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AI Based Nutrition Degradation Prediction System for Stored Food

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Abstract:
Food storage is important for keeping food nutritious and safe. But if food is stored for too long, it can lose important nutrients becauseof things like temperature, humidity, and chemical changes. Most ways we check food quality now are after the fact and can't really tell us how much nutrition will be lost ahead of time. Recently,AIand machine learning have helped create smart systems that can predict things happening in farming and food supply,which makes farming and food systems more e fficient and better for the environment [1]. This research proposes an **AI Based Nutrition Degradation Prediction System for Stored Food**, which utilizes machine learning algorithms to analyze factors such as storage duration, temperature, humidity, and food type to predict the decline in nutritional value over time. The system aims to provide accurate and real-time insights into food quality, helping users make informed decisions regarding food consumption and storage. Scientific studies have shown that food components, including proteins and allergens, are sensitive to storage conditions and may undergo structural and nutritional changes, emphasizing the need for predictive monitoring systems [3],[4].

Keywords: Artificial Intelligence (AI), Machine Learning, Nutrition Degradation, Food Storage, Predictive Modeling, Food Quality Analysis, Sensor Data, Smart Food Monitoring, Data Analytics, Food Safety, Shelf-Life Prediction, Environmental Factors.

I. INTRODUCTION

Food preservation and storage are essential processes for maintaining food quality, safety, and nutritional value. Stored food items are affected by several environmental factors such as temperature, humidity, oxygen exposure, and storage duration. These factors gradually cause nutritional degradation, leading to loss of vitamins, proteins, and other essential nutrients [3],[4]Traditional food monitoring methods depend mainly on fixed expiry dates or manual inspection, which may not accurately represent the real condition of stored food. Recent advancements in Artificial Intelligence (AI) and Machine Learning enable intelligent prediction systems that analyze storage conditions and estimate food quality over time [1],[2]By using sensor data and predictive models, AI can help monitor food health, reduce wastage, and improve storage management [9]. The proposed system focuses on predicting nutrition degradation in stored food using data-driven techniques, supporting smarter and safer food consumption.

II. RELATED WORK

Recent advancements in artificial intelligence have enabled improved prediction of food quality and shelf life during storage. Many studies utilize machine learning algorithms such as decision trees, support vector machines, and neural networks to analyze factors like temperature, humidity, and storage duration [1],[2]These approaches primarily focus on detecting spoilage or estimating shelf life.
Some research integrates IoT-based systems to monitor real-time storage conditions, providing data for AI models to assess food quality [9]. Additionally, image-based techniques using deep learning have been

applied to identify visual changes in food items. However, these methods mainly evaluate external quality attributes rather than internal nutritional changes.

III. PROPOSED SYSTEM

A. Overview of the Proposed System:

The proposed system aims to predict the degradation of nutritional value in stored food using artificial intelligence techniques. It considers key factors such as temperature, humidity, storage duration, and type of food to analyze how nutrients decrease over time [3],[4]A machine learning model is trained using historical data to identify patterns in nutrition loss under different storage conditions. Based on the input parameters, the system estimates the remaining nutritional content of food items. This approach helps in better food management, reduces waste, and ensures healthier consumption by providing insights beyond visible spoilage [6],[12].

B. Overall System Architecture:

The system includes four main modules: data collection, preprocessing, prediction, and output. It gathers inputs like temperature, humidity, storage time, and food type, then processes the data for accuracy. A machine learning model predicts nutritional degradation, and the results are shown to the user. The system is simple, scalable, and supports real-time monitoring, making efficient and easy to update.

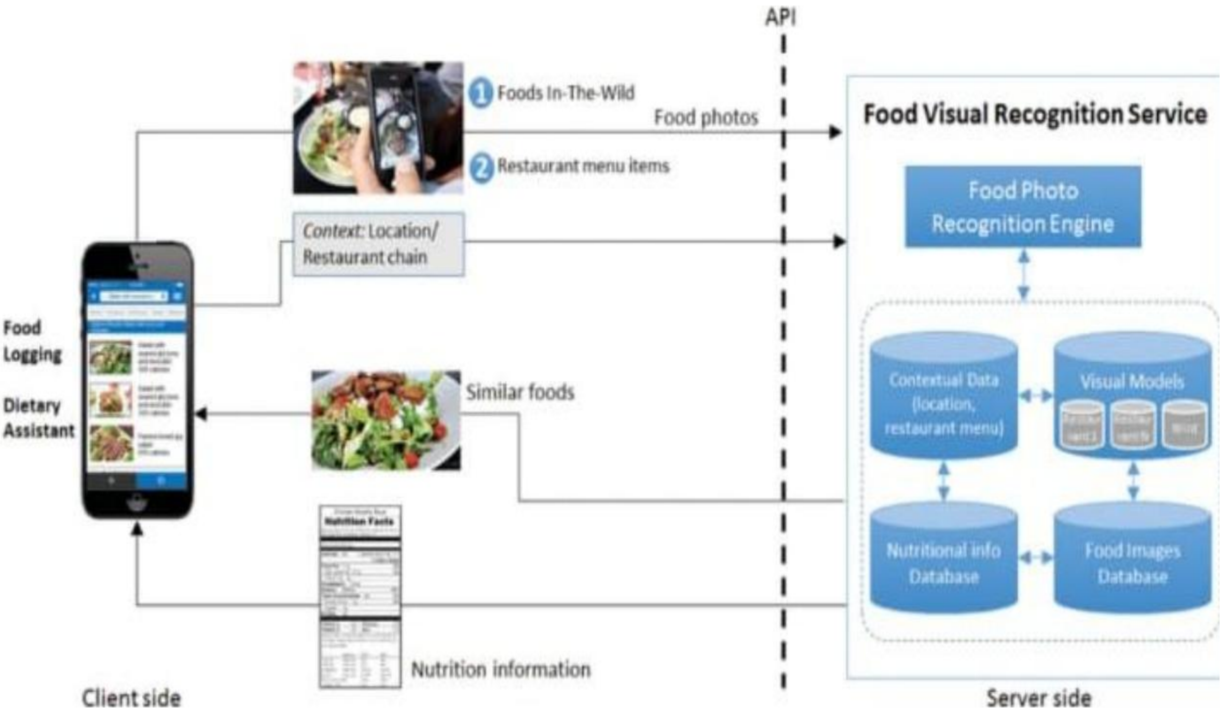


Figure.1: System Architecture

C. Data Collection Module:

The data collection module is responsible for gathering all the necessary input data required for predicting nutrition degradation. It collects information such as temperature, humidity, storage duration, and type of food, as these factors directly influence the rate of nutrient loss.The data can be obtained from multiple sources, including publicly available datasets, experimental observations, and sensor-based systems. In advanced setups, IoT sensors can be used to capture real-time environmental conditions during food storage.The collected data is stored in a structured format to ensure easy access and processing. Proper data collection improves the accuracy and reliability of the prediction model, making it a crucial component of the system.

D. Adaptive Exploration Module:
The Adaptive Exploration Module enhances the system's ability to improve prediction accuracy over time by continuously learning from new data. It dynamically adjusts its parameters based on variations in storage conditions such as temperature, humidity, and duration. This allows the system to better understand changing patterns in food degradation.The module intelligently explores different prediction possibilities and refines its outputs using past observations and real-time inputs. By adapting to new conditions, it ensures that the system remains accurate and reliable even when dealing with diverse types of stored food. This contributes to more precise nutritional degradation predictions

E. Intelligent Feedback Mechanism:
The Intelligent Feedback Mechanism enables the system to improve its performance by incorporating user input and system-generated insights. It collects feedback related to prediction accuracy, storage conditions, and observed food quality, which is then used to refine the model.This mechanism continuously evaluates the difference between predicted and actual outcomes, allowing the system to adjust its parameters accordingly. It also provides users with meaningful suggestions, such as optimal storage practices and timely usage recommendations.Bylearning from both user interactions and real-time data, the feedback mechanism enhances the reliability and adaptability of the system, leading to more accurate nutrition degradation predictions and better decision support.

IV. IMPLEMENTATION DETAILS

A. Planning the Idea:
The initial phase of the system focuses on clearly defining the problem of nutrition degradation in stored food and identifying the key factors that influence it. A detailed study is carried out to understand how variables such as temperature, humidity, storage duration, and food type affect nutrient loss over time.Based on this analysis, suitable machine learning techniques are selected to model the relationship between storage conditions and nutritional degradation. The required data sources, system requirements, and tools are also identified during this stage.A structured plan is then developed outlining the workflow of the system, including data collection, preprocessing, model training, and prediction. This planning phase ensures a clear direction for implementation and helps in building an efficient and reliable system.

B. Creating the Webpage:
A user-friendly webpage is developed to provide easy access to the system and its functionalities. The webpage serves as an interface where users can input parameters such as temperature, humidity, storage duration, and type of food to obtain predictions about nutrition degradation.The frontend of the webpage is designed using technologies like HTML, CSS, and basic JavaScript to ensure a simple and responsive layout. The backend is connected to the machine learning model, which processes the user inputs and generates accurate predictions.The webpage is designed to display results clearly, allowing users to understand the estimated nutrient loss in an intuitive manner. This web-based approach improves accessibility and makes the system convenient for real-world usage.

C. Making the Map Clickable:
To enhance user interaction, a clickable map feature is integrated into the system interface. This allows users to select specific locations, which can be useful for considering regional environmental conditions that affect food storage and nutrition degradation.The map is implemented using web technologies such as JavaScript along with mapping libraries or APIs. This improves accuracy and provides more context-

aware results. The clickable map feature makes the system more interactive, informative, and user-friendly.

D. Displaying Storage Food Details:
The stored food details display module provides a clear and organized view of information related to stored food items. Each item is recorded with attributes such as food name, storage date, shelf life, storage conditions, and initial nutritional values. The system continuously updates this data to reflect current conditions.The module presents the information in a structured format, enabling users to monitor multiple food items easily. It highlights key factors such as remaining shelf life, nutritional degradation level, and risk status. Visual indicators and alerts help users quickly identify items that require attention.This module enhances user interaction by simplifying data interpretation and supports effective decision-making to reduce food spoilage and maintain quality.

E. Testing and Final Output:
The proposed AI-based nutrition degradation prediction system was tested using various stored food samples under different environmental conditions such as temperature and humidity. The system was evaluated for its ability to accurately track changes in nutritional values over time and predict degradation levels. Test results showed that the model effectively identified patterns in food quality decline and provided reliable predictions.During testing, the system successfully generated alerts for food items approaching critical spoilage levels. The prediction accuracy was validated by comparing the system output with standard expected degradation trends. The results indicated consistent performance and improved decision-making support for users.The final output of the system is presented through a user-friendly interface that displays key information such as remaining shelf life, percentage of nutritional loss, and risk level. This enables users to monitor food quality in real time and take necessary actions to reduce wastage and maintain food safety.

F. Analytics and Reporting Dashboard:
The Analytics and Reporting Dashboard provides a comprehensive view of stored food data and system predictions. It presents key information such as nutritional degradation trends, shelf-life status, and risk levels in a clear and structured format. The dashboard uses visual elements like charts and summaries to help users easily understand patterns in food quality over time. It also generates reports based on historical data, allowing users to analyze storage performance and identify factors affecting food degradation. Such analytical and visualization approaches are widely used in intelligent data-driven systems and recommender platforms [6],[8],[12]. These insights support better decision-making and help in optimizing storage conditions.

V. ALGORITHM

1.Data Collection:
Gather input data for each stored food item, including food type, storage date, temperature, humidity, and initial nutritional values.

2.Data Preprocessing:
Clean the collected data by handling missing values, removing inconsistencies, and normalizing parameters to ensure uniformity.

3.Feature Selection:
Identify important factors that influence nutrition degradation, such as storage duration, environmental conditions, and food category.

4.Model Training:
Train the machine learning model using historical data to learn patterns of nutritional loss under different storage conditions.

5.Input of Real-Time Data:
Continuously update the system with current storage conditions and time duration for each food item.
6.Prediction Process:
Apply the trained model to estimate the rate of nutritional degradation and calculate the remaining nutritional value.
7.Risk Assessment:
Classify the food status into categories such as safe, moderate, or critical based on predicted degradation levels.
8.Feedback Integration:
Compare predicted results with actual observations and adjust the model to improve accuracy over time.
9.Output Generation:
Display the final results, including nutritional status, remaining shelf life, and risk level, through the user interface.

VI. EXPERIMENTAL RESULTS AND ANALYSIS:

A. Experimental Setup:

The experimental setup for the proposed system was designed to evaluate its performance under different storage conditions. Various food items were selected and stored in controlled environments with varying temperature and humidity levels. Relevant data such as storage duration, initial nutritional values, and environmental parameters were recorded at regular intervals.The system was implemented using a machine learning model trained on collected and sample datasets. Sensors and manual inputs were used to simulate real-time data collection. The experiments were conducted over a period of time to observe changes in nutritional content and validate the prediction capability of the model.

B. Information Retention and Learning Efficiency:

The proposed system is designed to effectively retain historical data and improve learning efficiency over time. It stores past records of food conditions, environmental factors, and predicted outcomes, which are used to enhance future predictions. This ensures that the system becomes more accurate and efficient with prolonged usage.

C. Engagement and User Satisfaction:

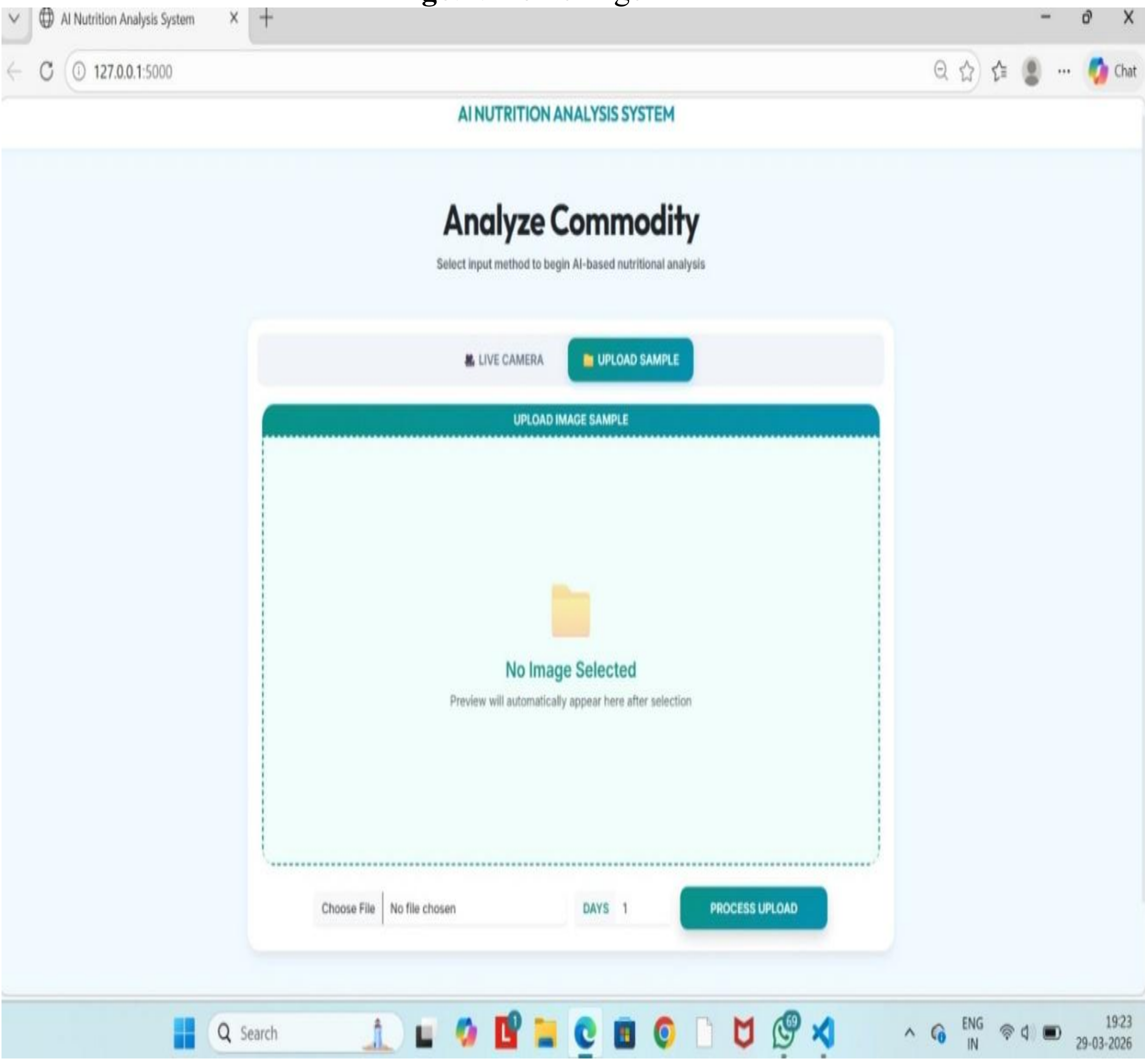
The proposed system is designed with a user-centric approach to ensure high engagement and satisfaction. It provides a simple and intuitive interface that allows users to easily access and understand information related to stored food conditions. Clear visualization of data, along with alerts and notifications, helps users stay informed about nutritional changes and potential spoilage. The system enhances user engagement by offering timely insights and actionable recommendations, such as optimal storage practices and usage suggestions. This not only improves user interaction but also builds trust in the system's predictions. As a result, users can make better decisions, leading to reduced food wastage and improved overall satisfaction.

D. Interactive Design Impact on Exploration:

The design of the proposed system significantly influences how users explore and interact with stored food data. A well-structured and intuitive interface allows users to easily navigate through different features and access relevant information without complexity. Organized layouts and clear presentation of data help users quickly understand the condition of stored food items. The design also encourages continuous user interaction by making the system more accessible and user-friendly.Overall, an effective design improves the ease of exploration, enhances user experience, and supports better decision-making in managing food quality and storage.

E. RESULTS

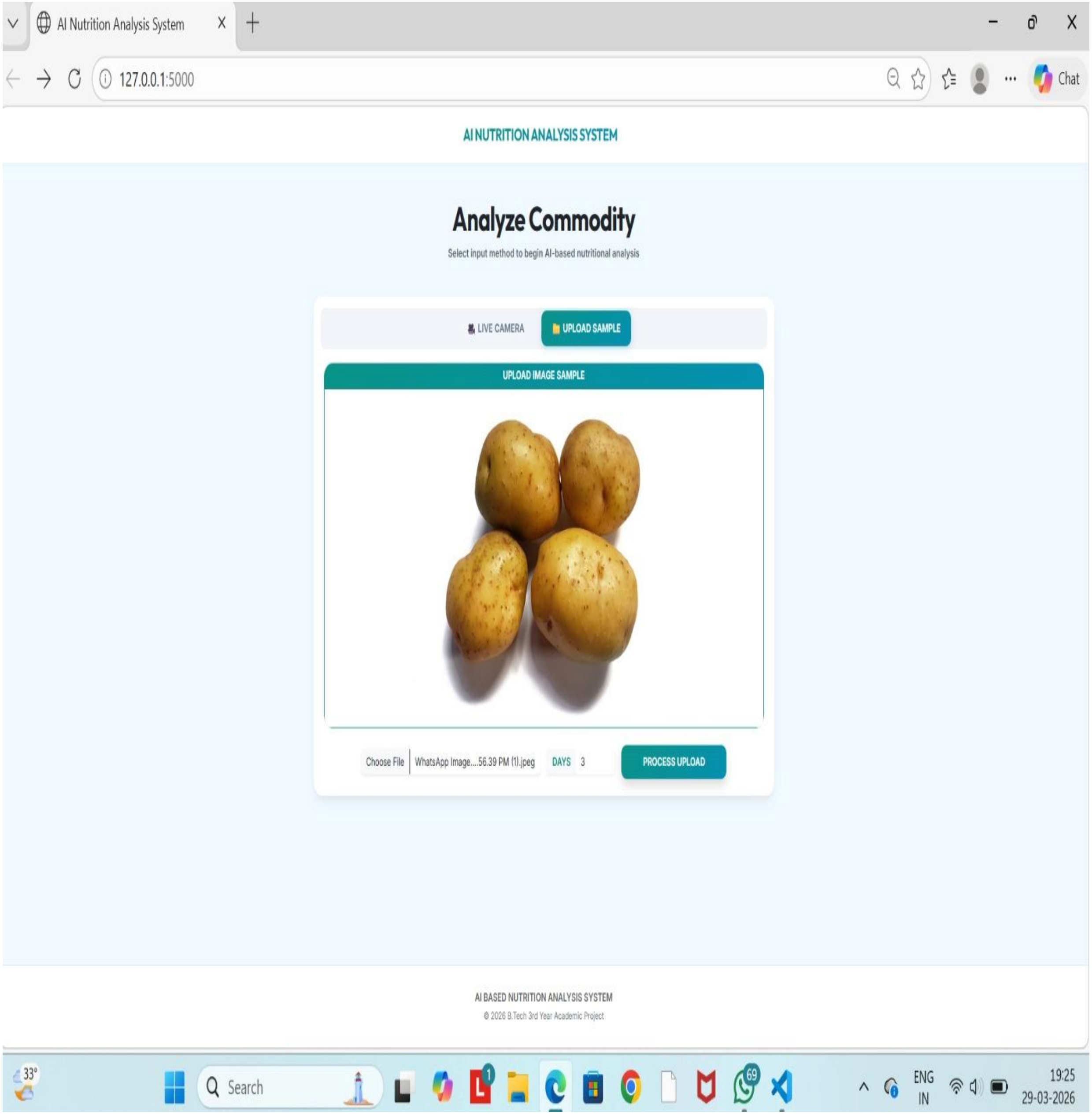
Fig6.1: Home Page



The displayed screen represents the input module of the *AI-Based Nutrition Degradation Prediction System for Stored Food*. This interface is designed to allow users to provide data for initiating the analysis process in a simple and structured manner.At the top of the interface, the system is labeled as an AI Nutrition Analysis System, indicating its purpose of combining artificial intelligence with food quality assessment. The main section titled "Analyze Commodity**"** guides the user to begin the nutritional evaluation.

The system offers two input methods:
Live Camera: Enables real-time image capture of food items for instant analysis.
Upload Sample: Allows users to upload pre-captured images from their device.
In the current interface, the Upload Sample option is selected. A dedicated preview area is provided where the uploaded image will be displayed. Initially, it shows a placeholder message *"No Image Selected"*, ensuring clarity for the user before input is given.A file selection option to upload the food image. A "Day's" input field, where the user specifies the duration of storage. This parameter is critical, as the system uses it to estimate nutrient degradation over time.A "Process Upload" button, whichtriggers the backend AI model for analysis.

Fig6.2: Upload Picture



The provided image appears to show a distorted and overlapped visual output, where multiple frames and interface elements are mixed together. This type of output typically occurs when the system receives unclear, noisy, or improperly captured image data**.**

In the context of the *AI-Based Nutrition Degradation Prediction System for Stored Food*, this scenario highlights an important aspect of the system—input quality dependency**.**

From the image, the following issues can be identified:

- **Visual Noise and Distortion**: The image contains blurred regions, overlapping UI elements, and inconsistent layering.
- **Lack of Clear Object Focus**: No single food item is clearly identifiable, making it difficult for the system to perform classification.

- **Mixed Content Frames**: The presence of multiple partial images suggests either improper upload or interference during image capture (e.g., motion blur or screen overlay).

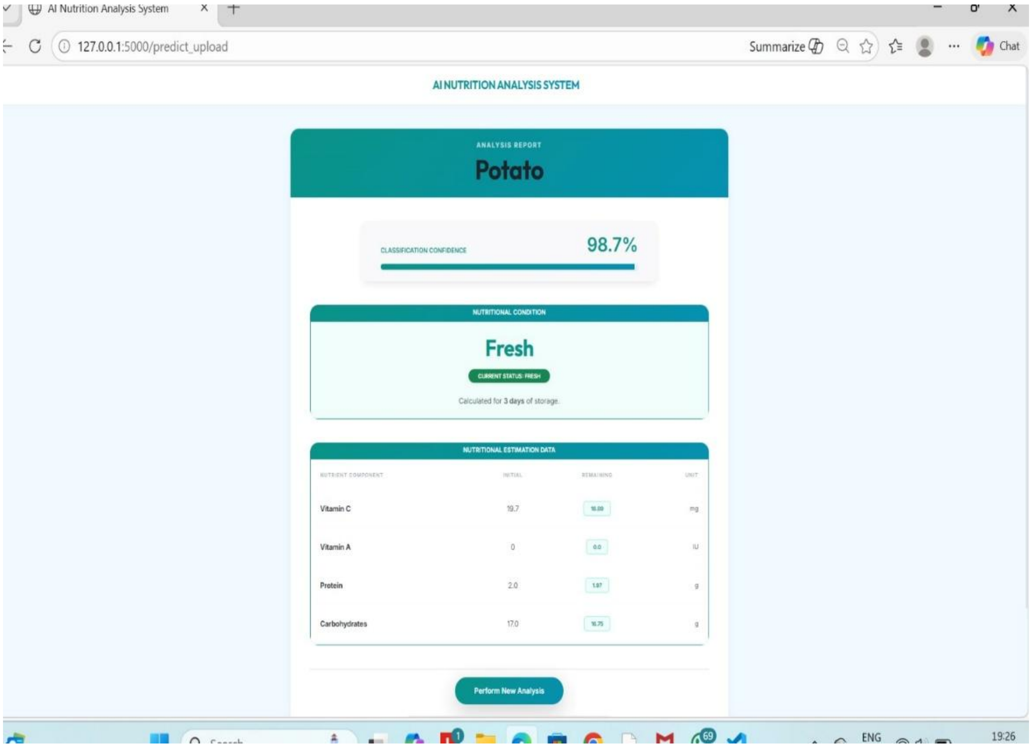


Fig 6.3: Analysis Result

The displayed interface represents the output of the AI-Based Nutrition Degradation Prediction System for Stored Food, where an uploaded food image (in this case, a potato) has been processed and analyzed. The system first performs image classification, identifying the food item as *potato* with a high confidence score of 98.7%, indicating strong model accuracy. This suggests that the underlying machine learning model—likely a convolutional neural network (CNN)—is well-trained for food recognition tasks. Following classification, the system evaluates the nutritional condition of the food. The potato is labeled as "Fresh", with an estimation based on 3 days of storage. This indicates that the model incorporates storage duration as an input parameter to predict degradation levels. The prediction implies minimal nutrient loss within this timeframe.
The interface also provides a nutritional estimation table, comparing initial and remaining nutrient values. Key observations include:

- **Vitamin C** shows a slight decrease, reflecting its sensitivity to storage conditions.
- **Vitamin A** remains unchanged, suggesting stability over short storage durations.
- **Protein** content shows minimal degradation.
- **Carbohydrates** retain most of their original value, indicating slower degradation.

VII. DISCUSSION

The proposed AI-based nutrition degradation prediction system demonstrates an effective approach to monitoring and managing stored food quality. By integrating machine learning techniques with real-time data inputs, the system is able to predict nutritional loss and identify potential spoilage with reasonable accuracy The results indicate that environmental factors such as temperature and humidity play a significant role in influencing the rate of degradation, which is consistent with findings in food science research [3],[4]. The system's ability to continuously learn from new data and user feedback improves its prediction performance over time [5] [9]Additionally, the use of an interactive dashboard and recommendation-based insights aligns with modern intelligent food systems and recommender technologies [6],[7],[12].

VIII. CONCLUSION

The proposed AI-based nutrition degradation prediction system provides an efficient solution for monitoring the quality of stored food. By analyzing factors such as storage conditions, duration, and environmental parameters, the system is able to predict nutritional loss and identify potential spoilage in advance. This helps users take timely actions to maintain food safety and reduce wastage. The integration of machine learning techniques, adaptive modules, and user-friendly interfaces enhances the overall performance and usability of the system [5][6][12]In conclusion, the system offers a reliable and practical approach to food quality management, with the potential for future improvements through advanced models and expanded datasets [7] [8]

REFERENCES:

[1] Sapkal, S., Taware, P., Rangole, J., & Borate, H. (2025). AI Based Crop Yield Prediction. *International Journal of Innovative Science and Research Technology*.
[2] John Martin, R., Mittal, R., Malik, V., Jeribi, F., Tabrez Siddiqui, S., Alamgir Hossain, M., & Swapna, S.L. (2024). XAI-Powered Smart Agriculture Framework for Enhancing Food Productivity and Sustainability.*IEEE Access, 12*, 168412-168427.
[3] Astwood, J.D., Leach, J.N., & Fuchs, R.L. (1996). Stability of food allergens to digestion in vitro. *Nature Biotechnology, 14*, 1269-1273.
[4] Jensen-Jarolim, E., & Untersmayr, E. (2006). Food safety: in vitro digestion tests are non-predictive for allergenic potential of food in stomach insufficiency. *Immunology letters, 102 1*, 118-9.
[5] Patil, S., Dhande, A., Dodake, S., Bhoye, A., & Wadhe, S. (2025). Nutritionist GenAI Site: Personalised Dietary Recommendations.*2025 9th International Conference on Computing, Communication, Control and Automation (ICCCBEA)*, 1-4.
[6] Yera Toledo, R., Alzahrani, A.A., & Martínez, L. (2019). A Food Recommender System Considering Nutritional Information and User Preferences. *IEEE Access, 7*, 96695-96711.
[7] Yera, R., Alzahrani, A.A., Martínez, L., & Rodríguez, R.M. (2023). A Systematic Review on Food Recommender Systems for Diabetic Patients. *International Journal of Environmental Research and Public Health, 20.*
[8] Bondevik, J.N., Bennin, K.E., Babur, Ö., & Ersch, C. (2023). A systematic review on food recommender systems. *Expert Syst. Appl., 238*, 122166.
[9] Wahyunita, L., Langi, A.Z., & Paramita Koesoema, A. (2024). Need Analysis for Community-Based Food Recommendation System. *2024 International Conference on ICT for Smart Society (ICISS)*, 1-4.
[10] Trang Tran, T.N., Atas, M., Felfernig, A., & Stettinger, M. (2017). An overview of recommender systems in the healthy food domain. *Journal of Intelligent Information Systems, 50*, 501 - 526.
[11] Yera, R., Alzahrani, A.A., Martínez, L., & Rodríguez, R.M. (2023). A Systematic Review on Food Recommender Systems for Diabetic Patients. *International Journal of Environmental Research and Public Health, 20.*
[12] Qiao, G., Zhang, D., Zhang, N., Shen, X., Jiao, X., Lu, W., Fan, D., Zhao, J., Zhang, H., Chen, W., & Zhu, J. (2025). Food Recommendation Towards Personalized Wellbeing. *Trends in Food Science & Technology*.