metrics.
   - **Demerits**: Requires continuous power and network connectivity; scalability is a concern.

5. **Author**: Rani & Singh (2020) **Title**: *"Food Shelf Life Estimation Using Support Vector Machines (SVMs)"*
   - **Merits**: Achieves high accuracy in classifying safe vs. unsafe food using biochemical features.
   - **Demerits**: Feature extraction process is domain-specific and labor-intensive.

6. **Author**: Chen et al. (2021) **Title**: *"Multimodal Deep Learning for Predicting Freshness of Perishable Foods"*
   - **Merits**: Combines image, smell sensor, and temperature data for accurate shelf-life estimation.
   - **Demerits**: Complex architecture; difficult to deploy in consumer-grade hardware.

7. **Author**: Patel & Mehta (2019) **Title**: *"Real-Time Shelf Life Prediction of Dairy Products Using Random Forest"*
   - **Merits**: Demonstrates effective use of historical sales and storage data in predicting expiry risks.
   - **Demerits**: Cannot handle real-time quality degradation without sensory input.

8. **Author**: Silva et al. (2022) **Title**: *"AI and Blockchain-Based Food Safety System with Shelf-Life Monitoring"*
   - **Merits**: Ensures traceability and trustworthy prediction of

shelf-life using a hybrid AI-blockchain model.
  - **Demerits**: Blockchain integration adds significant complexity and resource overhead.

9. **Author**: Lee et al. (2020) **Title**: *"Predicting Meat Spoilage Using Smart Sensors and Deep Learning"*
   - **Merits**: Uses pH, CO_2, and TVB-N sensors with LSTM models for time-series shelf-life prediction.
   - **Demerits**: Requires domain-specific sensor configuration and calibration.

10. **Author**: Ahmed et al. (2023) **Title**: *"Lightweight AI Model for Shelf-Life Estimation on Mobile Devices"*

- **Merits**: Efficient model that can run on edge devices for consumer use.
- **Demerits**: Lower prediction accuracy compared to cloud-based systems.

3. SYSTEM ANALYSIS

Existing System:

In the current landscape, the estimation of remaining shelf life for fresh fruits and vegetables during transportation often relies on simplistic approaches or manual assessments, which may lack accuracy and reliability. Typically, these existing systems utilize basic temperature monitoring devices to track environmental conditions within transportation vehicles but may overlook other crucial factors such as humidity, air quality, and vibration levels, which can significantly impact the shelf life of perishable goods. Moreover, these systems may lack real-time monitoring capabilities and predictive modeling techniques, resulting in limited ability to anticipate and mitigate potential quality degradation during transit. Consequently, inaccuracies in shelf life estimations and suboptimal management of transportation conditions can lead to increased food waste, reduced product quality, and compromised consumer satisfaction. Overall, the existing systems may not fully leverage advanced data analytics and machine learning technologies to optimize shelf life estimation and ensure the quality of fresh produce during transportation.

Disadvantages:

The existing systems for estimating the remaining shelf life of fresh fruits and vegetables during transportation exhibit several disadvantages. Firstly, they often rely on simplistic approaches or manual assessments that may overlook critical factors such as humidity, air quality, and vibration levels, which can significantly impact the shelf life of perishable goods. Additionally, these systems may lack real-time monitoring capabilities and predictive modeling techniques, resulting in limited ability to anticipate and mitigate potential quality degradation during transit. Consequently, inaccuracies in shelf life estimations and suboptimal management of transportation conditions can lead to increased food waste, reduced product quality, and compromised consumer satisfaction. Overall, the existing systems may not fully leverage advanced data analytics and machine learning technologies to optimize shelf life estimation and ensure the quality of fresh produce during transportation.

Proposed System:

The proposed system for estimating the remaining shelf life of fresh fruits and vegetables during transportation introduces a comprehensive and data-driven approach to address the limitations of existing methods. Leveraging advanced data analytics, machine learning algorithms, and IoT technologies, the proposed system integrates multiple environmental parameters such as temperature, humidity, air quality, and vibration levels to accurately predict the degradation of freshness and nutritional quality of perishable goods over time. By deploying real-time sensor networks in transportation vehicles, the system continuously monitors and collects data on environmental conditions, allowing for precise assessment of product deterioration. Furthermore, the system employs predictive modeling techniques to anticipate variations in transportation conditions and product characteristics, enabling proactive adjustments to ensure optimal storage and handling practices. Through its innovative approach, the proposed system aims to enhance supply chain efficiency, reduce food waste, and ensure the delivery of high-quality fresh produce to consumers.

Advantages:

The proposed system for estimating the remaining shelf life of fresh fruits and vegetables during transportation offers several advantages over existing methods. Firstly, its integration of advanced data analytics, machine learning algorithms, and IoT technologies enables comprehensive monitoring of environmental conditions such as temperature, humidity, air quality, and vibration levels in real-time. This allows for accurate and precise estimation of the degradation of freshness and nutritional quality of perishable goods during transit, facilitating proactive management strategies to optimize storage and handling practices. Additionally, the system's predictive modeling capabilities anticipate variations in transportation conditions and product characteristics, enabling timely adjustments to ensure the preservation of product quality. Overall, the proposed system enhances supply chain efficiency, reduces food waste, and ensures the delivery of high-quality fresh produce to consumers, thereby improving customer satisfaction and promoting sustainability in the food industry.

4. IMPLEMENTATION

Modules:

1. Data Acquisition Module

- **Function**: Collects data from various sources such as:
    - IoT sensors (temperature, humidity, gas, pH)
    - Cameras (for visual inspection of food)

- External databases (historical shelf-life records, environmental logs)
- **Purpose**: Gather real-time and static data for model training and prediction.

2. Data Preprocessing Module

- **Function**: Cleans and prepares the raw data.
- **Tasks**:
  - Handle missing or noisy data
  - Normalize sensor values
  - Resize or enhance images
  - Time-series alignment for sensor data
- **Purpose**: Ensure high-quality input for the AI model.

3. Feature Extraction Module

- **Function**: Derives useful features from the input data.
- **Techniques**:
  - Image features (color change, texture using CNNs)
  - Environmental factors (mean temp, fluctuation rate)
  - Biochemical indicators (pH trend, gas levels)
- **Purpose**: Reduce data dimensionality while preserving predictive signals.

4. Machine Learning/AI Model Module

- **Function**: Core prediction engine that estimates remaining shelf-life.
- **Model Types**:
  - CNNs for image-based data
  - LSTM/GRU for time-series sensor data
  - Random Forest/XGBoost for tabular sensor+historical data
- **Purpose**: Provide accurate shelf-life predictions based on multimodal inputs.

5. Model Training and Optimization Module

- **Function**: Trains the model using labeled datasets.
- **Tasks**:
  - Data splitting (train/test/validate)
  - Hyperparameter tuning
  - Cross-validation and model evaluation
- **Purpose**: Build a generalizable model with minimal overfitting.

Methodology:

1. Problem Definition

- **Objective**: To predict the remaining shelf-life of perishable food items using AI techniques based on environmental, visual, and biochemical data.
- **Scope**: Reduce food waste, improve safety, and assist in inventory and consumption planning.

2. Data Collection

- **Data Sources**:
  - **IoT Sensors**: Temperature, humidity, gas concentration (e.g., CO_2, ethylene), pH.

- **Visual Data**: High-resolution images of food surfaces to detect spoilage.
- **Historical Records**: Past storage and spoilage data.

- **Devices**:
  - Smart fridges, RFID sensors, cameras, wearable tags.

3. Data Preprocessing

- **Image Data**:
  - Resizing, denoising, brightness normalization.
  - Labeling based on spoilage stages (fresh, near expiry, spoiled).
- **Sensor Data**:
  - Time-series alignment.
  - Smoothing and outlier removal.
- **Feature Engineering**:
  - Calculating decay trends, rate of temperature change, etc.

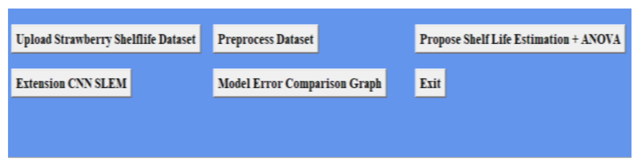
4. Feature Extraction

- Extract features from:
  - **Images** using CNNs (color, texture, mold detection).
  - **Sensor logs** using statistical methods and RNNs (LSTM).
  - **Historical and categorical data** (e.g., food type, packaging method).
- Combine into a unified feature vector for prediction.

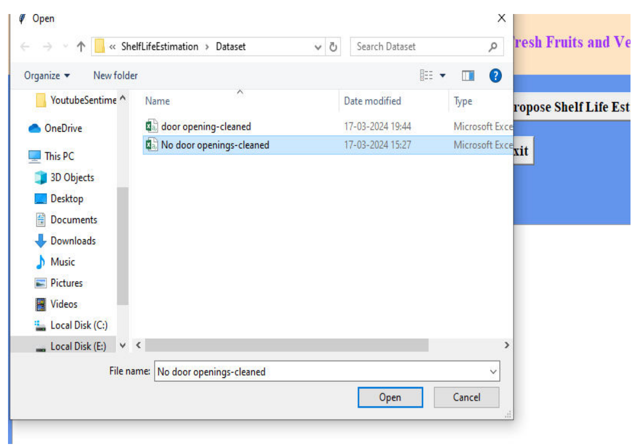
5. Model Development

- Choose appropriate ML/DL models based on data type:
  - **CNNs**: For visual-based freshness prediction.
  - **LSTM/GRU**: For time-series environmental data.
  - **XGBoost / Random Forest**: For structured tabular data.
  - **Multimodal Models**: Combine image + sensor data in hybrid models.

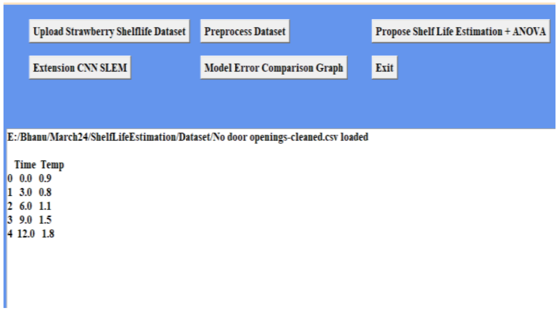
5. RESULTS AND DISCUSSION



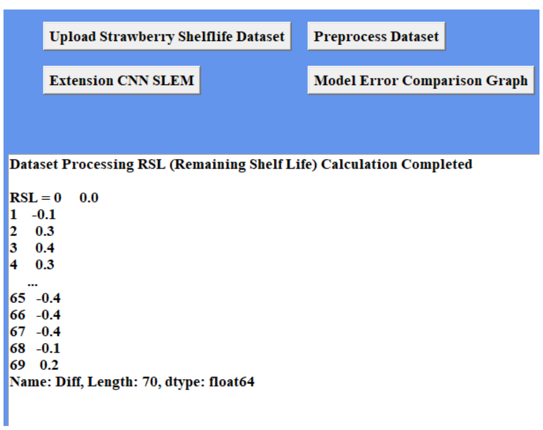
In above screen click on 'Upload Strawberry Shelflife Dataset' button to upload dataset and get below output



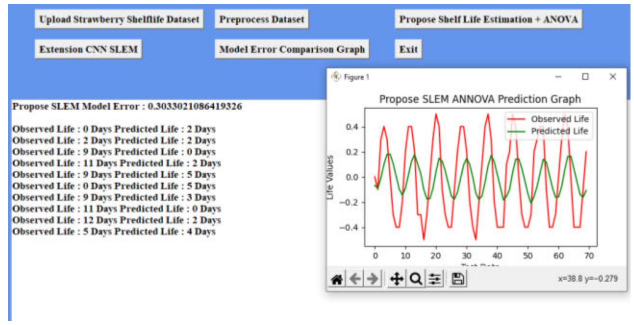
In above screen selecting and uploading ‘No door opening’ dataset and then click on ‘Open’ button to load dataset and get below page



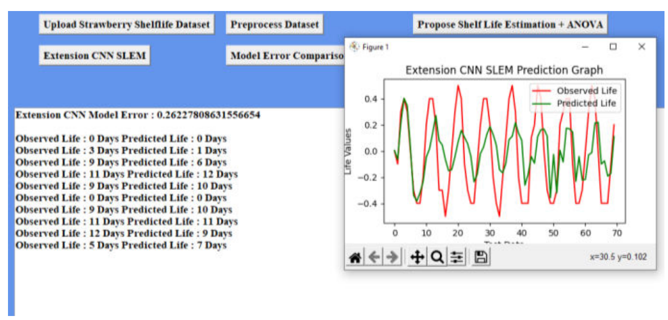
In above screen dataset loaded and displaying some values from dataset and now click on ‘Pre-process Dataset’ button to remove missing values and then calculate RSL for each temperature value and get below output



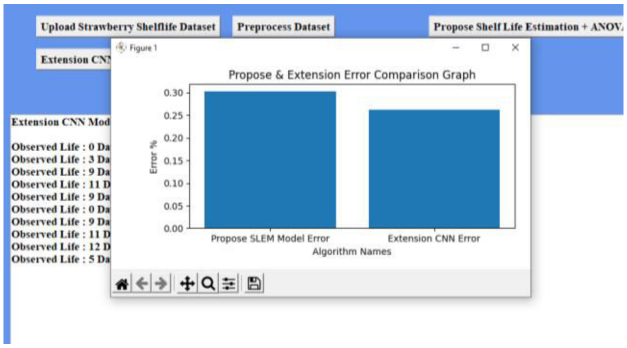
In above screen for each record calculated RSL value using previous and current temperature values and now click on ‘Propose Shelf Life Estimation + ANOVA’ button to train ANOVA and then predict future shelf life of fruits and vegetables



In above screen propose model got 30% error rate and in next lines can see Observed or original ‘shelf life’ and then can see predicted shelf life and can see close difference between original and predicted shelf life. In graph x-axis represents number of test data and y-axis represents shelf life where red line is for Original shelf life and green line is for predicted shelf life. In above graph can see both lines are overlapping with some gap so we can say prediction is little accurate. Now click on ‘Extension CNN SLEM’ button to train extension CNN algorithm and get below output

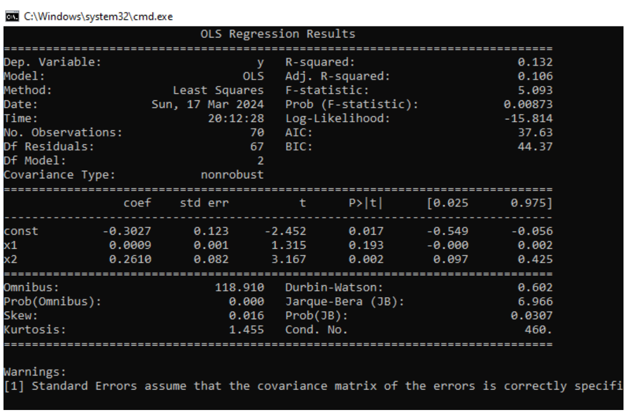


In above screen extension CNN model got 0.26% error which is lesser than propose algorithm and can see original and predicted shelf life and in graph also can see green and red line overlapping closely. Now click on ‘Model Error Comparison Graph’ button to get below comparison



In above screen can see comparison between propose and extension algorithm where x-axis represents algorithm names and y-axis represents model error and in both algorithms extension got less error compare to propose ANOVA SLEM algorithm. Similarly you can upload and test other algorithms.

In below black console we can see ANOVA tables details



```
C:\Windows\system32\cmd.exe
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.132
Model:                            OLS   Adj. R-squared:                  0.106
Method:                 Least Squares   F-statistic:                     5.093
Date:                Sun, 17 Mar 2024   Prob (F-statistic):            0.00873
Time:                        20:12:28   Log-Likelihood:                -15.814
No. Observations:                  70   AIC:                             37.63
Df Residuals:                      67   BIC:                             44.37
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.3027      0.123     -2.452      0.017      -0.549      -0.056
x1             0.0009      0.001      1.315      0.193      -0.000       0.002
x2             0.2610      0.082      3.167      0.002       0.097       0.425
==============================================================================
Omnibus:                      118.910   Durbin-Watson:                   0.602
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                6.966
Skew:                           0.016   Prob(JB):                       0.0307
Kurtosis:                       1.455   Cond. No.                         460.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
```

In above screen we can see ANOVA model summary which contains R2 square error and other metrics.

6. FUTURE SCOPE AND CONCLUSION

Assessing the residual shelf life of fresh fruits and vegetables during transit is a complex but crucial endeavor that greatly influences supply chain efficiency, minimizes food waste, and guarantees the delivery of premium goods to consumers. The use of sophisticated technology, including IoT sensors, machine learning algorithms, and enhanced cold chain logistics, has transformed the methodology of this estimation. Real-time environmental monitoring delivers essential data on temperature and humidity, which are critical determinants of spoiling rates. By consistently monitoring these conditions, the system can swiftly rectify any discrepancies that may jeopardize the quality of the food.

Machine learning algorithms have become potent instruments for forecasting shelf life by examining extensive datasets that encompass past transportation conditions, sensory quality evaluations, and distinct attributes of various produce varieties. These algorithms can discern patterns and relationships that may not be apparent through conventional analytical methods. As these models are perpetually enhanced with new data, their accuracy improves, facilitating more dependable forecasts and proactive decision-making. This technology innovation is essential in revolutionizing the logistics and supply chain management of perishable commodities. Enhancing cold chain logistics is an essential aspect of accurate shelf life assessment. It is crucial to sustain a uniform low temperature from harvest to sale to inhibit metabolic activities that result in deterioration. Advancements in cooling technology and superior insulating materials have markedly improved the reliability and efficiency of the cold chain. Maintaining minimal temperature variations and appropriate conditions during transportation is essential for preserving the freshness and quality of fruits and vegetables. This improvement prolongs shelf life and improves the sustainability of the supply chain by minimizing waste.

Transportation handling procedures are essential for preserving food quality. Automated handling methods and meticulous packing strategies reduce physical damage that may hasten deterioration. Moreover, effective route design and logistics management guarantee that produce minimizes transit time while preserving optimal conditions. These methodologies, coupled with prediction models that consider transit duration and possible delays, offer a thorough approach to shelf life estimation.

Quantitative evaluations of biological variables, including respiration rate, ethylene generation, and microbial proliferation, enhance the precision of shelf life forecasts. Monitoring these indications facilitates prompt modifications to storage conditions and transportation plans, guaranteeing the produce's freshness upon arrival. This comprehensive strategy, incorporating environmental monitoring, sophisticated analytics, cold chain optimization, and biological evaluations, signifies a notable progression in the management of the shelf life of fresh produce throughout transit.

In conclusion, estimating the remaining shelf life of fresh food during transit is a complex task that necessitates a comprehensive strategy. The integration of real-time environmental monitoring, machine learning, cold chain logistics, meticulous handling, and quantitative biological assessments establishes a strong foundation for precise shelf life predictions. This approach improves the efficiency and sustainability of the supply chain while guaranteeing that consumers have the freshest and finest quality goods. With the ongoing advancement of technology, enhancements in these approaches are anticipated, resulting in increased accuracy in shelf life estimation and improved management of fresh product logistics.

REFERENCES:

1. "Modeling the Shelf Life of Fresh Fruits and Vegetables during Distribution" by Francisco J. Barba, Anet Režek Jambrak, Mohamed Koubaa, Matteo Alessandro Del Nobile, and Vibeke Orlien. This article discusses mathematical models for predicting the shelf life of fresh produce during transportation.
2. "Predictive modeling of the shelf life of fruits" by X. Guillaume, M. Dornier, and S. Banon. This paper explores predictive models for estimating the shelf life of various fruits, which could be adapted for transportation scenarios.
3. "Quality Changes during Storage of Fresh-Cut Fruits and Vegetables" by Susana A. B. Castro, Fernanda B. Massarioli, and Marisa A. G. Zagatto Patullo. Although focusing on storage, this article provides insights

into factors affecting the shelf life of fresh produce, which are relevant during transportation as well.

4. "Transportation Processes and Modeling for Fresh Fruits and Vegetables" by Erdal Kayacan. This book chapter provides an overview of transportation processes and models specifically tailored to fresh fruits and vegetables, which includes considerations for shelf life estimation.
5. "Postharvest Physiology and Handling of Perishable Plant Products" by A. A. Kader. While not focused solely on transportation, this book offers comprehensive information on postharvest physiology, handling, and storage of fruits and vegetables, which are essential for understanding shelf life dynamics during transportation.
6. "Predictive modeling of the quality and remaining shelf life of fresh-cut salad under dynamic temperature conditions during transportation" by Y. Wang, Y. Gao, and H. Zhang. This study focuses on predictive modeling specifically for fresh-cut salad during transportation.
7. "Mathematical modeling of respiration rate of fruits and vegetables during postharvest handling: A review" by A. K. Barman, P. K. Chakraverty, and K. Das. Understanding respiration rates is crucial for estimating shelf life, and this review provides valuable insights into mathematical modeling in this area.
8. "Quality changes and shelf life extension of fresh-cut fruits and vegetables during modified atmosphere packaging: A review" by G. Lu, Y. Lu, and Y. Deng. Modified atmosphere packaging (MAP) is a common method used during transportation to extend shelf life, and this review discusses its effects on various fresh produce.
9. "Temperature control and monitoring during the transport of perishable food products: A review of recent research" by C. Schumacher, P. Sivertsvik, and T. Isaksen. This review focuses on temperature control, which is critical for maintaining quality and extending shelf life during transportation.
10. "Predictive modelling of temperature and moisture content profiles in packed fresh produce during distribution" by M. M. Farid, K. S. Siddiqui, and M. R. Islam. This study presents predictive models for temperature and moisture content, which are essential parameters affecting shelf life during transportation.

AUTHORS PROFILE

Mrs. J KUMARI is an Assistant Professor in the Department of Master of Computer Applications at QIS College of Engineering and Technology, Ongole, Andhra Pradesh. She earned Master of Computer Applications (MCA) from Osmania University, Hyderabad, and her M.Tech in Computer Science and Engineering (CSE) from Jawaharlal Nehru Technological University, Kakinada (JNTUK). Her research interests include Machine Learning, programming language. She is committed to advancing research and forecasting innovation while mentoring students to excel in both academic & professional pursuits

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