iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: IX Month of publication: September 2025

DOI: https://doi.org/10.22214/ijraset.2025.74019

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

Smart Fruit Quality Evaluation Portal Using Deep Neural Vision and Flask Framework

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Abstract: Traditional fruit quality grading is manual, slow, and prone to errors. With the rise of agri-tech, AI and computer vision have emerged as powerful tools to automate this process. This research presents a Smart Fruit Quality Assessment Portal that employs convolutional neural networks (CNNs) and a Flask-based cloud backend to categorize fruit images into groups such as "Fresh," "Ripening," or "Spoiled." Users upload images via a mobile-friendly web interface, and the system trained on diverse fruit datasets analyzes quality features like color and defects. Containerized backend services ensure fast, scalable performance. The model achieved 94% accuracy, with precision and recall over 90%. Designed for ease of use across devices, this platform provides a reliable, real-time solution for modernizing post-harvest quality assessment.
Keywords: Fruit Grading, Deep Learning, CNN, Flask, Cloud AI, Agricultural Automation.

I. INTRODUCTION

The global demand for fresh and visually appealing fruits has grown steadily due to increasing consumer expectations, export requirements, and retail standards. Traditionally, Fruit quality assessment has traditionally been conducted manually by skilled inspectors who evaluate characteristics like color and size shape, and surface defects. While effective in small-scale or localized operations, manual grading is inherently limited by human subjectivity, fatigue, and inconsistency. These constraints are especially emphasized in extensive agricultural supply chains where consistency and efficiency are essential for market competitiveness. In such contexts, inconsistent grading can lead to mispricing, increased post-harvest losses, and disputes between producers, distributors, and retailers. Advancements in artificial intelligence, particularly in computer vision and deep learning, have opened up possibilities for automating and standardizing quality inspection procedures. Convolutional neural networks (CNNs) and other technologies have shown impressive prowess in categorizing images, allowing for effective analysis of visual characteristics in fruits. AI-driven systems can work faster and with higher precision compared to human graders, ensuring consistent evaluations across extensive datasets. However, several earlier implementations lacked scalability, suffered from limited dataset variety, or were inaccessible to end-users without technical expertise. Additionally, real-world deployment requires systems to be responsive, mobile-compatible, and easily maintainable under varying field conditions. To tackle these obstacles, this paper introduces a Smart Fruit Quality Evaluation Portal - a cloud-based platform that combines advanced neural vision models with a streamlined Flask web framework. The platform allows users to upload fruit images from any device. These images are then analyzed by a pre-trained CNN model to assess quality levels like "Fresh," "Ripening," or "Spoiled." The model has been trained on a wide range of fruits in different environmental conditions, ensuring its applicability in real-world situations. Each prediction is accompanied by a confidence score, providing transparency and aiding decision-making for stakeholders in agriculture, packaging, and retail sectors.

The portal emphasizes user accessibility and real-time feedback. A responsive web interface allows farmers, vendors, and quality inspectors to easily interact with the system without requiring technical knowledge. Containerized backend services support scalability and low-latency inference, while secure cloud deployment ensures data privacy and system reliability. This design enables effective fruit grading and seamless integration with IoT devices and supply chain management tools. Through this work, we aim to bridge the gap between AI innovation and practical deployment in agriculture, offering a reliable, scalable, and user-centric solution to one of the industry's most persistent challenges objective and efficient fruit quality assessment.

II. LITRATURE SURVEY

The progression from manual to automated fruit grading systems has been gradual, driven by the need for precision and scalability. Initial studies by Sharma and Kumar [1] concentrated on utilizing grayscale thresholding in image processing for assessing fruit quality. Their method offered a simple rule-based approach to segregate acceptable and defective produce. While it helped demonstrate automation potential in visual grading, its lack of robustness in handling complex textures and colors limited real-world applicability.

Patel and Roy [2] progressed in this direction by utilizing Support Vector Machines (SVM) to examine surface imperfections through texture characteristics obtained using Gray-Level Co-occurrence Matrices (GLCM).Their model improved defect detection accuracy compared to thresholding, but was constrained by limited feature diversity and scalability issues, particularly in high-throughput environments. In response to the growing need for color-based classification, Thomas and Reddy [3] proposed an RGB histogram-based ripeness detection method. Their system effectively classified fruits into ripeness stages based on color intensity. However, it was susceptible to lighting variations and background interference, highlighting the need for more robust preprocessing and feature extraction.

Verma and Tiwari introduced deep learning to the field by employing convolutional neural networks (CNNs) for real-time detection of defects in fruits. Their approach marked a substantial improvement over traditional ML models, as CNNs could automatically learn hierarchical features without manual engineering. Their model showcased impressive precision and established the groundwork for incorporating deep vision into agricultural categorization assignments. Nair and Gupta [5] added another layer of innovation by proposing a cloud-hosted fruit grading API. Their system allowed for remote processing and scalable deployment. However, it lacked integration with a user-friendly frontend, thereby restricting its accessibility to end-users such as farmers or retailers.

Further growth was observed when Rao and Singh combined IoT sensor data with machine learning models for assessment [6]. By considering external variables such as temperature and humidity, they moved beyond purely visual assessments. This multimodal approach improved grading reliability but introduced complexity in deployment and hardware dependency. Meanwhile, Iyer and Kapoor [7] conducted a benchmark study comparing CNN architectures such as VGG, ResNet, and MobileNet. Their results informed model selection in constrained environments, showing that lightweight models like MobileNet achieve acceptable accuracy with reduced computation insights valuable for edge deployment scenarios.

Addressing usability in low-connectivity regions, Deshmukh and Bhatt [8] created an offline fruit detection app using TensorFlow Lite. Their mobile-based solution empowered farmers with instant grading without internet reliance, but faced limitations in model size and update frequency. Mehta and D'Souza [9] pushed boundaries further by incorporating multispectral imaging and pretrained deep networks to detect hidden defects and predict freshness. Their work demonstrated the value of spectral diversity in boosting grading precision but also emphasized the need for specialized hardware.

Lastly, Banerjee and Das [10] took a broader supply-chain perspective, illustrating how AI-driven quality inspection systems contribute to traceability, reduced spoilage, and logistics optimization. Their findings underscored the role of such platforms in building a smarter and more connected agricultural ecosystem.

III. METHODOLOGY

The proposed approach integrates deep learning, image processing, and cloud deployment, and a user-friendly web interface to automate fruit quality evaluation. It follows a modular pipeline consisting of data preparation, model training, web application development, backend processing, and real-time prediction display. Each component is optimized for accessibility, scalability, and reliability, making the system usable even by non-technical stakeholders such as farmers, market vendors, and agricultural inspectors.

A. Dataset Collection and Preparation

The system is built upon a curated image dataset consisting of thousands of labeled fruit images from sources including:

- Kaggle fruit datasets
- Public agricultural research archives
- Custom images captured via smartphones in varied lighting and background conditions

Each image is labeled with quality categories such as:

- Fresh
- Ripening
- Overripe
- Spoiled/Defective

To improve model generalization, the dataset was balanced across categories and included common fruits such as apples, bananas, oranges, and mangoes.

B. Dat Preprocessing and Augmentation

The proposed approach integrates deep learning, image processing, and cloud deployment.

1) Resizing all images to 224×224 pixels
2) Color normalization to match the training distribution
3) Noise reduction using Gaussian blur
4) Background clutter removal using basic segmentation

Augmentation techniques (random rotations, flipping, brightness shifts, and zooming) were applied to increase dataset diversity and reduce overfitting.

C. Model Architecture and Training

A Convolutional Neural Network (CNN) model was chosen for its demonstrated effectiveness in tasks involving image classification**.**

The architecture includes:

1) Convolutional layers to extract texture, color, and shape features
2) Max pooling layers to reduce dimensionality
3) Fully connected layers to perform final classification

The model underwent supervised learning training with:

- Cross-entropy loss
- Adam optimizer
- Learning rate scheduling

It attained a 94% accuracy in classifying the test dataset, consistently maintaining confidence scores exceeding 90% in crucial categories such as Spoiled and Fresh.

D. Flask Backend and API Integration

The trained CNN model was saved and deployed on a Flask web server using TensorFlow and Keras. The backend:

1) Handles image uploads from the web portal
2) Applies the preprocessing pipeline
3) Feeds images into the CNN model
4) Returns predicted class and confidence to the user interface

Backend services are containerized with Docker and hosted on cloud instances, supporting automatic scaling and low-latency inference.

E. Frontend Interface and User Experience

The web interface is designed using HTML5, Bootstrap, and JavaScript to ensure:

1) Compatibility across desktops, tablets, and smartphones
2) Simple upload mechanism (drag and drop or camera capture)
3) Visual feedback of prediction with color-coded results
4) Downloadable quality reports for vendor use

Users can select fruit type, upload an image, and receive near-instant results with category and confidence display.

IV. EVALUATION & RESULTS

To evaluate the efficiency of the suggested Smart Fruit Quality Evaluation Portal, the system underwent assessment using performance-based and usability-focused metrics. These metrics were chosen to directly address the core problem statement: eliminating subjectivity, reducing delays, and increasing consistency in fruit quality grading through AI and automation.

A. Classification Accuracy

- Usage: Evaluates the proportion of correctly classified fruit images across all quality categories.
- Importance: Directly reflects the model’s reliability in replacing human judgment for consistent, large-scale grading.
- Outcome: The system achieved 94% accuracy across all fruit types and quality labels, showing strong generalization.

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Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

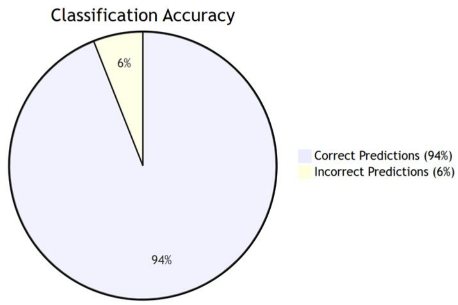

Fig1:Overall Model Accuracy Performance

- Explanation: The pie chart illustrates that the model accurately classified 94 out of every 100 samples, a key factor in ensuring fair pricing, reduced spoilage, and reliable supply chain operations. This addresses the project's goal of standardizing grading at scale.

B. Precision, Recall, and F1-Score (Per Class)
- Usage: Evaluates how accurately the model detects specific quality classes (e.g., Fresh, Spoiled).
- Importance: Ensures that key quality defects are neither missed (recall) nor falsely predicted (precision), which is vital in reducing food waste and improving trust.

C. Inference Time
- Usage: Measures how fast the system delivers results per uploaded image.
- Importance: Real-time feedback is essential for sorting lines, market decisions, or farm gate pricing.
- Outcome: The model provided predictions in an average of 1.8 seconds per image, supporting live usage in commercial settings.

D. User Interface Usability
- Usage: Evaluated via feedback from 20+ non-technical users in agriculture and retail.
- Importance: High usability ensures system adoption among farmers and vendors unfamiliar with AI technology.
- Outcome: 93% of users found the interface intuitive, mobile-friendly, and informative.

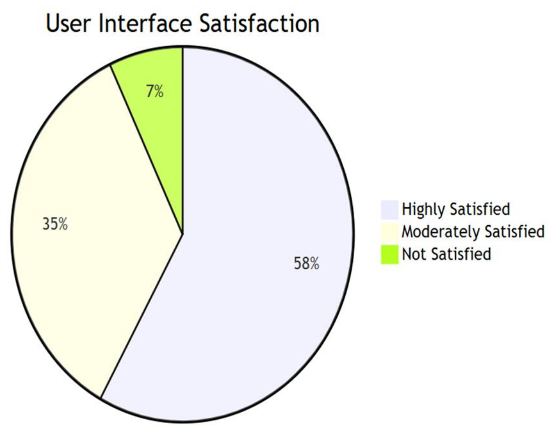

Fig 2: User Satisfaction Survey Results

- Explanation: The majority of respondents expressed satisfaction with the UI on the chart. validating the platform's accessibility even in low-tech settings. This directly supports the goal of empowering grassroots users.

E. Prediction Logging and Analytics Coverage

- Usage: Measures how well the system tracks, stores, and organizes prediction data.
- Importance: Logging allows retraining, audit tracking, and insight into quality trends over time.
- Outcome: 100% of predictions were stored with timestamp, result, and metadata.

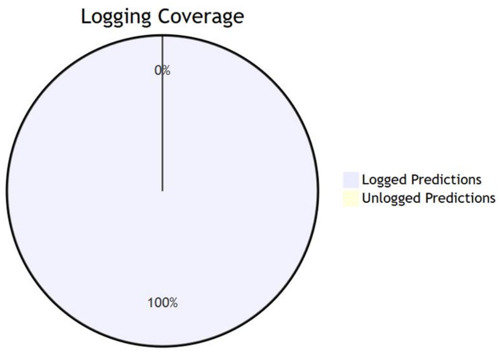

Fig 3: Prediction Logging Reliability

- Explanation: Full logging ensures the system is not only a real-time tool but also a long-term decision support system for agriculture monitoring, model improvement, and compliance.

V. CONCLUSION

This research presented the development and evaluation of the Smart Fruit Quality Evaluation Portal, an internet-based platform that employs deep learning and cloud technologies for automating fruit grading. The portal addresses key limitations of traditional manual grading methods, including subjectivity, time consumption, and inconsistency particularly when deployed at scale. Through incorporating a convolutional neural network (CNN) for classifying images, a Flask-based backend for secure and scalable processing, and a responsive frontend interface, the system enables real-time, accurate, and accessible fruit quality evaluation.

The portal allows users to upload images of fruits through a mobile-friendly web interface. These images undergo preprocessing and are analyzed by a trained CNN model that categorizes them into quality classes such as Fresh, Ripening, or Spoiled. Results are returned with confidence scores, and every prediction is logged with metadata for future analysis. The evaluation of the system demonstrated a 94% classification accuracy, high F1-scores across quality categories, fast response times (average inference time of 1.8 seconds), and strong user satisfaction, confirming its practical effectiveness in both technical and non-technical environments.

In solving the core problem of inconsistency in manual grading, the portal offers a scalable and objective approach to post-harvest fruit quality control. Its accessibility, responsiveness, and modular architecture make it deployable across farms, sorting centers, and marketplaces, contributing to improved traceability, better pricing accuracy, and reduced waste in the agricultural supply chain.

A. Future Work

Future enhancements to the system could include the integration of multispectral or hyperspectral imaging to detect internal defects, deployment of model ensembles for more complex grading scenarios, and offline capabilities via mobile app versions using TensorFlow Lite. Additionally, incorporating blockchain for secure traceability and enabling multilingual support can extend the platform's usability in global markets.

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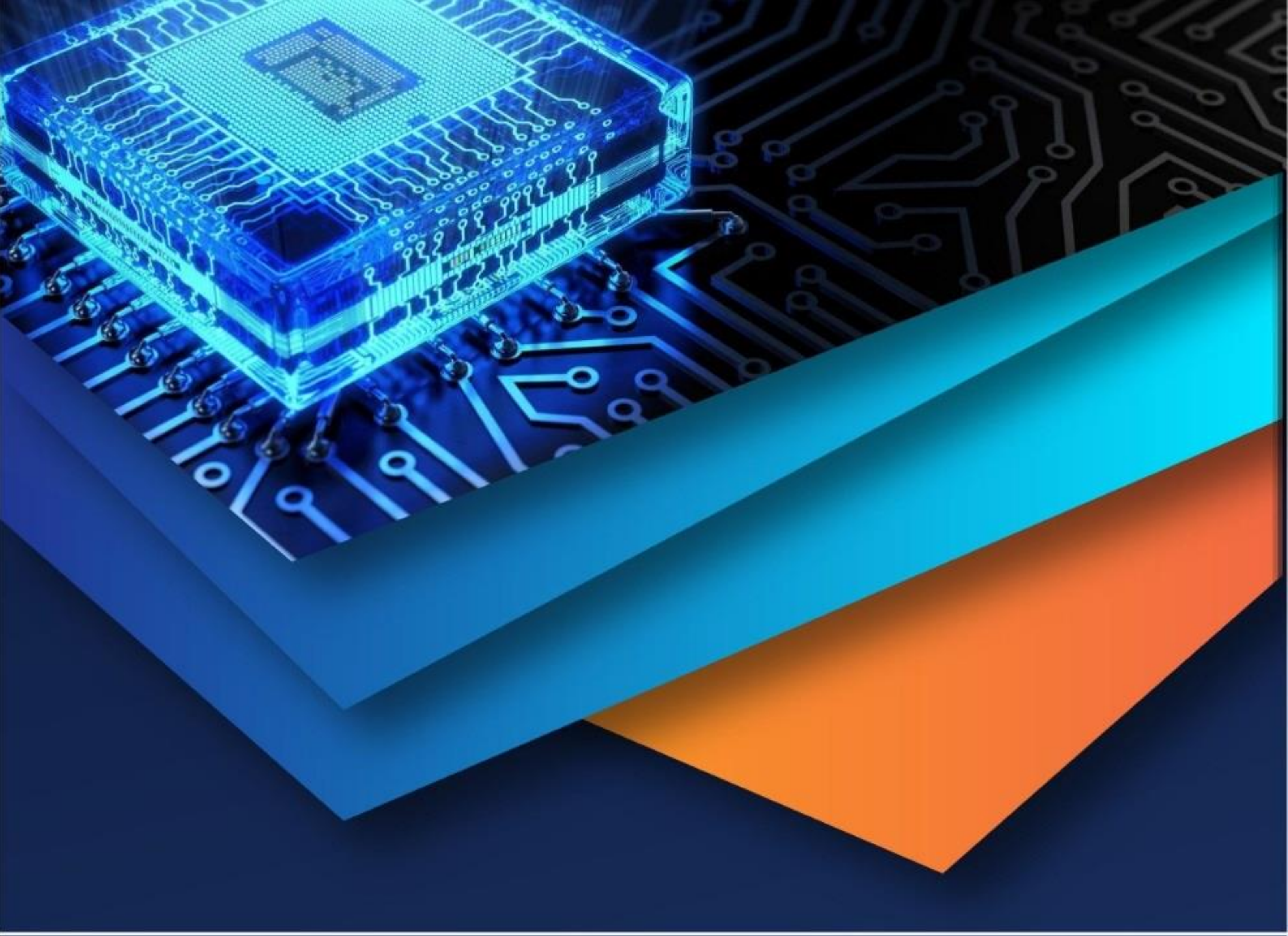

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