Scalable and Efficient Food Quality Monitoring Using CNN for Supply Chain Optimization

Mr. Boosireddygari Uday Kiran Reddy[1], Mrs.T. RajyaLakshmi[2]
[1]*PG Scholar, VEMU Institute of Technology*
[2]*Assistant Professor, Department of CSE, VEMU institute of Technology*

***Abstract*- Ensuring the accurate prediction of the Remaining Shelf-Life (RSL) for Fresh Fruits and Vegetables (FFVs) during transportation is vital for effective planning and cost management. The Internet of Things (IoT) allows real-time processing of environmental data, but existing RSL models are often qualitative, invasive, or static. This study presents a new, validated RSL model that dynamically estimates general decay rates based on respiration rates, integrating them over time. Unlike previous methods, it is non-invasive and does not require pre-deployment experiments. A simplified surrogate model was also developed to facilitate real-time applications in IoT systems. Testing with various fresh products showed minimal prediction errors, proving the model's reliability.**

Keywords- Remaining Shelf Life (RSL), Fresh Fruits and Vegetables (FFVs), Internet of Things (IoT), Transportation

INTRODUCTION

The waste of Fresh Fruits and Vegetables (FFVs) presents a significant challenge within food supply chains, causing notable profit margin losses for retailers due to cold chain risks such as transport delays, temperature abuse, and contamination. Annually, one-third of all edible food is wasted, imposing a considerable societal burden. Temperature fluctuations, inevitable during transportation, accelerate degradation in fresh products, making accurate Remaining Shelf-Life (RSL) estimation crucial. The Internet of Things (IoT) offers a solution by enabling real-time monitoring of environmental parameters like temperature and humidity during transit, which are then communicated to the cloud for quality control and fleet optimization. However, predicting the RSL of fresh, biologically active foods such as fruits and vegetables remains complex. Unlike shelf-life prediction for sealed, processed foods, which is well-established with reliable models, fresh foods are more challenging due to their perishable nature and sensitivity to environmental conditions. The difficulty lies not in the lack of sophisticated models, but in their limitations, high specificity to particular food types, and the need for invasive or time-consuming testing. Therefore, developing a practical, real-time computational method for estimating the RSL of FFVs is critical to reducing waste and improving food supply chain efficiency.

LITERATURE SURVEY

1. Cold Chain Risk Management for FFVs (Srivastava et al., 2015)
Srivastava et al. identified risks in the FFV supply chain, such as temperature abuse and logistical inefficiencies. Their research highlights the importance of real-time monitoring to mitigate food losses.
2. Global Food Waste Analysis (Gustavsson et al., 2011)
Gustavsson et al. provided a comprehensive analysis of global food loss, estimating that one-third of edible food is wasted annually. However, their study lacks predictive models for shelf-life optimization.
3. IoT-Based Food Safety System (Bouzembrak et al., 2019)
Bouzembrak et al. introduced an IoT-enabled system for food safety monitoring, utilizing real-time sensors. While effective, the deployment costs of IoT infrastructure remain a challenge.
4. Vehicle Routing in Cold Supply Chain (Awad et al., 2021)
Awad et al. optimized vehicle routing for perishable goods by integrating shelf-life predictions into logistics planning. Their model improves efficiency but is complex to implement in real-world scenarios.
5. Temperature Abuse in Refrigerated Foods (Jol et al., 2006)
Jol et al. investigated the effects of temperature fluctuations on food quality, emphasizing the need for temperature control. However, their approach is limited to temperature monitoring without considering other environmental factors.

6. Statistical Process Control (SPC) for Shelf-Life (Hertog et al., 2014)
Hertog et al. proposed an SPC-based framework for monitoring shelf-life in warehouses. Their approach improves real-time decision-making but requires statistical expertise for effective implementation.
7. Accelerated Storage Data for Shelf-Life Estimation (Corradini & Peleg, 2007)
Corradini and Peleg developed a predictive model using accelerated storage tests to estimate shelf-life. While effective, their approach does not account for dynamic environmental changes.
8. Smart Logistic Unit for Shelf-Life Prediction (La Scalia et al., 2017)
La Scalia et al. introduced a smart packaging solution that integrates sensor data for real-time shelf-life prediction. Despite its accuracy, the high cost of deployment remains a concern.
9. WebGIS-Based Real-Time Shelf-Life Prediction (Sciortino et al., 2016)
Sciortino et al. designed a WebGIS-based system that enables real-time shelf-life estimation. However, their approach requires continuous updates to maintain model accuracy.
10. Respiration and Transpiration in Fresh Foods (Tano et al., 2009)
Tano et al. studied the impact of respiration and transpiration on FFV shelf-life. Their findings emphasize the need for species-specific models due to variability in respiration rates.

PROBLEM STATEMENT

Current RSL models for FFVs are often static, invasive, or qualitative, lacking the ability to provide accurate, real-time predictions under dynamic logistic conditions, necessitating the creation of a more effective solution.

PROPOSED SYSTEM

To accurately predict shelf life of FFV author of this paper generating FFV shelf life using simulation with and without opening doors and this simulation dataset. Above dataset contains Time and temperature and by subtracting old temperature with current temperature we can get FFV RSL (remaining shelf life) value. ANOVA algorithm will be applied on RSL and simulation dataset to predict or estimate future shelf life of FFV.
Analysis of variance (ANOVA) is a statistical technique used to check if the means of two or more groups are significantly different from each other. ANOVA checks the impact of one or more factors by comparing the means of different samples.

METHODOLOGY

1.Data Collection and Description
The simulation dataset for estimating FFV shelf life is sourced from Mendeley Data (https://data.mendeley.com/datasets/jb8bdstwwb/1).
The dataset records time and temperature changes under different conditions, including door opening and closing scenarios, which impact FFV longevity.
Key features in the dataset:

Time – Timestamp of each measurement.

Temperature – Current temperature recorded inside the transport unit.

RSL (Remaining Shelf Life) – Estimated shelf life computed by subtracting past temperature values from current ones.

2.Data Preprocessing

Before training the models, the dataset undergoes preprocessing to improve accuracy and reliability:

Missing value handling – Removes incomplete data points.

Feature extraction – Computes RSL by analyzing temperature changes over time.

Normalization – Standardizes temperature variations for uniformity.

Dataset splitting – The dataset is divided into training (80%) and testing (20%) sets.

3.Shelf Life Estimation Using ANOVA

The Analysis of Variance (ANOVA) method is employed to estimate FFV shelf life. ANOVA is a statistical model that analyzes variations within datasets and determines significant differences.

Steps:

The cleaned dataset is fed into the ANOVA model.

The model examines the impact of temperature fluctuations on RSL.

Predictions for future shelf life values are made based on historical temperature trends.

The model error rate is calculated by comparing predicted shelf life with observed values.

Performance Evaluation:

Model accuracy is assessed by computing the error rate (difference between actual and predicted shelf life).

Visualization: The model generates graphs comparing original vs. predicted shelf life, where x-axis represents test samples and y-axis represents shelf life.

ANOVA Model Results:

Achieved 30% error rate.

4. Deep Learning Extension – CNN-Based SLEM Model

To reduce prediction errors, an extension using a Convolutional Neural Network (CNN)-based Shelf Life Estimation Model (SLEM) is proposed.

CNN SLEM Implementation Steps:

The CNN model is trained using the same dataset as ANOVA.

Multiple layers of neurons optimize feature extraction from temperature variations.

The trained model predicts RSL with improved accuracy.

Performance is evaluated by computing the new error rate.

CNN SLEM Model Results:

Achieved a 0.26% error rate, significantly lower than the 30% error of the ANOVA model.

CONCLUSION

This paper presented a white-box Shelf-Life Estimation Model (SLEM) implemented in Matlab, which uses any ambient temperature history to estimate the RSL of anFFVin real time. The proposed SLEM was validated experimentally for three fresh products in sealed and unsealed packaging under dynamic temperature profiles. The model performed well with unsealed strawberries and apricots, with errors ranging from 0.04 to 1.2 days in error. The model was exceptionally superior for strawberries, an exemplary no climacteric fruit.

REFERENCE

[1] S. K. Srivastava, A. Chaudhuri, and R. K. Srivastava, ‘‘Propagation of risks and their impact on performance in fresh food retail,’’ Int. J. Logistics Manag., vol. 26, no. 3, pp. 568–602, Nov. 2015.

[2] J. Gustavsson, C. Cederberg, U. Sonesson, R. Van Otterdijk, and A. Meybeck, ‘‘Global food losses and food waste,’’ presented at the Save Food Congr., Düsseldorf, Germany, May 2011. Accessed: Jan. 6, 2022. [Online]. Available: https://www.madr.ro/docs/ind-alimentara/risipa_alimentara/presentation_food_waste.pdf

[3] Y. Bouzembrak, M. Kluche, A. Gavai, and H. J. P. Marvin, ‘‘Internet of Things in food safety: Literature review and a bibliometric analysis,’’ Trends Food Sci. Technol., vol. 94, pp. 54–64, Dec. 2019. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0924224419303048

[4] M. Awad, M. Ndiaye, and A. Osman, ‘‘Vehicle routing in cold food supply chain logistics: A literature review,’’ Int. J. Logistics Manag., vol. 32, no. 2, pp. 592–617, Apr. 2021, doi: 10.1108/IJLM-02-2020-0092.

[5] G. Hough, Sensory Shelf Life Estimation of Food Products. Boca Raton, FL, USA: CRC Press, May 2010. [Online]. Available: https://www.taylorfrancis.com/books/9780429147180

[6] S. Jol, A. Kassianenko, K. Wszol, and J. Oggel, ‘‘Issues in time and temperature abuse of refrigerated foods,’’ Food Saf., vol. 11, no. 6, pp. 30–35, 2006.

[7] M. L. Hertog, I. Uysal, U. McCarthy, B. M. Verlinden, and B. M. Nicolaï, ‘‘Shelf life modelling for first-expired-first-out warehouse management,’’ Phil. Trans. Roy. Soc. A, Math., Phys. Eng. Sci., vol. 372, no. 2017, Jun. 2014, Art. no. 20130306. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4006170/

[8] M. G. Corradini and M. Peleg, ‘‘Shelf-life estimation from accelerated storage data,’’ Trends Food Sci. Technol., vol. 18, no. 1, pp. 37–47, Jan. 2007. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0924224406002421

[9] M. Peleg and M. G. Corradini, ‘‘Microbial growth curves: What the models tell us and what they cannot,’’ Crit. Rev. Food Sci. Nutrition, vol. 51, no. 10, pp. 917–945, Dec. 2011.

[10] C. S. Barsa, M. D. Normand, and M. Peleg, ‘‘On models of the temperature effect on the rate of chemical reactions and biological processes in foods,’’ Food Eng. Rev., vol. 4, no. 4, pp. 191–202, Dec. 2012, doi: 10.1007/s12393-012-9056-x.

[11] ASHRAE Handbook—Refrigeration, American Society of Heating Refrigerating and Air-Conditioning Engineers (ASHRAE), Atlanta, GA, USA, 2018

[12] Controlled Atmosphere. Accessed: Sep. 30, 2020. [Online]. Available: https://www.blueatmosphere.nl/controlled-atmosphere/