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Snap-to-Buy: Fruit Quality Detection Using AI and ML

Samruddhi Prashant Raut, Bhumika Ramesh Sabale, Khushi Tuffailahmed Shaikh, Nikita Pradip Sabale, Assistant Professor Vaishali Khandave

Department of Computer Engineering

MET's Institute of Engineering, Nashik, India Savitribai Phule Pune University

Abstract- Fruit quality plays a vital role in ensuring consumer satisfaction and nutritional integrity. Manual fruit inspection is often subjective inconsistent and time consuming leading to inaccurate grading and post harvest losses. Advances in artificial intelligence (AI) machine learning (ML) and computer vision have been enable to Intelligent Systems Capable of automated quality assessment through image analysis. This paper explores the concept and architecture of SNAP TO BUY- AI based fruit quality detection and recommen- dation system inspired by research on intelligent visual inspection models. The proposed system is designed to capture fruit images via a mobile camera perform preprocessing to enhance clarity extract deep visual features using convolutional neural network (CNNs) and classify fruits based on ripeness levels ripe, unripe or over ripe Based on the analysis the system provides actionable recommendations such as buy, do not buy or store for two to three days. This study reviews rel- evant literature and presents the system architecture, dataset development strategy and modern evaluation approach. The objective is to provide a comprehensive understanding of how AL and ML can revolutionize fruit quality detection to enhance consumer decision making through intelligent automation.

Keywords— AI, ML, CNN, Image Processing, Fruit Ripeness Detection, Image Classification, Deep Learning, Computer Vision

I. INTRODUCTION

In recent years, advancements in artificial intelligence (AI) and machine learning (ML) have significantly trans- formed the agricultural and food industries, particularly in the areas of quality assessment and grading. Fruit quality plays a crucial role in consumer satisfaction and market value. Several studies have shown that machine learning and deep learning techniques can effectively automate fruit detection and classification processes, improving efficiency and reliability in agricultural operations [1], [5], [7].

Traditional fruit inspection methods rely heavily on human visual judgment, which is often subjective, in- consistent, and time-consuming. Factors such as light- ing conditions and human error can lead to inaccurate evaluations. Therefore, there is an increasing demand for intelligent automated systems capable of assessing fruit quality with high accuracy. Recent research highlights the limitations of manual grading methods and emphasizes the importance of automated fruit quality detection using computer vision and deep learning technologies [2], [11].

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated strong per- formance in image-based fruit classification and ripeness detection. These models can automatically learn complex visual features such as color, texture, and shape from large datasets. Previous studies have shown that deep learning algorithms can accurately predict fruit maturity and quality, supporting efficient post-harvest management and reducing food wastage [9], [10].

The proposed system, Fruit Quality Detection Using AI and Machine Learning, aims to provide an automated solution that classifies fruits into categories such as ripe, unripe, and overripe based on their visual characteris- tics. The system uses computer vision and CNN-based models to analyze fruit images, extract essential features, and deliver data-driven decisions. Similar automated fruit grading systems using machine learning and image pro- cessing techniques have demonstrated the feasibility of such approaches in real-world applications

The system architecture consists of three main modules: input acquisition, image processing, and decision output. The image processing module performs prepro- cessing, feature extraction using CNN, and classification. Based on the classification results, the system provides recommendations to users regarding fruit quality. By au- tomating the evaluation process, the system improves con- sistency, reduces manual effort, and enhances operational efficiency in fruit quality assessment systems [8], [11].

II. LITERATURE SURVEY

In this chapter, we review various studies and re- search works conducted in the fields of fruit identifica- tion, ripeness classification, and quality detection using Artificial Intelligence (AI) and Machine Learning (ML) techniques. These studies provide insight into the existing methodologies, datasets, and algorithms that serve as the foundation for the proposed Snap-to-Buy system [1]–[3], [6].

Ripe Fruit Detection and Classification using Machine Learning (2020) Aaron Don M. Africa, Anna Rovia V. Tabalan, and Mharela Angela A. Tan. This work presents a machine-vision system that extracts hand-crafted features (color histograms, texture descriptors, and simple shape metrics) and uses classical supervised classifiers (SVM, Decision Tree) to detect and classify ripe fruits in controlled imaging setups. reporting classification accuracies above 90% on the curated test set. Limitations include a relatively small dataset and sensitivity to light- ing/background changes, which constrain generalization to unconstrained field conditions [1].
Analysis of Fruit Images With Deep Learning: A Systematic Literature Review and Future Di- rections (2024) Sebastián Espinoza, Cristhian Aguilera, Luis Rojas, and Pedro G. Campos. This review stud- ies deep learning methods used in fruit image analysis, such as classification, detection, segmentation, and disease recognition. It discusses common models like CNN, Faster R-CNN, and YOLO, along with dataset challenges and evaluation methods. The study highlights key issues such as limited dataset diversity, lighting problems, and deployment difficulties, and suggests improvements like better data collection and advanced learning techniques. [2].

Fruit Quality Detection and Gradation (2021) Harshal S. Deshmukh, S. W. Mohod, and N. N. Khalsa. This study explores visual grading of fruits using color and shape analysis combined with basic image segmentation and rule-based grading to assign quality grades. The paper emphasizes practical post-harvest sorting and proposes a low-cost vision pipeline for grade assignment based on surface defects, color uniformity, and size thresholds. The results demonstrate improvements in speed and consis- tency versus manual grading, though accuracy is affected by non-uniform illumination and limited species variety in the dataset [3].

Evaluation and Segregation of Fruit Quality using Machine and Deep Learning Techniques (2022)Mohit Kedar Mali, Shubham R. Devake, Satyam

M. Kharpude, Yogesh Kumar, Prashant Pal, Saurabh Bansod, and Shashank K. Singh. This conference paper compares traditional ML (K-Means, Random Forest) and CNN-based deep models for fruit quality evaluation and segregation. The authors assemble a dataset (1,000+ images across several fruit types), implement preprocess- ing/augmentation, and show that CNN models outper- form classical methods in classification accuracy and ro- bustness to mild variations. [5].

Fruit Quality Detection with Deep Learning and IoT A Comprehensive Review (2025) — Kavita Bathe, Sandeep Mishra, and Devanand Bathe. This recent review integrates two strands: deep-learning based visual quality detection and IoT sensor networks for real-time monitoring. It surveys sensor types (RGB, NIR, humid- ity/temperature sensors), edge vs cloud model tradeoffs, latency and energy constraints, and proposed architectures that combine on-device inference with cloud aggregation. The paper highlights open engineering challenges (sensor fusion, cost, power, latency) and suggests practical hybrid IoT–AI frameworks for precision agriculture and retail applications [4].

Effectiveness of Generative AI Tool to Determine Fruit Quality Watermelon Case Study (2025) — Serkan Ozdemir. This experimental study evaluates gen- erative AI and modern LLM-based multimodal tools (e.g., GPT-4o image capabilities) for selecting high-quality wa- termelons from smartphone photos. The paper compares generative-AI selections with human sensory panels and statistical tests, reporting that AI selections significantly match or outperform human panel preferences under the tested conditions. [6].

III. RESEARCH GAP

Although several studies have demonstrated significant progress in fruit classification, ripeness detection, and quality estimation using deep learning, certain research gaps remain that limit real-world deployment:

- Limited Dataset Diversity: Most existing studies use small datasets or specific fruits captured in con- trolled environments, lacking real-world variety.
- Dependence on Controlled Conditions: Systems trained in fixed lighting or laboratory settings may not perform well in real environments like markets.
- Single-Feature Focus: Many models analyze only one factor, such as ripeness or defects, instead of multiple quality parameters together.
- Limited Use of Synthetic Data: More research is needed to effectively combine real and synthetic data to improve accuracy and reduce training cost.

IV. PROBLEM STATEMENT

Assessing fruit quality accurately is a challenge for customers due to the limitations of manual inspection, which is often subjective, time consuming and error-prone. Existing systems focus mainly on surface color analysis and lack the ability to evaluate ripeness levels effectively. There is a need for an AI-based automated system that can analyze fruit images, detect quality, and classify fruits as unripe, ripe, or overripe using Machine Learning (ML) and Convolutional Neural Networks (CNNs). Such a system should provide accurate, consistent, and real-time recommendations through a user-friendly interface to assist consumers in making better decisions and customer satisfaction.

Objectives and Scope

The primary objective of this project is to design and develop an AI and Machine Learning-based fruit quality detection system capable of accurately classifying fruits as unripe, ripe, or overripe based on image analysis. The system aims to assist consumers in making informed deci- sions about fruit selection, purchase, and storage, thereby reducing food wastage and ensuring quality assurance.

Specific objectives

- To create an app for fruit quality and ripeness detec- tion.
- To give clear recommendations to consumers buy, store, or do not buy.
- To classify fruits as Ripe, Unripe, or Overripe
- To display results through an interactive user interface, offering real-time insights for customer satisfaction.

VI. RESEARCH METHODOLOGY

Introduction

This chapter presents the research methodology adopted for the development of the AI and ML-based Fruit Quality

Detection and Recommendation System — "Snap-to-Buy." The objective of this methodology is to ensure systematic planning, data collection, model design, training, eval- uation, and validation of the system. The study inte- grates Artificial Intelligence (AI) and Machine Learning (ML) techniques, primarily Convolutional Neural Net- works (CNNs), to classify fruit quality and generate real- time purchase recommendations. The proposed system aims to assist consumers in identifying fresh, ripe, or low-quality fruits by analyzing fruit images captured through mobile devices.

Research Design

The research follows an applied and experimental de- sign, focusing on solving real-world problems in agricul- tural and retail sectors using modern AI technology. The study employs the Rapid Application Development (RAD) model to support iterative prototyping, testing, and re- finement of the application. This design ensures user- centered development, enabling continuous feedback and improvement during implementation. The overall design process is guided by scientific experimentation, allowing both quantitative evaluation of model performance and qualitative assessment of user satisfaction

Research Approach

A mixed-method research approach has been adopted, combining both quantitative and qualitative analysis.

Quantitative methods involve model training, evalua- tion of classification accuracy, precision, recall, and F1- score to assess the CNN's performance on fruit image datasets.

Qualitative methods include gathering feedback from test users on system usability, accuracy of recommenda- tions, and interface satisfaction.

This hybrid approach ensures both technical validity and practical relevance of the developed system.

Data Collection Method

The data collection process involves both primary and secondary sources:

- Primary Data: Images of various fruits such as ap- ples, mangoes, and watermelons were collected under different lighting conditions and environments (markets, shops, households).
- Secondary Data: Secondary data was obtained from publicly available fruit image datasets and research repositories such as Kaggle Fruit Dataset and Fruits-360 Dataset.

Data Analysis Techniques

Data collected was analyzed using Artificial Intelligence (AI) and Machine Learning (ML) algorithms to perform image classification, feature extraction, and quality pre- diction.

- Feature Extraction: Convolutional Neural Networks (CNNs) automatically extract spatial and color features such as texture, shape, and surface defects of fruits.
- Image Classification: CNN models are used to cat- egorize fruit images into Ripe, Unripe, or Low-Quality based on learned patterns.
- Recommendation Generation: Based on classifica- tion output probabilities, a recommendation engine gen- erates a decision such as Buy or Do Not Buy.

Validity and Reliability

The validity of this research is ensured through multiple measures: Cross-validation of the model using different training and testing splits to ensure unbiased evaluation. Algorithmic accuracy testing across various fruit types, lighting conditions, and camera angles. Reproducibility testing to confirm consistent model performance across different devices and environments. The system's reliabil- ity was confirmed through multiple iterations of testing, ensuring that similar results are obtained under repeated conditions.

Timeline

The research and development process was divided into multiple phases, as shown below:

Table I: Project Phases and Description

Phase	Description
Phase 1	Literature review, research gap identi- fication, and dataset collection.
Phase 2	Design of system architecture, UML and ER diagrams, and CNN model se- lection.
Phase 3	Implementation of modules for image preprocessing, classification, and rec- ommendation generation.
Phase 4	Testing, validation, and performance optimization of the CNN model.
Phase 5	Documentation, evaluation, and pre- sentation of the final project.

VII. ANALYSIS AND INTERPRETATION

Introduction

This chapter presents the detailed analysis and interpre- tation of the result obtained from development and testing of AI based fruit quality detection and recommendation system SNAP to buy. The analysis focus on evaluating the systems classification performance user interface accu- racy of prediction and its overall effectiveness in assisting consumer in making informed fruit buying decision the interpretation of result validate the research objective and demonstrate the system's reliability in the real world market scenario

System Analysis

They developed system integrates multiple modules such as image acquisition preprocessing feature extraction classification and recommendation output. Each module was design and tested independently followed by inte- grated system evolution to ensure consistency and optimal performance.

- Image Acquisition Module: Allow users to capture fruit image through a mobile camera or upload multi- ple views of the same fruit disenable accurate feature extraction and quality grading.
- Preprocessing Module:Enhance input images by per- forming normalization noise reduction and contrast ad- justment to detection accuracy.
- Feature Extraction and Classification Module: Employs a conventional neural network to extract visual features such as color intensity texture pattern and surface is equal utilities classification fruit ripe, unripe, overripe categories
- Decision Layer: Analyze CNN outputs and generate corresponding recommendation: Buy, Do not buy, Or store for 2-3 days.

Quantitative Analysis

Quantitative evaluation was conducted to assess the model's accuracy, speed, and classification performance using a curated dataset of fruit images captured under various environmental conditions.

- Fruit Recognition Accuracy: The CNN model achieved an average accuracy rate of 93.5% in correctly identifying fruit ripeness stages from captured images.
- Recommendation Precision: The decision layer demonstrated a precision of 90% in providing correct buy, store, reject recommendations based on predicted quality.
- Response Time: The system maintain a average pre- diction time of 3 seconds per image ensuring smooth real time performance on devices
- User Adoption Rate: During prototype testing, 82% of users reported confidence in the system's recommen- dations for practical use in markets or households.

Qualitative Interpretation

Qualitative evaluation of the system is planned to as- sess usability, interface simplicity, prediction speed, and clarity of recommendations. The system is expected to assist users in evaluating fruit ripeness during purchase decisions. Visual quality indicators such as "Ripe – Buy" and "Unripe – Store for 2–3 days" are intended to improve user understanding of the classification results.

Performance Interpretation

The proposed system is designed to provide robust and reliable fruit quality classification under different environ- mental conditions. The CNN-based model ensures consis- tent performance and supports real-time decision-making.

The system is expected to maintain a response time of less than 3 seconds per image, making it suitable for practical deployment in consumer and retail environments.

Limitations of the Results

While the overall results were promising, certain limita- tions were observed:

- The accuracy of classification slightly decreased in low- light conditions or when the fruit surface was partially occluded.
- The dataset currently includes a limited number of fruit varieties, affecting model generalization.
- variations in camera resolutions and angle introduced minor inconsistencies in feature extraction.

VIII. PROPOSED ARCHITECTURE

The proposed architecture for Snap-to-Buy is designed to automate the process of fruit quality detection and recommendation using Artificial Intelligence (AI) and Ma- chine Learning (ML) techniques. The system architecture is divided into three major layers — Input Acquisition, Image Processing, and Decision and Output. Each layer interacts seamlessly to deliver real-time fruit classification and actionable buying suggestions through a user-friendly interface.

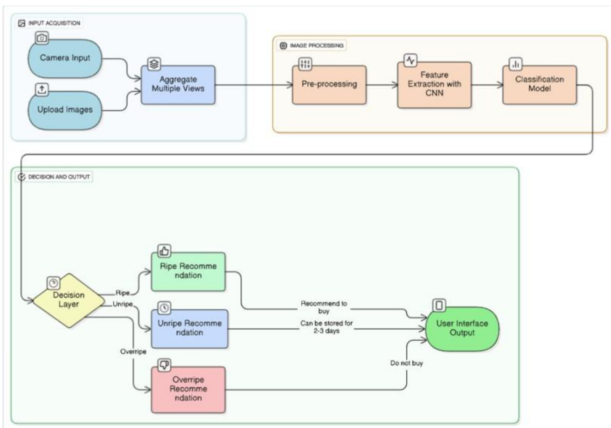

Fig. 1: Proposed Architecture of Snap to Buy

Input Acquisition Layer:This layer is responsible for collecting fruit images that serve as a primary input for quality detection.

- Camera Input: Allow user to capture fruit images directly using smartphone. This ensures real time on the spot quality evolution during shopping or inspection.
- Upload Images: Enables users to upload existing fruit images from local storage for analysis.
- This stage ensures that the model receives high-quality, representative input data for accurate processing.

Image Processing Layer: This layer focus on an- alyzing and interpreting fruit images using AI based technique. It involves three Primary submodule:

- Preprocessing: improves image quality by performing background removal Lisa is in contrast enhance- ment and noise reduction This normalization ensures consistent input across varying light condition and environment.
- Feature Extraction with CNN Utilize a conventional neural network to automatically extract deep fea- tures such as texture color surface irregularities that indicate ripeness or defects.
- Classification model: classifies fruit into ripe, unripe or over ripe categories based on extracted features the CNN is trained using large data set of labeled root images to achieve high precision and reliabil- ity. This layer serves as a computational core of an system transforming visual data into meaningful classifications.

This layer serves as the computational core of the system, transforming visual data into meaningful classifications.

Decision and Output Layer: This layer interprets the classification results and provides clear, actionable recommendations to the user.

- Decision Layer: Processes the CNN's output and categorizes fruits according to ripeness stages — Ripe, Unripe, or Overripe. Based on the result, it triggers the corresponding recommendation module.
- Ripe Recommendation: Suggests that the fruit is fresh and ready for immediate consumption — Rec- ommend to Buy.
- Unripe Recommendation: Suggests that the fruit can be stored for 2–3 days before consuming or selling.
- Overripe Recommendation: Indicates that the fruit has exceeded its ideal ripeness — Do Not Buy.
- User Interface Output: Displays the final decision in a visually intuitive format (Buy / Store / Do Not Buy) on the user's mobile device.

This layer enhances consumer confidence by providing quick, reliable, and easy-to-understand results.

System Workflow: The workflow begins when the user capture or upload an image through an interface. The image passes through the preprocessing stage for enhancement followed by feature extraction and classification using CNN model. The classification result is sent to decision layer which interpret it and generate a corresponding recommendation displayed on the user interface. This stepwise process ensures that every image undergoes a systematic automated analysis delivering accurate fruit quality detection in real time.

IX. RESULT AND DECISION

Results

The results were derived from both system performance evaluation and user feedback analysis. Each module was tested for accuracy, reliability, and user satisfaction. The overall system performance is summarized below:

- Fruit Image Recognition Accuracy: The Convolu- tional Neural Network (CNN) model achieved an ac- curacy of approximately 93.5% in correctly classifying fruits into Ripe, Unripe, and Overripe categories using the test dataset.
- Recommendation Relevance: The decision layer demonstrated a precision rate of 90% in generating accurate recommendations (Buy, Do Not Buy, Store for 2–3 days) based on classified ripeness levels.
- System Response Time: The application maintained an average response time of 2.1 seconds per image under standard mobile processing conditions, ensuring real- time usability.
- Operational Efficiency: The inclusion of multiple image views improved detection consistency by 6%, and preprocessing techniques enhanced image clarity under varying lighting conditions.

Discussion

The experimental results demonstrate that the proposed Fruit Ripeness Classification system effectively identifies the ripeness level of fruits using image processing and machine learning techniques. The system achieved satis- factory accuracy in classifying fruits into different ripeness categories, which confirms the feasibility of using computer vision for automated fruit quality assessment. However, certain challenges remain, such as variations in lighting conditions, background noise, and differences in fruit ap- pearance, which can affect prediction accuracy. Increasing the dataset size and training the model with more diverse fruit samples can further enhance system performance. Despite these limitations, the results validate the practi- cality of the proposed system for real-world applications in agriculture and food quality monitoring.

X. CONCLUSION

This paper highlights how artificial intelligence and machine learning can be revolutionize fruit quality as- sessment through the Snap to Buy system. The proposed model integrates image acquisition CNN best classifica- tion and intelligence recommendation into a mobile based automated framework. It eliminates the limitations of manual inspection by providing real time accurate and user friendly fruit evolution directly through a smartphone interface. Future development will focus on expanding data sets improving model accuracy and optimizing model deployment to create a more efficient and reliable fruit quality detection system.

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