

AI-Based Dynamic Shelf-Life Prediction System for Packaged Foods

**B. Ramyasri¹, M. Sai Akshita², K. Mokshitha³,
G. Keerthana⁴, K. Vyshnavi⁵**

¹Assistant Professor, ^{2,3,4,5}B. Tech 3rd year students
^{1,2,3,4,5}CSE(AI&ML), Vignan's Institute of Management and Technology for Women, Kondapur,
Ghatkesar, Hyderabad-501301

Abstract:

Food wastage is an inclining problem food supply chains and households, majorly because expiry dates printed on packaging are fixed and they do not consider the actual storage conditions [1],[9]. Temperature and humidity directly impact on how fast the food spoils, yet most of the people rely on the printed date. This study introduces FreshSense, an AI-Based dynamic shelf-life prediction system that uses real-time sensor data to estimate the actual remaining shelf-life of packaged food items. An Arduino Uno is linked to a DHT22 sensor to continuously track humidity and temperature. That collected data is then fed into a Random Forest Regression model trained on food-specific baseline data. Predictions are shown on a real-time web dashboard that also allows mobile access and sets off visual, audio and email warnings. The system showed excellent predicted accuracy in a range of storage settings, with an R2 score of 0.964.

Keywords: Random Forest Regression, FreshSense, DHT22, Arduino Uno, Food specific base-line, Shelf-life prediction.

I. INTRODUCTION:

Every day, large quantities of food are wasted simply because of their printed expiry date has crossed, even when the food is still safe to consume. Relatively, food that has been stored in poor conditions may spoil even before the stated date[1],[9]The central problem is that expiry dates are calculated assuming optimal environment, which rarely reflect the reality.

Temperature is one of the most significant factors affecting food shelf life[6].Products stored at 30°C decay far more quickly than those stored at 4°C. Humidity is another crucial component; too much promotes the formation of mould, while too little causes drying and rapid rotting. Traditional food storage systems do not provide any mechanism to justify these real- time variations.

With the rise of affordable IoT sensors and accessible machine learning libraries, it is now possible to build low-cost systems that dynamically predict shelf-life based on actual storage conditions[5],[7],[10]This project, FreshSense, addresses this gap by combining hardware sensing with machine learning and a user-friendly web interface. The system is designed to be practical for warehouses, supermarkets, food delivery companies, cold storage units, grocery stores and households that need a simple but reliable way to monitor perishable goods.

II. RELATED WORK:

Numerous studies have investigated the application of machine learning sensors and in food quality monitoring. For cold chain monitoring in logistics, IoT-based systems with temperature and humidity



sensors have been suggested. Research has shown that the Random forest models perform well in regression tasks involving environmental parameters due to their ability to handle non-linear relationships and multiple input features without requiring extensive data preprocessing[5].

In order to obtain accurate forecasts, studies on food rotting prediction have emphasized the significance of integrating baseline shelf-life data with current environmental variables[6],[8] However, most existing solutions need cloud access, are too expensive for widespread use, or lack a real-time user interface. In order to overcome these constraints, our solution offers a fully functional interactive dashboard with alert capabilities while operating just locally and not relying on the cloud.

III. PROPOSED SYSTEM:

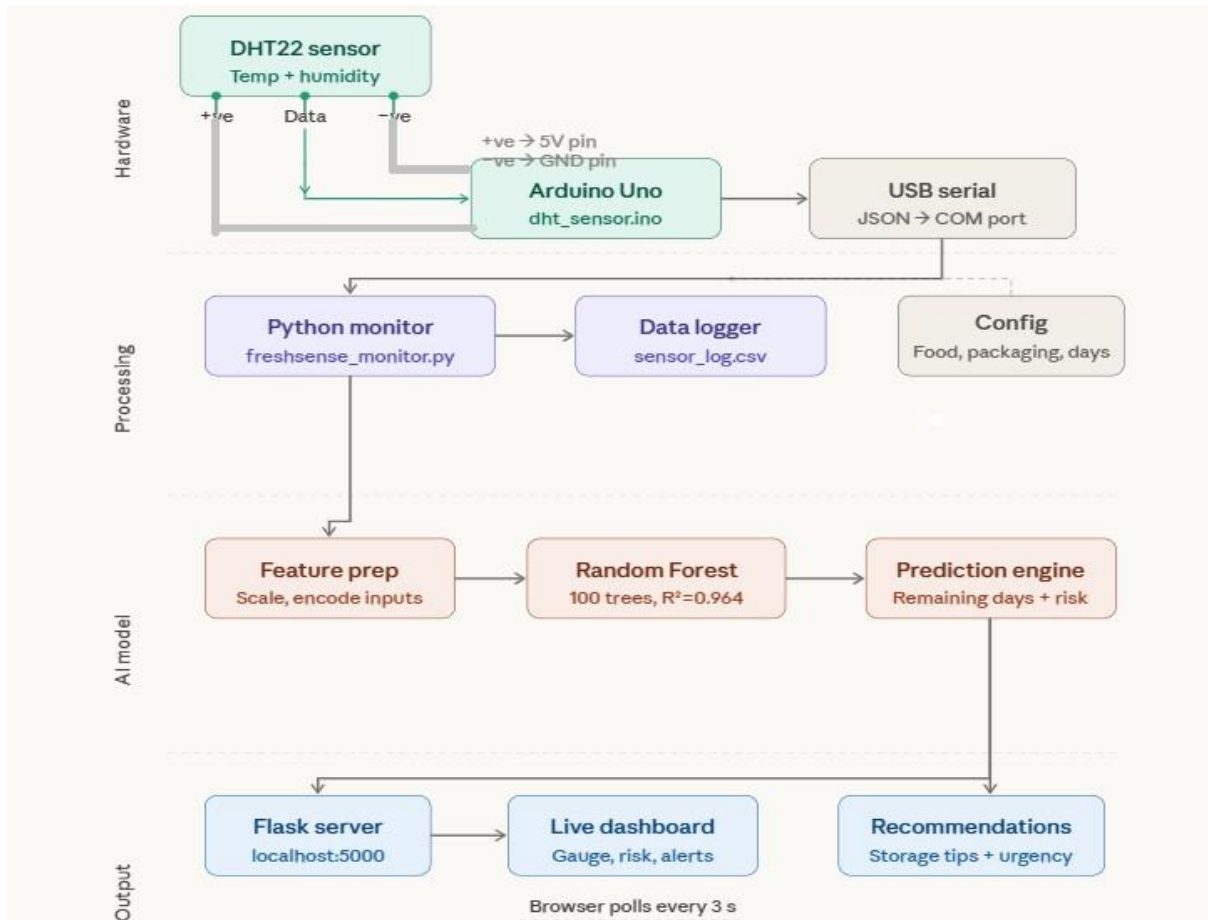
A. Overview

FreshSense is an IoT integrated, locally hosted shelf-life prediction system[7] For every five seconds, an Arduino Uno- connected DHT22 temperature and humidity sensor records ambient data, which is then sent via USB serial to a python backend. A Flask web application provides predictions from a trained Random Forest Regression model that operates on the backend. A browser-based dashboard that is compatible with desktop and mobile devices allows users to engage with the system.

The technology allows for the simultaneous monitoring of several food items[8]. The user inputs the food type, packaging type, manufacturing date, expiration date, and number of days that each product has been stored. Based on the current sensor measurements, the AI model then forecasts the actual remaining shelf-life. The system initiates a visual alert, a beep sound, a speech announcement, and an email alert to the configured address if the prediction falls below half of the products overall shelf-life length.

B. System Architecture

There are four layers in the overall architecture. The Arduino Uno and DHT22 sensor, which continuously record and send temperature and humidity values in JSON format via serial connection, make up the hardware layer. The backend layer is a Python application that controls email notifications, model inference, serial reading, and web interface serving via Flask. For every three seconds, the frontend layer-A browser-based dashboard composed with HTML, CSS, and JavaScript-polls the backend to display the information in real time. Visual alerts, spoken announcements via the Web Speech API, audio beeps via the Web Audio API, and automated Gmail messages via SMTP are all managed by the alert layer.



C. Data Collection Module:

Temperature and humidity are among the environmental data that the system continuously gathers from the DHT22 sensor via the Arduino. This data is saved in a common data structure in the backend after being received via serial communication in JSON format.

Users manually enter product-related data, such as food kind, packaging type, manufacturing date, expiration date, and number of days stored through the web dashboard, in addition to sensor data. The entire dataset needed for prediction is created by combining real-time and user-defined data. To guarantee consistency, the gathered data is dynamically updated, formatted, and evaluated. Additionally, it is recorded in a CSV file for future analysis and historical tracking. This module guarantees that the prediction model always has access to correct and current data.

IV. IMPLEMENTATION DETAILS:

A. Development Framework

Front-end, back-end, and machine learning technologies were used to develop the FreshSense AI-Shelf-Life Prediction System. The user interface is constructed with HTML, CSS, and JavaScript to produce an interactive dashboard for real-time monitoring. A Random Forest Regression model is used by the Python back-end to forecast shelf life depending on temperature, humidity, length of storage, food type, and packaging[5].

An Arduino receives sensor data via serial transmission from a DHT22 sensor. The Flask framework connects the machine learning model to the web interface and efficiently handles API calls.

B. UI/UX Personalization and Exploration Logic:

The system's user-friendly dashboard allows users to add items and monitor their conditions. It displays real-time sensor measurements, risk levels (Low to Critical), and expected shelf life.

Users may promptly recognize important circumstances and take appropriate action with the aid of color-coded notifications, progress indicators, and dynamic recommendations. Notifications and voice alerts improve responsiveness and usability even further.

C. Cloud-Based Deployment and Infrastructure:

The system can be extended to cloud platforms for scalability, centralized data storage, and remote access[7],[10]By allowing users to monitor multiple storage units, preserve records, and receive alerts from any place, cloud deployment improves system accessibility and efficiency.

D. Data Security and Access Management:

To guarantee data integrity, fundamental security procedures like input validation and restricted access are put in place. Access control guarantees that only authorized users can alter system data, and secure communication techniques can be incorporated to safeguard data transmission.

E. Testing and Performance Evaluation:

The correctness, dependability, and real-time performance of the system are tested. The model uses metrics like R2, MAE, and RMSE to attain excellent prediction accuracy. Functional and usability testing verifies efficient real-time alert creation and seamless device functioning.

V. MODULE SPLIT-UP:

A. Sensor and Hardware Module

Purpose: The purpose of this system is that it gets the temperature and humidity from the place where things are stored right now. It is really good, at capturing the real-time temperature and humidity from the storage environment.

Functionality:

- Every five seconds, the DHT22 sensor records the temperature and humidity of the storage space and transmits the information to the Arduino Uno for processing.
- After that, the Arduino Uno transforms this data into JSON format and sends it over a serial connection at a baud rate of 9600.
- The shared data store is updated after the JSON is parsed by the python serial reader.

B. AI Prediction Module

Purpose: FreshSense uses sensor data and product details to forecast the food's remaining shelf-life

Functionality:

- A Random Forest Regressor is trained using 1000 samples. There are 100 trees in this regressor with a maximum depth of 10.
- Training data is made using food-specific baseline shelf-life values, packaging factors, temperature and humidity penalty.
- The formula used is:

Shelf Life = (Base Life * Packaging factor) - days stored - (Temperature-4) * 0.3 - |Humidity-80| * 0.05

- Before training, Label encoding and standard scaling are applied.

- Model performance:
 $R^2 = 0.964$, MAF=1.09 days, RMSE=1.47 days.

C. Web Dashboard Module

Purpose: For monitoring and control, it offers an interactive real-time interface.

Functionality:

- Uses color-coded indicators to show current temperature and humidity data.
- Shows AI prediction as a circular gauge per product with risk level (Critical, High, Medium, Low).
- Hosts a product monitoring table where users enter food details and receive live predictions.
- Displays expiry progress bar, storage recommendations, live sensor trend chart, and reading history.
- Fully responsive layout that adapts to mobile screens.

D. Alert Module

Purpose: It Alerts people when the shelf-life falls below acceptable limits.

Functionality:

- Visual alarm banner appears when prediction falls below half the total shelf-life duration.
- Audio beep plays for every 5 seconds during an active alarm.
- Voice announcement reads out the product name, predicted days remaining and storage recommendations.
- Email alert sent via Gmail SMTP with product details, temperature, humidity and recommended actions.
- Email cooldown of one hour per product to avoid repeated alerts.

VI. ALGORITHM

Step 1: Initialize system

Start the Python application. Load and train the Random Forest model on synthetic food shelf- life data.

Step 2: Connect to Sensor

The COM port detects Arduino automatically. Establish a serial 9600 baud connection.

Step 3: Examine sensor data

Measure the DHT22's temperature and humidity every five seconds using an Arduino. A serial stream can be used to parse JSON.

Step 4: Update Dashboard

Browser polls/API endpoint every 3 seconds. Update temperature card, humidity card, sparkline chart, and history table.

Step 5: Predict Shelf-life

For each product with food type, packaging, days stored, manufacturing date, and expiry date entered: apply label encoding and scaling, run Random Forest prediction, compute risk level.

Step 6: Check Alert Conditions

If predicted days < half of total shelf-life duration: trigger alarm banner, beep, voice announcement, and send email alert. Apply one-hour cooldown per product.

Step 7: Log data

Add each reading to the list of readings-temperature, humidity, and date in a CSV file

Step 8: Repeat

Go back to step 3 for ongoing observation.

VII. PSEUDO CODE:

BEGIN

INITIALIZE system and load ML model CONNECT sensor

WHILE system is running DO READ temperature, humidity

GET user inputs (food, packaging, days, mfg, exp)

PREPROCESS inputs predicted_life \leftarrow model prediction total_life \leftarrow exp - mfg

threshold \leftarrow total_life / 2

IF current_date > exp THEN SEND "Expired" alert

ELSE IF predicted_life < threshold THEN SEND "Warning" alert

ELSE IF predicted_life \leq 1 THEN SEND "Critical" alert

END IF

DISPLAY results on dashboard END WHILE

END

VIII. RESULTS:

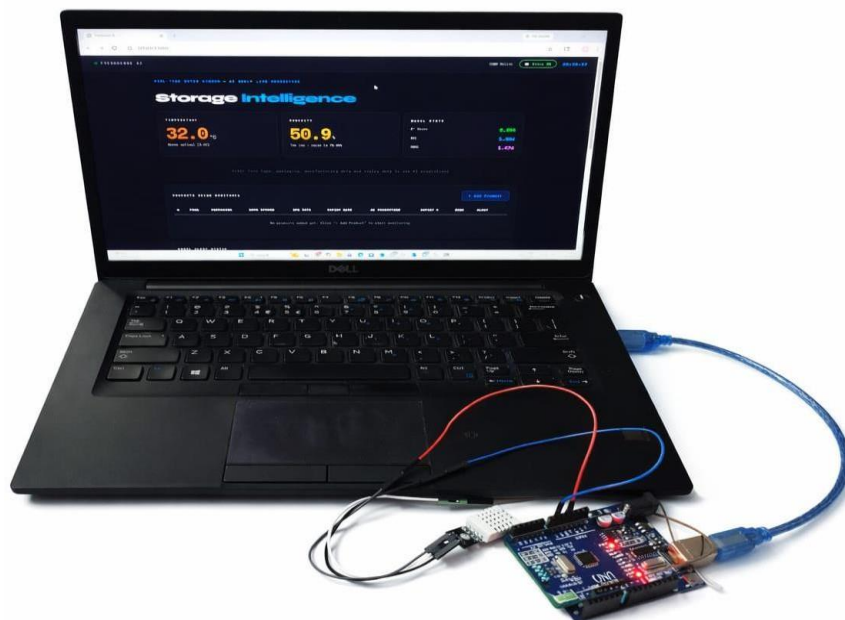


Fig.1 Hardware of the system

Figure.1 The image shows the real-time implementation of the FreshSense system, where an Arduino Uno connected with a DHT22 sensor collects temperature and humidity data. The sensor data is transmitted to a laptop via USB and processed using the machine learning model for shelf-life prediction. The dashboard displayed on the screen visualizes live environmental conditions and predicted shelf-life with alert indicators.

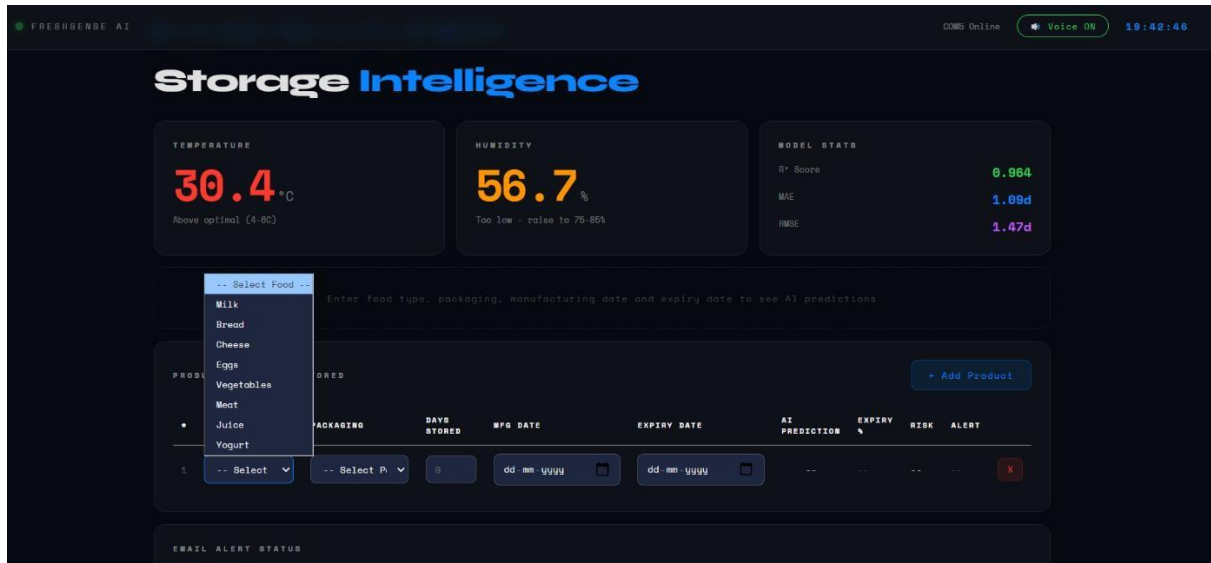


Fig.2. Main Dashboard

Figure.2. shows the storage environment's temperature, humidity, and model performance indicators in real time. Users can browse AI-based shelf-life forecasts, choose food items, and enter storage information.

READING HISTORY		
TIME	TEMP (°C)	HUMIDITY (%)
10:41:52	30.4	56.7
10:41:47	30.5	56.7
10:41:42	30.5	56.6
10:41:37	30.5	56.7
10:41:32	30.5	56.7
10:41:27	30.5	56.7
10:41:22	30.5	56.7
10:41:17	30.5	56.6
10:41:07	30.5	56.7
10:41:02	30.5	56.7

Fig.3. Reading History Panel

Figure.3. Shows logs time-stamped temperature and humidity readings captured at regular intervals. It helps in monitoring environmental trends and analysing storage condition stability over time.

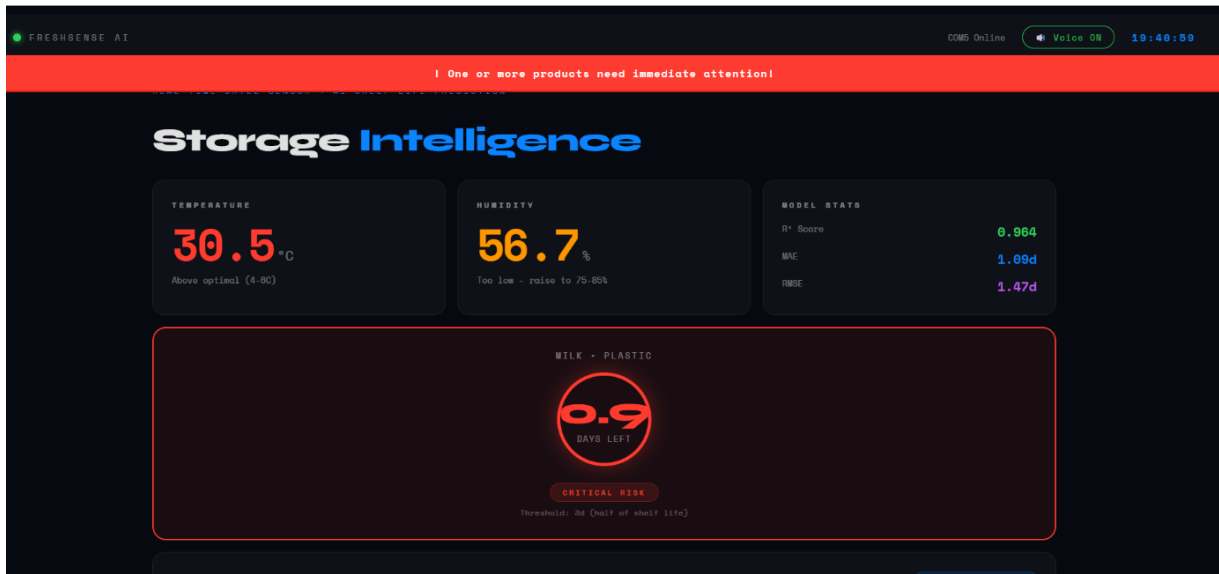


Fig.4. Alert / Critical Risk State

Figure.4. Highlights products that are nearing spoilage with a visual alert and risk classification. It provides predicted days left and triggers warnings when values fall below safe thresholds.

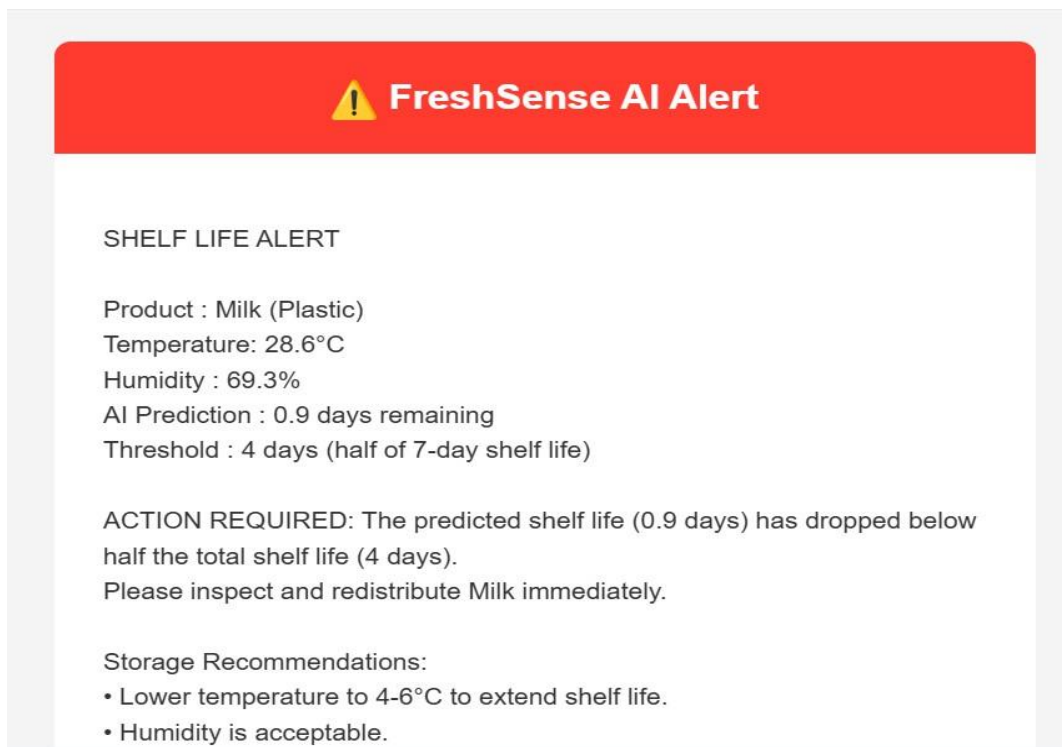


Fig.5. Shelf-Life Alert Notification

Figure.5. shows the system alerts that milk's predicted shelf life has dropped to 0.9 days, below the safety threshold. Immediate action is recommended, along with lowering the temperature to extend shelf life.



Fig.6. Critical Alert Dashboard

Figure.6. displays the dashboard indicates inadequate humidity and temperature levels in the storage room, as well as real-time environmental variables and model performance. Additionally, it highlights the need for quick action and displays the remaining shelf life when a product is at urgent risk.

IX. CONCLUSION:

By merging IoT-based environmental monitoring with machine learning-driven shelf-life prediction, the FreshSense AI system shows how to effectively reduce food waste [1], [9]. The technology offers real-time insights and early warnings for possible spoiling by continually monitoring temperature and humidity using sensors and analysing the data using a prediction algorithm [5].

The combination of hardware and software components ensures a practical, scalable solution for smart storage environments such as cold storage units and supermarkets. By offering accurate forecasts and useful suggestions, FreshSense AI improves food safety, inventory control, and sustainable resource use.

REFERENCES:

- [1] **Food and Agriculture Organization**, “Global Food Losses and Food Waste -Extent, Causes and Prevention”, FAO, 2011. <https://www.fao.org/3/i2697e/i2697e.pdf>
- [2] **World Health Organization**, “Food Safety and Food Quality Guidelines”, WHO Reports. <https://www.who.int/foodsafety>
- [3] **B.K. Bala, M.A. Hossain, and S. Manjumdar**, “Post Harvest Loss and Technical Efficiency of Rice, Wheat and Maize Production System”, Agricultural Systems Journal. <https://www.sciencedirect.com/journal/agricultural-systems>
- [4] **J. Gustavsson, C. Cederberg, U. Sonesson**, “Global Food Losses and Food Waste”, FAO Study, 2011. <https://www.fao.org/3/i2697e/i2697e.pdf>
- [5] **H. Feng, Y. Yan, and J. Yu**, “Application of Machine Learning in Food Shelf-Life Prediction”, Journal of Food Engineering. <https://www.sciencedirect.com/journal/journal-of-food-engineering>
- [6] **S. A. Rahman**, “Food Preservation Techniques and Shelf-Life Extension”, Food Science and Technology Journal. <https://www.sciencedirect.com/topics/food-science/food-preservation>
- [7] **A. Kamilaris and F. X. Prenafeta- Boldú**, “Deep Learning in Agriculture: A Survey”, Elsevier, Computers and Electronics in Agriculture, 2018. <https://doi.org/10.1016/j.compag.2018.01.009>
- [8] **M. Aung and Y.S. Chang**, “Traceability in a Food Supply Chain: Safety and Quality Perspectives”, Food Control Journal. <https://www.sciencedirect.com/journal/food-control>



- [9] **United Nations Y. S. Chang**, “*Food Waste Index Report*”, UNEP, 2021. <https://www.unep.org/resources/report/unep-food-waste-index-report-2021>
- [10] **K. P. Ferentinos**, “*Deep Learning Models for Agriculture Applications*”, Computers and Electronics in Agriculture. <https://www.sciencedirect.com/science/article/pii/S0168169917308803>