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Detecting Freshness of Food Using AI

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A B S T R A C T

In the era of AI-driven smart systems, food quality and safety remain a critical concern. This project proposes an intelligent system that leverages deep learning and machine learning techniques to detect the freshness of food items based on image analysis. A Convolutional Neural Network (CNN) integrated with a Softmax classifier is utilized to categorize food images into Fresh, Half-Fresh, Spoiled, or Non-Food. To further enhance the model's accuracy and interpretability, a Random Forest classifier is incorporated to analyze color and texture-based features such as hue and brightness, extracted using OpenCV. The system features a user-friendly frontend built with React.js for image upload and result display, while the backend, developed using Python Flask, manages image preprocessing, model inference, and API communication. This hybrid approach combines the deep visual learning capability of CNNs with the feature-based decision-making strength of Random Forests, making it a robust and practical solution for real-world food freshness detection across households, restaurants, and food delivery services.

Keywords: Food Freshness Detection; Convolutional Neural Network (CNN); Random Forest;

Image Classification; OpenCV; React.js; Flask; Deep Learning; Machine Learning; Image Processing;

AI in Food Industry; Smart Applications.

1. INTRODUCTION

Ensuring food quality and safety is a growing concern in today's fast-paced, technology-driven society. Food spoilage not only leads to significant economic losses but also poses serious health risks to consumers. Conventional methods of detecting food freshness are often manual, subjective, and inconsistent, leading to inaccurate assessments.With the advancement of Artificial Intelligence (AI) and computer vision, there is a strong potential to revolutionize how food quality is evaluated. Intelligent systems can now analyze visual cues and patterns in food items that are often missed by the human eye. These technologies allow for automation, standardization, and increased reliability in freshness detection.This project focuses on developing a smart AI-powered system to detect food freshness using image-based classification techniques. It integrates a Convolutional Neural Network (CNN) for deep visual learning with a Random Forest algorithm for feature-based analysis. By combining both approaches, the system achieves improved accuracy, robustness, and interpretability.Color and texture features such as hue, saturation, and brightness are extracted using OpenCV to support decision-making. A user-friendly frontend built with React.js enables users to upload or capture images easily. The backend, developed using Flask, handles image processing and prediction delivery via RESTAPIs.This hybrid model can be effectively used in households, restaurants, and food delivery services to prevent foodborne illnesses and reduce waste. It serves as a practical example of how AI can be leveraged in the food industry to improve safety, efficiency, and user confidence.

2.LITRATURE SURVEY

2.1 Optical Sensing for Real-Time Detection of Food-Borne Pathogens in Fresh Produce Using Machine Learning

It explores the use of optical sensing technologies combined with machine learning algorithms for the real-time detection of food-borne pathogens in fresh produce. It highlights the limitations of traditional microbiological testing methods, which are often time-consuming, labor-intensive, and not suitable for rapid on-site inspections. The study proposes a non-invasive, real-time solution using hyperspectral and multispectral imaging to capture the spectral signatures of contaminated produce. These data are then analyzed using machine learning models such as SVM (Support Vector Machine) and Random Forest, which classify samples based on extracted features like spectral reflectance. The work demonstrates high classification accuracy, sensitivity, and specificity, proving the feasibility of real-time, portable food safety monitoring. The review also emphasizes the importance of developing integrated optical systems that can be scaled for industrial use. This paper serves as a critical reference for designing intelligent food safety systems, particularly those using computer vision and AI for freshness or contamination detection.

2.2 Vegetable Classification Using Deep Learning for Real-Time Applications

Bhargava et al. (2019) proposed a deep learning-based approach using Convolutional Neural Networks (CNNs) for real-time classification of vegetables based on image data. The model effectively identified various vegetable types such as tomatoes, brinjals, and bell peppers with high accuracy, showcasing the strength of CNNs in handling food-related visual classification tasks. Preprocessing steps like resizing, normalization, and data augmentation were employed to enhance model robustness and performance under diverse conditions. The system was optimized for real-time deployment with low latency, making it suitable for practical use in retail and agricultural settings. Although the study did not focus on assessing food quality or freshness, its methodology provides a strong foundation for similar AI applications in the food industry. The work demonstrates the feasibility of using deep learning for automated food recognition and offers valuable insights for extending such models to freshness detection and quality assessment systems.

3.SYSTEM STUDY

3.1 EXISTING SYSTEM

Detecting food-borne pathogens or freshness in produce predominantly relies on traditional microbiological techniques. These include culture-based methods, PCR (Polymerase Chain Reaction), and ELISA, which, although accurate, are time-consuming and require laboratory settings. Such methods are not suitable for on-site or real-time applications due to long incubation periods and the need for skilled technicians. In terms of technological systems, most industrial setups use manual inspection or basic sensor-based models to check surface quality attributes like color and texture. These systems lack the capacity to detect internal contamination or microbial presence. There is also limited integration of advanced computer vision or optical sensing methods in commercial food quality monitoring. Conventional imaging systems capture only RGB features, which are insufficient to detect subtle changes caused by pathogens. Moreover, many models do not leverage machine learning, thereby lacking adaptability to different produce types. Existing systems often generate false negatives or fail to provide rapid alerts. Their inability to scale in fast-paced supply chains reduces effectiveness. Current systems also offer minimal automation, depending heavily on human decision-making. Overall, the limitations in speed, accuracy, and real-time detection capability demand a more intelligent, sensor-driven AI model.

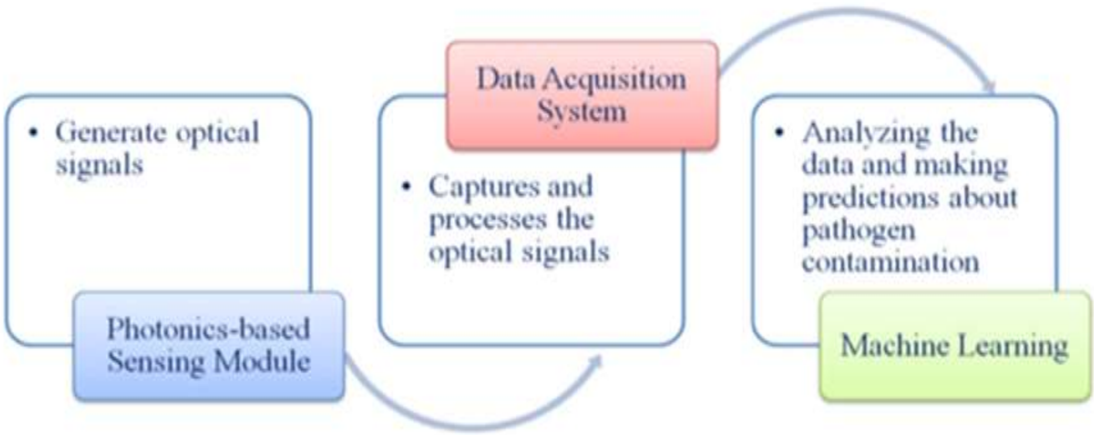


Figure 3.1.1 Existing System

3.2 PROPOSED SYSTEM

The proposed system utilizes a hybrid AI approach to detect the freshness of food items accurately and in real time. It integrates a Convolutional Neural Network (CNN) for deep visual analysis of food images, enabling classification into categories such as Fresh, Half-Fresh, Spoiled, and Non-Food. The CNN is trained on a large dataset of labeled food images and uses a Softmax classifier to predict freshness levels based on extracted visual features. To improve reliability, a Random Forest algorithm is incorporated, which analyzes color and texture features such as hue, saturation, and brightness extracted using OpenCV. The system employs a React.js frontend, allowing users to upload or capture images through a clean, responsive interface. A Flask-based backend handles image preprocessing, feature extraction, and model inference. Communication between the frontend and backend is enabled through RESTful APIs. The combination of deep learning and traditional machine learning makes the system both accurate and interpretable. The architecture supports real-time prediction and can be deployed in homes, restaurants, or food delivery platforms. It enables non-invasive inspection and reduces dependency on manual judgment. The design ensures modularity for future enhancements, such as including more food categories or real-time video analysis.

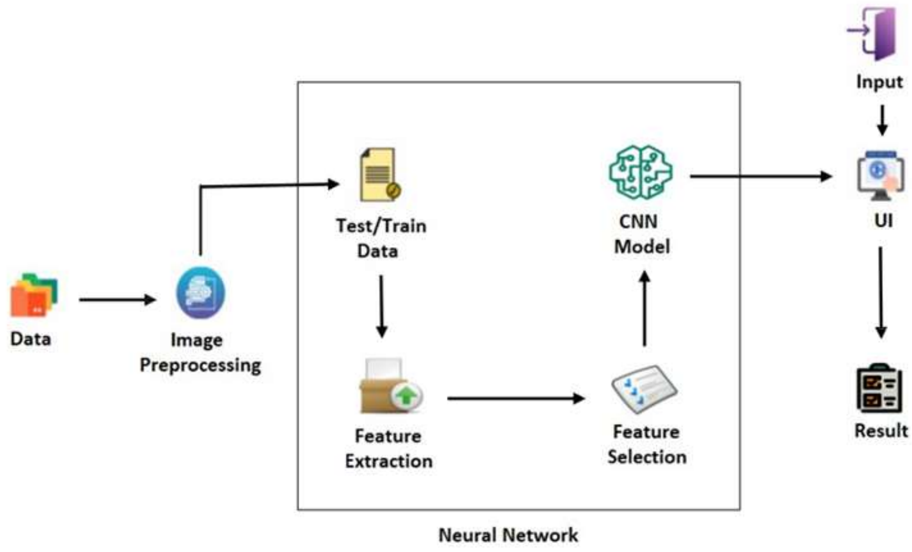


Figure 3.2.1 System Architecture

4. Methodology

4.1 Image Dataset Preparation

Food images are collected and labeled into four categories: Fresh, Half-Fresh, Spoiled, and Non-Food. Images are preprocessed using OpenCV (resizing, normalization, augmentation).

4.2 Feature Extraction

Visual features are extracted using a CNN for deep learning, and color-texture features (hue, saturation, brightness) are extracted using OpenCV for Random Forest analysis.

4.3 Model Training

A CNN model is trained for image classification with a Softmax layer, while a Random Forest model is trained on handcrafted features to enhance interpretability and support hybrid predictions.

4.4 System Development

The frontend is built using React.js for image input, and the backend is developed using Flask to handle processing, prediction, and API communication.

4.5 Prediction and Evaluation

The hybrid model predicts freshness in real-time, and results are evaluated using metrics like accuracy, precision, and recall to ensure system performance.

5. Module Implementation

The implementation of the proposed food freshness detection system was carried out in a structured manner, aligned with the previously defined modules. This section outlines the methodologies, tools, and technologies employed in the development of each module.

5.1 LIST OF MODULES

- Data Collection Module
- Data Preprocessing Module
- Model Development Module
- Model Evaluation Module

- Prediction Module

5.2 MODULE DESCRIPTION

5.2.1 DATA COLLECTION MODULE

Images of various food items were gathered to represent three categories of freshness: *Fresh*, *Half-Fresh*, and *Spoiled*. Data sources included publicly available image repositories and a custom dataset created by capturing images under varied lighting and environmental conditions. The images were manually labeled and organized into directories based on their freshness levels to facilitate supervised learning.

5.2.2 DATA PREPROCESSING MODULE

To ensure consistency and improve model training, all images underwent preprocessing. This involved resizing the images to a uniform resolution and normalizing pixel values to a common scale. Additionally, data augmentation techniques such as rotation, horizontal flipping, and zooming were applied to increase the variability of the dataset and enhance the model's generalization capability. These preprocessing steps were implemented using libraries such as OpenCV, NumPy, and TensorFlow.

5.2.3 MODEL DEVLOPMENT MODULE

The core of the system is a Convolutional Neural Network (CNN) developed using the TensorFlow and Keras frameworks. The network was designed to automatically extract spatial features from food images and classify them into one of the three freshness categories. The model architecture consisted of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for decision making. The output layer used a Softmax activation function to enable multi-class classification. The model was optimized using the Adam optimizer, with the categorical crossentropy loss function employed for training**.**

5.2.4 MODEL EVALUATION MODULE

After training, the model's performance was evaluated using standard metrics, including accuracy, precision, recall, and F1-score. A confusion matrix was also generated to analyze the distribution of correct and incorrect predictions across the three classes. The evaluation was conducted on a separate validation dataset to ensure the model's effectiveness and robustness.

5.2.5 PREDICTION MODULE

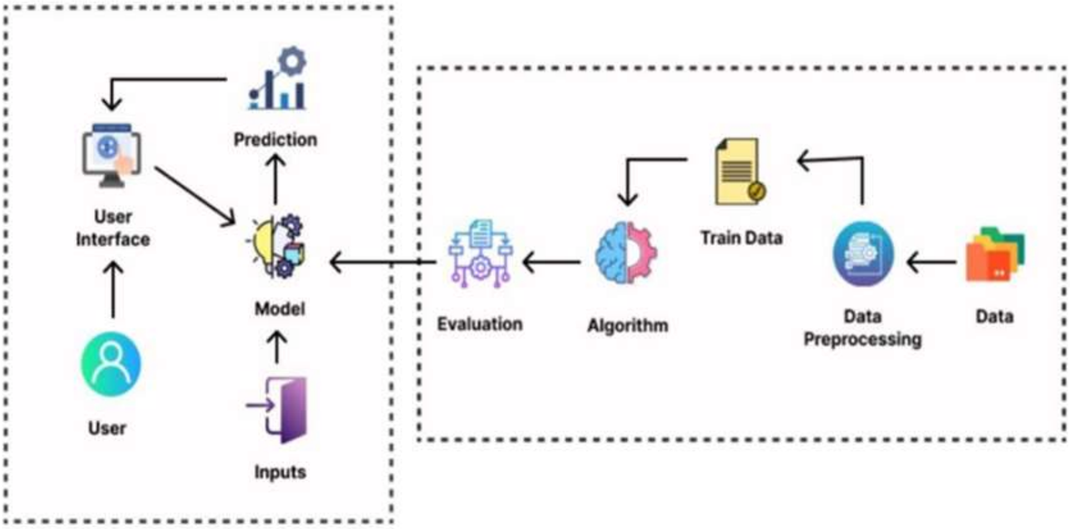
This module enables real-time classification of new food images. When an image is provided, it is first preprocessed in the same manner as the training data and then passed through the trained model. The model predicts the freshness category and outputs a label indicating whether the food item is fresh, half-fresh, or spoiled. The output is designed to be interpretable and accessible for non-technical users.

5.6 USER INTERFACE MODULE

To enhance user interaction, a simple graphical user interface was optionally developed using tools used for frontend. This interface allows users to upload an image and receive immediate feedback on the freshness status of the food item, thereby extending the system’s usability beyond research and into practical applications.

SYSTEM ARCHITECTURE

The system architecture consists of five key components: image acquisition, preprocessing, CNN-based classification, prediction and user interface, Input images of food are first captured or uploaded into the system. Preprocessing involves resizing, normalization, and augmentation to standardize the data A trained Convolutional Neural Network (CNN) processes the images to extract features. The model classifies each image into one of three categories: Fresh, Half-Fresh, or Spoiled. The prediction result is then interpreted and displayed to the user through an interface. This modular architecture enables accurate, real-time freshness detection with scalable deployment.



6.EXPERIMENTAL RESULTS

Figure 6.1 Choosing or Capture the Food Image

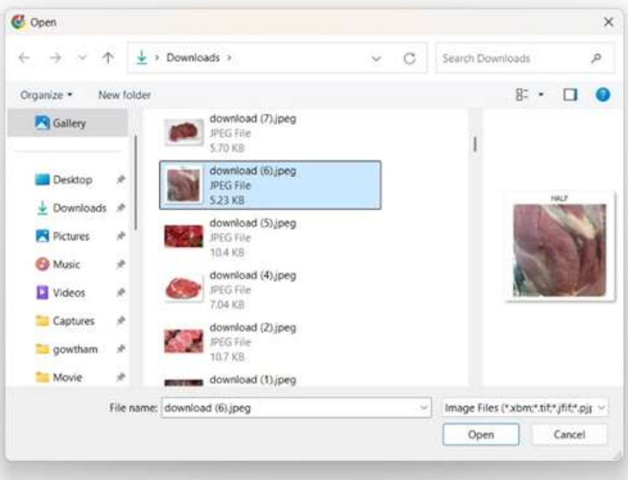


Figure 6.2 Choosing the Food Image

Figure 6.3 Chosen Food Image

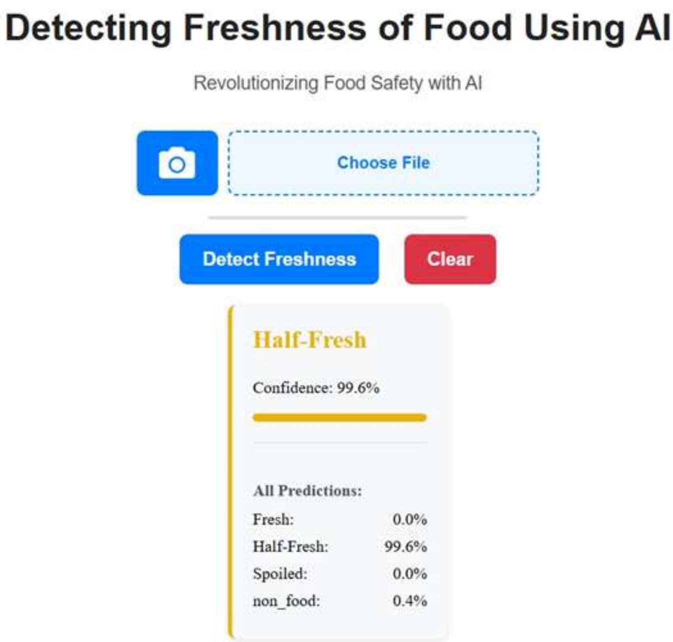


Figure 6.4 Freshness Detected

CONCLUSION AND FUTURE ENHANCEMENT

CONCLUSION

The project successfully demonstrates the potential of artificial intelligence in assessing food freshness, offering a more efficient and accurate alternative to traditional methods. By leveraging machine learning algorithms and sensor data, the system can detect spoilage indicators, thereby enhancing food safety and reducing waste. The implementation showcases the feasibility of integrating AI into everyday applications, paving the way for smarter food quality monitoring systems.

FUTURE ENHANCEMENT

1. **Multimodal Data Integration:** Incorporate various data types such as images, gas sensor readings, and temperature logs to improve the accuracy of freshness detection.
2. **Real-Time Monitoring:** Develop capabilities for continuous monitoring of food items, providing instant alerts when spoilage is detected.
3. **Mobile Application Development:** Create a user-friendly mobile app that allows consumers to check the freshness of food items using their smartphones.OpenAI Community
4. **Cloud-Based Data Analysis:** Implement cloud computing solutions to handle large datasets, enabling more complex analyses and better scalability.
5. **Integration with Supply Chain Systems:** Connect the freshness detection system with supply chain management to optimize inventory and reduce food waste.
6. **User Feedback Mechanism:** Incorporate a feature that allows users to provide feedback on the system's accuracy, facilitating continuous improvement through machine learning.

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