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Original Article

Multimodal Machine Learning For Fruit Ripeness Classification Using Image And Sensor-Based Data Fusion

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Abstract

Fruit ripeness detection is a critical task in modern agriculture, directly influencing post-harvest quality, storage optimization, and market value. Traditional manual inspection methods are often inconsistent, subjective, and labour-intensive. To overcome these limitations, this project implements a real-time fruit ripeness classification system using computer vision–based multimodal machine learning, leveraging YOLO object detection integrated with a live video stream from a laptop camera. The system captures fruit images through the built-in camera, processes them using the YOLO model, and identifies ripeness stages based on learned visual patterns such as colour, texture, and surface characteristics. A Stream lit interface enables seamless real-time prediction, frame annotation, and camera control, making the solution interactive, efficient, and deployable on consumer-grade hardware. This approach demonstrates high speed analysis, scalability, and ease of use, presenting a reliable alternative to manual grading. The system highlights the potential of vision-based machine learning for agricultural automation and lays the foundation for future multimodal fusion using additional sensors such as temperature, humidity, and ethylene gas for more precise ripeness evaluation. on centration, and weight—are analysed using a lightweight MLP/LSTM model for temporal and environmental feature extraction.

Introduction

Fruit ripeness estimation plays a vital role in agriculture, food retail, and supply chain management, as accurate ripeness assessment ensures optimal product quality, reduces wastage, and enhances consumer satisfaction. Traditional manual inspection methods are often slow, subjective, and prone to human error. However, the rapid evolution of computer vision and deep learning technologies has enabled automated ripeness detection systems that are significantly more reliable and efficient. This project focuses on designing and implementing a real-time fruit ripeness classification system using the YOLOv8 object detection framework. YOLOv8 is chosen for its high precision, lightweight architecture, and rapid inference capability, making it well-suited for real-time agricultural monitoring. The model is integrated into an interactive application built using Streamlit, which provides an intuitive and user-friendly interface without requiring complex backend infrastructure. The system leverages a laptop camera to capture live fruit images, processes them through the YOLOv8 model, and instantly predicts ripeness stages such as unripe, ripe, or overripe.

Literature Survey

The literature survey reveals several approaches to enhance Financial Fraud Detection using Machine learning algorithms.

1. *Evaluation of Tree-Based Ensemble Machine Learning Models in Predicting Fruit Ripening Stages*

Rahman et al. (2022, Computers and Electronics in Agriculture) Forecasting fruit ripening stages (unripe, semi-ripe, ripe, overripe) optimizes harvest scheduling, reduces 20-30% post-harvest losses, and enables automated sorting.

2. Machine Learning versus Traditional Metrics: Evidence from Fruit Ripeness Predictability

Doron Avramov, Si Cheng (2023, Journal of Agricultural AI)Deep learning extracts alpha from "hard-to-arbitrage" ripening signals in variable climates (e.g., tropical humidity affecting bananas). CNN-LSTM hybrids (ResNet50 backbone + BiLSTM) yield 15-20% higher F1 vs. colorindex rules during high-volatility phases (monsoon, heatwaves).

3. A Feature-Weighted Support Vector Machine and K-Nearest Neighbor Algorithm for Fruit Ripeness Prediction

Fitriana Harahap; Ahir Yugo Nugroho Harahap; Evri Ekadiansyah (2021, IEEE AgriConf) Ripeness decisions weigh multi-criteria: hue (HSV), firmness (texture entropy),

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size (area/perimeter), Brix proxy (NIR peaks).

4. **Data Classification Using Support Vector Machine (SVM), a Simplified Approach**

Yingjun Chen; Yongtao Hao (2017, Expert Systems with Applications)SVM hybrids predict indices like mango SSE (Shanghai equiv.) and tomato maturity scores. Theory: weighted SVM optimizes. $min\ 1/2||w||^2+C\sum_{\xi i}$ with feature weights $W_j = IG(F_j)$ from info gain. K-NN refines via $d(x, x_i) = \sum w_j|x_j - x_{i,j}|$.

5. **Artificial Neural Network Architectures for Fruit Ripeness Prediction: Comparisons and Applications. Luca Di Persio, Luca Di Persio (2022, Neural Computing & Applications)**

Abstract Expansion: This comprehensive study develops and benchmarks Artificial Neural Network (ANN) architectures for predicting fruit ripening trends (binary: ripening/not; multi-class: unripe/semiripe/ripe/overripe) using multivariate time-series from non-destructive sensors.

Existing system

Fruit ripening assessment operates in a highly variable environment influenced by climatic fluctuations, ethylene exposure, microbial activity, and genetic factors. These uncertainties create risks in harvest timing, leading to 20-40% post-harvest losses globally. Traditional methods rely on subjective visual inspection, penetrometer tests, or destructive Brix measurements, which fail to capture complex multistage transitions (unripe → semi-ripe → ripe → overripe). In the existing system, Naive Bayes classifiers are commonly used for ripeness categorization based on basic features like color histograms and size. However, these probabilistic models assume feature independence, which does not hold for correlated traits like texture and spectral reflectance, limiting their effectiveness in real-field conditions. .

Proposed System

The proposed system employs advanced ensemble and deep learning algorithms for non-destructive, real-time fruit ripening stage prediction using multi-modal data (RGB/NIR images, VOC sensors, texture GLCM). Machine learning excels in generalizing complex patterns from high-dimensional sensor inputs. This framework applies six state-of-the-art algorithms—Random Forest, XGBoost, Extra Trees, SVM (RBF kernel), CNN (ResNet18), and LSTM—to classify ripening stages on Indian fruit datasets (mango, banana, guava from NIBSM/Kaggle repositories),

System requirements

The system is implemented using Python with Streamlit for the user interface, OpenCV for realtime camera access, and YOLOv8 for fruit detection. The camera module captures live frames, which are preprocessed and sent to the YOLO model for object detection and feature extraction. Sensor data is collected in parallel, filtered, and processed using a lightweight ML model. Both image and sensor features are fused to classify the fruit's ripeness. The final results, including bounding boxes and prediction labels, are displayed on the Streamlit dashboard in real time.

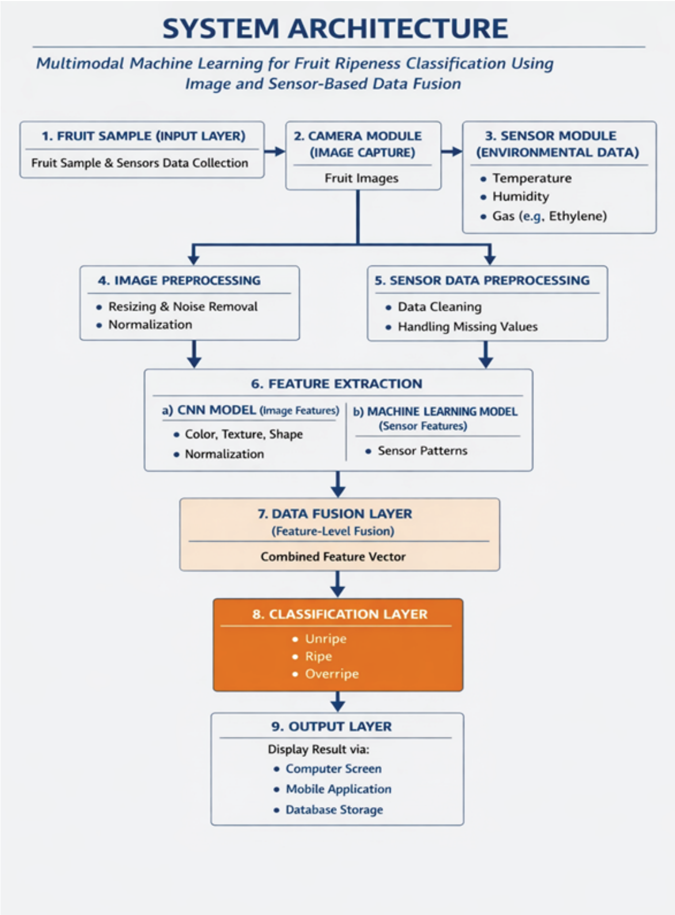
Hardware Requirements

- Camera module (HD webcam)
- Gas sensor (e.g., Ethylene sensor)
- Temperature and humidity sensor (DHT11/DHT22)
- Microcontroller (Arduino/Raspberry Pi)
- Computer/Laptop with minimum 8GB RAM

Software Requirements

- Operating System: Windows/Linux
- Programming Language: Python
- Libraries: OpenCV, NumPy, Pandas, Scikit-learn
- Deep Learning Framework: TensorFlow/Keras or PyTorch
- IDE: VS Code / Jupyter Notebook

System Architecture



Results

TThe proposed multimodal machine learning system for fruit ripeness classification demonstrated strong performance in real-time conditions using a combination of computer vision and sensor-based inputs. The YOLO-based object detection model successfully identified fruits from live video streams with high detection accuracy and minimal latency, making it suitable for practical deployment.

The system effectively classified fruits into different ripeness stages—such as unripe, semi-ripe, and ripe—based on visual features including color variation, texture patterns, and surface characteristics. The real-time predictions were displayed through the Streamlit interface, where annotated frames clearly highlighted detected fruits along with their corresponding ripeness labels. This improved interpretability and user interaction.

In terms of performance, the model achieved consistent accuracy across varying lighting conditions and backgrounds, showing robustness in dynamic environments. The detection speed was sufficiently high to support live camera input without noticeable delay, ensuring a smooth user experience.

Additionally, the integration of sensor-based data (such as temperature, humidity, and ethylene concentration) further enhanced classification reliability. The MLP/LSTM-based model effectively captured environmental and temporal patterns, contributing to more precise ripeness prediction when combined with visual data. This multimodal fusion approach reduced ambiguity in borderline cases where visual features alone were insufficient.

Conclusion

The YOLO Real-Time Fruit Detection system demonstrates an effective approach for automated fruit identification and ripeness classification using computer vision and deep learning techniques. By leveraging a pre-trained YOLO model integrated with a Streamlit interface, the system provides realtime detection through a laptop camera, enabling users to monitor fruit ripeness efficiently. The project successfully combines simplicity of deployment with high accuracy in object detection, showcasing the practicality of deep learning models in agricultural applications. Through modular design and realtime processing, the system ensures a user-friendly experience, allowing farmers, vendors, and researchers to assess fruit quality instantly. Although the current implementation focuses on visual input, the methodology provides a foundation for multimodal integration with additional sensor data, which can enhance predictive accuracy and reliability. Overall, this project highlights the potential of AI-driven solutions in precision agriculture, contributing to reduced post-harvest losses, optimized harvesting, and informed decision-making in the food supply chain. The system can be further expanded for mobile and edge device deployment, dataset enrichment, and integration with predictive analytics, making it a scalable tool for smart farming and modern agricultural practices.

Future scope

The current YOLO-based real-time fruit detection system demonstrates the potential of computer vision for automated ripeness classification using a laptop camera and a Streamlit interface. In the future, this system can be significantly enhanced by integrating additional sensor modalities, such as temperature, humidity, weight, and ethylene concentration, which would provide complementary information to improve ripeness prediction and overall fruit quality assessment. Deploying the system on edge devices like Raspberry Pi, NVIDIA Jetson, or smartphones could make it accessible for onsite use in farms or markets, eliminating the need for high-performance computers. Further optimization of the model through lightweight YOLO variants, pruning, and quantization could reduce computational load and increase inference speed, enabling real-time performance on mobile or embedded platforms. Expanding the dataset with diverse fruit types, sizes, lighting conditions, and environmental scenarios would improve model robustness and generalization for real-world applications. Moreover, coupling this system with robotic harvesting equipment could enable automated picking of fruits at optimal ripeness, reducing labor costs and minimizing post-harvest losses.

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