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AI-Powered Fruit Profiling System for Detection, Ripeness, and Calorie Estimation

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Abstract: This project presents a machine learning-driven fruit profiling system utilizing advanced deep learning and computer vision techniques to analyse fruit images. The system comprises two main components: fruit type identification with caloric estimation, and fruit ripeness classification. The first component detects various categories of fruits providing estimated nutritional information based on recognized types. The second component assesses the ripeness stage, distinguishing different maturity and spoilage levels across multiple fruit varieties. Both components employ the YOLO V9 algorithm for accurate and efficient detection. By integrating static nutritional data with dynamic quality assessment, the system offers a comprehensive tool for evaluating produce through image analysis. This approach enables quick, automated classification and quality estimation, facilitating applications in nutrition tracking, agricultural management, and supply chain monitoring.

Keywords: Fruit profiling, deep learning, computer vision, YOLO V9, fruit classification, caloric estimation, ripeness detection, image analysis, nutritional assessment, produce quality, machine learning, object detection.

I. INTRODUCTION

Fruit Profiling System is an AI-powered platform designed to guide aspiring farmers and retailers from the spark of an idea to a successful fruit quality assessment launch. Built with intelligent algorithms and real-time data analysis, the system helps users validate their fruit analysis concepts, match with compatible fruit types, and generate tailored strategic roadmaps for growth. By combining natural language processing, market trend analysis, and skill-based team building, Fruit Profiling System bridges the common gaps faced by early-stage founders, uncertainty about market fit, difficulty in building a team, and lack of actionable direction. The platform empowers users with clarity, confidence, and connection, turning uncertainty into structured opportunity.

Key Features:

- **AI-Based Idea Validation** using real-time market and trend analysis
- **Co-Founder Matchmaking Engine** driven by skill compatibility and fruit quality assessment goals
- **Strategic Roadmap** Generation to provide personalized, step-by-step fruit analysis guidance
- **Feasibility Mapping** for informed decision-making
- **Smart Input Validation System** to refine fruit quality assessment ideas from the start

II. RELEVANT LITERATURE

A. Fruit Classification and Ripeness Estimation using Deep learning Models

Asha Gowda Karegowda, Hemashree DU, and S.J. Sheela's paper "Fruit Classification and Ripeness Estimation using Deep Learning Models" (June 2023) provides a thorough analysis of ripeness classification for four fruits—grapes, papaya, pomegranate, and strawberry—across three stages: unripe, ripe, and overripe. The authors compare DenseNet201, MobileNetV2, InceptionV3, and VGG16 CNN architectures using a dataset of 7,783 images. With an accuracy of 92%, DenseNet201 performs the best, successfully capturing minute color and texture variations that distinguish different ripeness levels. Strong generalization under various visual conditions is ensured by extensive image augmentation and transfer learning from ImageNet. Additionally, DenseNet201 exhibits superior recall, precision, and F1-scores, demonstrating its consistency across all fruit categories. According to the study's findings, deep learning models—in particular, DenseNet201—provide an automated fruit ripeness assessment that is dependable, scalable, and effective, making them ideal for real-time agricultural monitoring and decision-making systems.

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B. Detection of Fruit from an Image Using a Single Shot Detector for Accurate Calorie Estimation

Sravya Sri Jandhyala, Ashutosh Satpathy, Shaik Hussain Saitaj, and Lanka Niharika's paper "Detection of Fruit from an Image Using a Single Shot Detector for Accurate Calorie Estimation" presents a mobile-friendly calorie estimation system that combines image processing with a Single Shot Detector (SSD) and CNNs, specifically SSD MobileNet V2. Bounding boxes and estimates are used by the system to identify fruits in pictures their caloric content by estimating volume using camera model assumptions and calculating fruit area. A database of known fruit densities and average nutritional data is used to calculate calorie values. The model, which was trained on the FooDD dataset that included six fruits—apple, banana, grape, kiwi, orange, and watermelon—achieved a remarkable 99% detection accuracy and 87.02% calorie estimation accuracy. Fruit labels, bounding boxes, and calorie counts are displayed through a mobile interface, making the system quick, easy to use, and efficient for dietary tracking. The study shows great promise for enabling real-time nutrition tracking on portable devices and extending calorie estimation to a larger variety of food items.

C. Image-Based Fruit Recognition and Classification

Alexandru Marin and Emilian Radio's paper "Image-Based Fruit Recognition and Classification" addresses the drawbacks of conventional manual classification techniques, which are frequently slow and prone to human error, by presenting a machine learning approach for automatic fruit identification. In order to accurately recognize new, unseen samples, the system uses a convolutional neural network (CNN) to extract key visual features from labeled fruit images, such as shape, texture, and color. Preprocessing techniques like image normalization, resizing, and augmentation were used to improve the model's resilience in a variety of lighting and background scenarios. The suggested approach has great practical potential for real-world applications like self-checkout systems, automated sorting in the food industry, and mobile consumer applications, despite the authors' failure to supply specific model parameters or performance metrics. In order to boost the system's efficacy and adaptability, the paper also identifies areas for future development, such as adding ripeness or freshness detection and broadening the variety of fruit categories.

III. SYSTEM DESIGN

A. Introduction of Input Design:

In an information system, input is the raw data that is processed to produce output. During the input design, the developers must consider the input devices such as PC, MICR, OMR, etc.

Therefore, the quality of system input determines the quality of system output. Well-designed input forms and screens have following properties

- It should serve specific purpose effectively such as storing, recording, and retrieving the information.
- It ensures proper completion with accuracy.
- It should be easy to fill and straightforward.
- It should focus on user's attention, consistency, and simplicity.
- All these objectives are obtained using the knowledge of basic design principles regarding −
    - What are the inputs needed for the system?
    - How end users respond to different elements of forms and screens.

B. Objectives for Input Design:

The objectives of input design are −

- To design data entry and input procedures
- To reduce input volume
- To design source documents for data capture or devise other data capture methods
- To design input data records, data entry screens, user interface screens, etc.
- To use validation checks and develop effective input controls.

C. Output Design:

The design of output is the most important task of any system. During output design, developers identify the type of outputs needed, and consider the necessary output controls and prototype report layouts.

D. Objectives of Output Design:

The objectives of input design are:

- To develop output design that serves the intended purpose and eliminates the production of unwanted output.
- To develop the output design that meets the end user's requirements.
- To deliver the appropriate quantity of output.
- To form the output in appropriate format and direct it to the right person.

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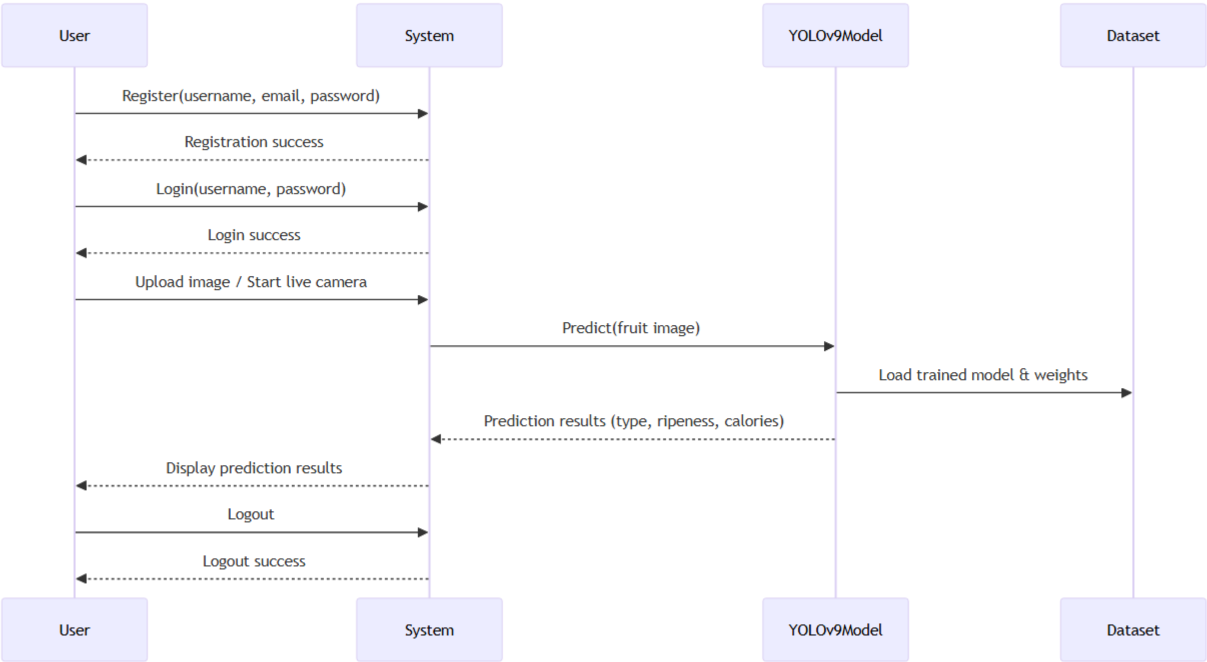
- To make the output available on time for making good decisions.

E. SEQUENCE DIAGRAM:

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.



IV. METHODOLOGY

YOLOv9 is the latest iteration in the You Only Look Once (YOLO) family of real-time object detection algorithms, designed to improve accuracy and speed for complex detection tasks such as fruit profiling. It builds upon its predecessors by incorporating novel architectural and training improvements that optimize performance on large-scale and multi-class datasets.

1. Architecture

- **Backbone**: YOLOv9 uses an improved backbone network that efficiently extracts rich hierarchical features from input images. This backbone combines convolutional layers with advanced attention mechanisms (e.g., coordinate attention or transformer modules) to focus on relevant regions, improving feature representation of objects such as fruits.
- **Neck**: The neck aggregates and refines features from different scales using feature pyramid networks (FPN) and path aggregation networks (PAN), enabling the model to detect objects at multiple sizes — critical for fruits that vary in size and proximity.
- **Head**: The detection head outputs bounding boxes, class probabilities, and abjectness scores. YOLOv9 uses anchor-free or anchor-based prediction heads, along with improved loss functions (e.g., Wise IoU or distribution focal loss) to enhance localization accuracy.

2. Input Processing

YOLOv9 preprocesses images by resizing them to fixed dimensions (e.g., 640x640 pixels), normalizing pixel values, and applying data augmentation techniques such as random scaling, flipping, and color jitter to improve robustness.

3. Training

- **Label Assignment**: YOLOv9 utilizes dynamic label assignment strategies, which adaptively assign ground truth boxes to predictions during training, improving convergence and reducing false positives.

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- **Loss Function**: The overall loss combines classification loss, bounding box regression loss (using improved IoU-based metrics), and abjectness loss, guiding the network to better predict both the presence and precise location of fruits.
- **Optimization**: The model is trained using stochastic gradient descent (SGD) or Adam optimizers with learning rate schedulers like cosine annealing to improve generalization.

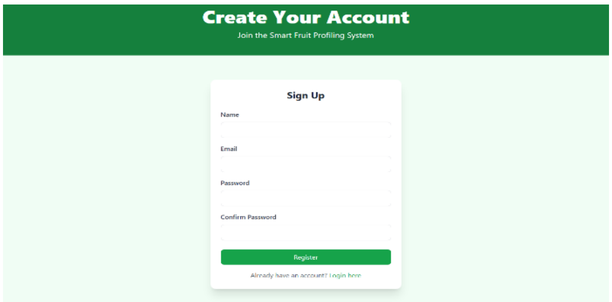
4. Inference

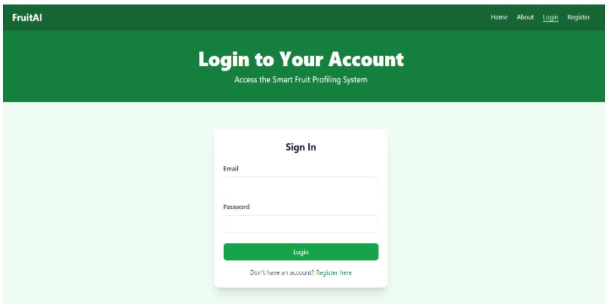
During inference, YOLOv9 predicts bounding boxes with associated class scores in a single forward pass, ensuring real-time detection. Non-Maximum Suppression (NMS) filters overlapping boxes, retaining the highest confidence detections.

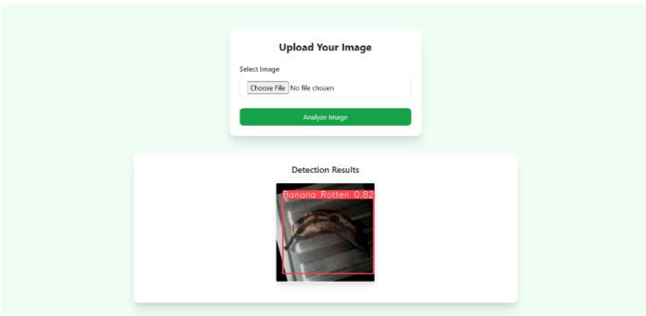
V. RESULTS AND DISCUSSION

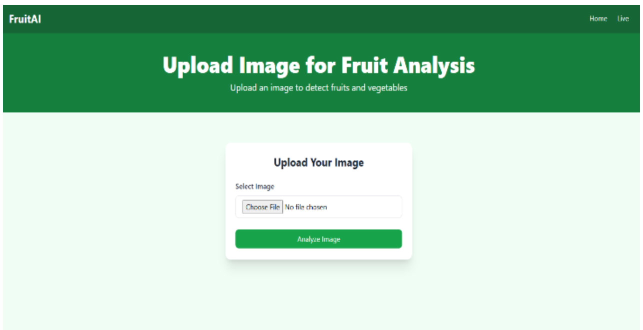
All losses—box, classification, and DFL—continue to smoothly decline in the training and validation graphs, indicating that the model is learning effectively and gradually increasing its accuracy. The model is not overfitting and performs well on fresh data because both curves exhibit a similar pattern. As training goes on, precision and recall steadily rise, indicating that the model is accurately identifying fruits and missing fewer objects. While the more stringent mAP@0.5–0.95 also performs well, though there is some space for improved localization, the mAP@0.5 reaches a high value, demonstrating strong detection accuracy. All things considered, the model learns efficiently, generalizes well, and produces good fruit detection and calorie estimation results; only minor tweaks are required for even greater accuracy.

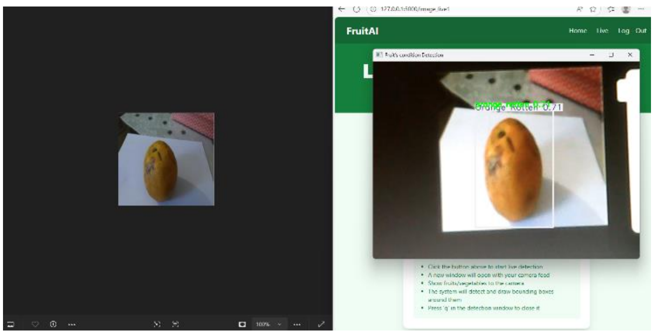
The development and testing of the Fruit Detection and Calorie Estimation System went well. It has an easy-to-use interface, and the YOLO-V9 model accurately detects fruits, checks for ripeness, and calculates calories. The system operates efficiently and produces dependable results, as demonstrated by the screenshots and outcomes.











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VI. CONCLUSION AND FUTURE WORK

Both models' training and validation curves demonstrate smooth and steady learning, with box loss, classification loss, and distribution focal loss steadily declining. This indicates that the models are getting better at detection, classification, and localization. Strong generalization without overfitting is indicated by the close match between training and validation trends. Model robustness is confirmed by performance metrics like precision, recall, and mAP, which also gradually improve. Although there is a discernible difference between mAP@0.5 and mAP@0.5–0.95 in the first model, The second model performs better, with precision and recall above 0.9 and stronger mAP results, indicating that localization can be improved. All things considered, both models show strong accuracy, dependable convergence, and efficient learning, which qualifies them for practical detection applications.

Future Scope: In the future, model performance can be enhanced by investigating better architectures, such as attention-based models, for higher accuracy and faster inference, and improving localization accuracy through stronger data augmentation. Expanding the dataset with more varied samples will help the model handle real-world variations like lighting, occlusion, and scale changes, while using ensemble methods can boost robustness. Continuous learning or domain adaptation will help maintain accuracy as real-world data changes, and optimizing the model for edge devices will allow for quicker, lighter deployment. Finally, by providing users with a better understanding of model decisions and confidence levels, explainability and uncertainty estimation can increase trust.

VII. ACKNOWLEDGMENT

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