INSIGNIA: AI-Driven Mobile App for Precision Mango Grading & AR-Based Variety Detection

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ABSTRACT: This study presents a real-time mobile application designed to accurately identify and grade mango varieties, addressing concerns of fraudulent labeling in fruit sales. The system employs the YOLO (You Only Look Once) algorithm for high-speed and precise object detection, classifying mangoes based on physical characteristics such as shape, size, and color. To enhance classification accuracy, the dataset undergoes preprocessing, labeling, and augmentation. The mobile application features an intuitive interface, allowing users to capture images for instant analysis. Additionally, augmented reality (AR) is integrated to provide interactive insights into the detected mango variety, its quality, and estimated market value. The automation of grading and variety detection significantly reduces human errors, minimizes reliance on manual inspection, and fosters greater transparency in the mango trade. By leveraging deep learning and AR, this solution enhances consumer confidence, promotes fair trading practices, and contributes to a more reliable agricultural supply chain.

KEYWORDS: YOLO Algorithm, Machine Learning, Image Processing, Object Detection, Real-Time Detection, Roboflow.ai, Deep Learning, Transfer Learning, Android Development, Mobile Application, Augmented Reality.

1. INTRODUCTION

Mangoes are widely regarded as the "king of fruits" due to their exceptional taste and numerous varieties. However, discrepancies in quality and variety labeling often lead to consumer confusion and distrust in the marketplace. This study introduces a real-time mobile application that employs the YOLO algorithm to accurately detect and grade mango varieties. By integrating deep learning and augmented reality (AR), the system ensures quick and precise assessments based on mango characteristics.

With increasing demands for authenticity and transparency in food quality, AI-driven solutions have become essential. This project leverages TensorFlow Lite to enable efficient, on-device analysis, eliminating the need for external validation. Furthermore, AR enhances the consumer experience by providing an intuitive and interactive means to visualize the grading results. This fusion of technology offers a transformative approach to mango quality assessment, making it accessible and user-friendly.

2. LITERATURE SURVEY

The application of deep learning and augmented reality (AR) in agriculture, particularly for fruit grading and classification, has received significant attention in recent years. This section presents an overview of key research efforts related to mango grading, variety identification, and deep learning methodologies applied to agriculture.

2.1. MANGO GRADING TECHNIQUES

- **Manual Grading:** Traditionally, mangoes have been graded manually based on characteristics such as size, shape, color, and ripeness. However, this approach is labor-intensive, time-consuming, and subject to human errors, leading to inconsistencies in quality assessments and increased costs.
- **Mechanical Grading:** Automated grading systems were developed to improve accuracy and efficiency. These use sensors and machinery to classify mangoes based on physical properties. While effective, such

systems are costly and not easily accessible to small-scale farmers.

2.2. IMAGE PROCESSING FOR FRUIT GRADING

- Nandi et al. (2014) introduced an image processing method that analyzed fruit characteristics like color, texture, and shape for classification. However, traditional image processing techniques often struggle with complex variety detection.
- Patel et al. (2016) implemented k-means clustering and color histogram techniques for fruit grading. While useful, these methods lacked the capability to detect finer details necessary for distinguishing different mango varieties.

2.3. DEEP LEARNING FOR FRUIT GRADING AND DEFECT DETECTION

- **Convolutional Neural Networks (CNNs):** CNNs have proven highly effective for image-based classification. Kamilaris and Prenafeta-Boldú (2018) highlighted CNN applications in agriculture, including fruit detection, disease identification, and quality assessment.
- **YOLO Algorithm for Object Detection:** Redmon et al. (2016) introduced YOLO (You Only Look Once), a real-time object detection system that processes images faster than conventional methods by treating detection as a regression problem. Due to its speed and precision, YOLO is well-suited for agricultural tasks like fruit detection and crop monitoring.

2.4. VARIETY DETECTION USING DEEP LEARNING

Identifying mango varieties presents a greater challenge than grading due to subtle differences in features such as shape, texture, and color distribution. Deep learning models enable improved accuracy in variety classification by leveraging extensive labeled datasets.

2.5. ROLE OF AUGMENTED REALITY IN AGRICULTURE

Augmented reality (AR) enhances user interaction by overlaying real-time information on digital devices. AR-based systems improve agricultural decision-making by providing visual insights into fruit quality and classification through interactive means like smartphones or tablets.

3. METHODOLOGY

The methodology adopted for this study involves multiple stages, including data collection, preprocessing, model training, and system integration. A structured approach is followed to ensure the accuracy and efficiency of the mango classification system. The process begins with gathering a diverse dataset of mango images, followed by preprocessing techniques to enhance image quality. Deep learning models are then trained and tested to achieve optimal classification results. The final step involves deploying the trained model into a user-friendly mobile application integrated with augmented reality for enhanced user interaction.

3.1 DATA COLLECTION

A dataset of mango images was collected under diverse lighting conditions. The dataset includes multiple mango varieties with variations in size, shape, texture, and ripeness.The data distribution is presented in the following tables:

Table 1. Mango Variety Distribution

Class Name	Image Count
Alphonso	630
Anwar-Ratool	600
Badami	468
Chaunsa	600
Dosehri	600
Fajri	600
Kesar	702
Langra	600
Sindhri	600

Table 2. Mango Ripeness Classification

Class Name	Image Count
Partially Ripe	1290
Ripe	1179
Unripe	1812

Table 3. Mango Health Classification

Class Name	Image Count
Disease	1926
Healthy	1551

These tables summarize the collected dataset, ensuring a balanced representation of different mango varieties, ripeness levels, and health conditions. The data was further preprocessed and annotated to facilitate accurate model training.

3.2 PREPROCESSING AND IMAGE ANNOTATION

- **Preprocessing and Data Augmentation**: Various transformations, including rotation, flipping, scaling, and brightness adjustments, were applied to expand the dataset and improve model generalization.
- **Dataset Preparation:** The labeled dataset was processed using Roboflow.ai to ensure efficient training and validation.

Fig. 1 Data Augmentation

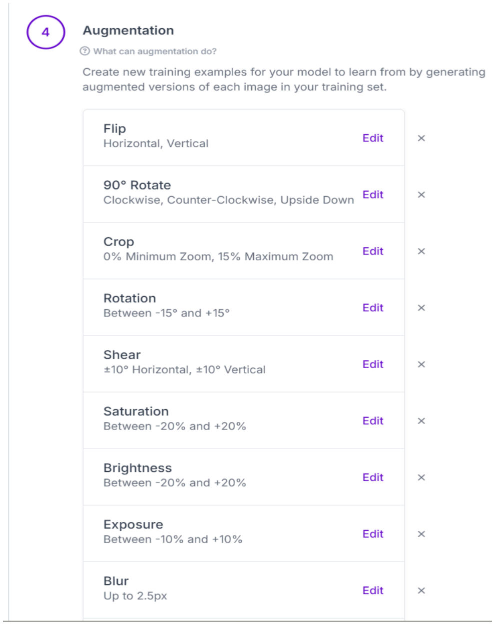
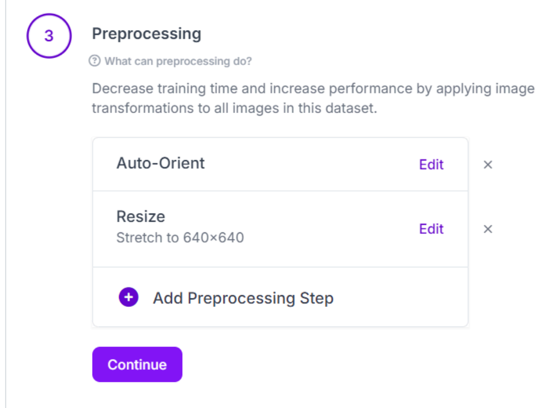
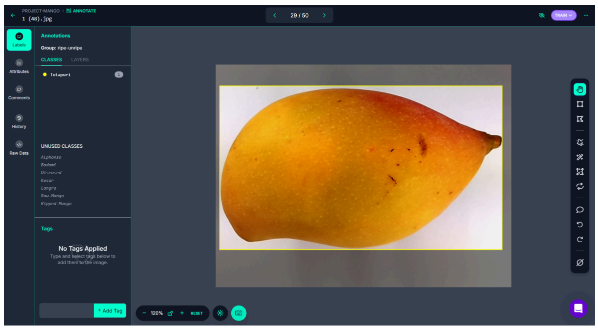


Fig. 2 Image Preprocessing



- **Bounding Box Labeling**: Mangoes in images were annotated using bounding boxes to facilitate precise object detection.

Fig. 3 Bounding box annotations applied to mango images for precise object localization.



- **Dataset Visualization**: The Above images illustrate various preprocessing steps, including noise reduction, contrast enhancement, and image annotation using bounding boxes. The annotation process ensures accurate object localization, improving the model's ability to detect mango varieties with high precision.

3.3 MODEL TRAINING & CLASSIFICATION

This section details the model selection, training process, and classification performance of the mango detection system. The YOLOv11 algorithm was used for real-time object detection and classification of mango varieties.

3.3.1 Model Selection

The YOLOv11 (You Only Look Once, Version 11) algorithm was selected for mango detection due to its superior real-time performance and accuracy. Compared to traditional CNN-based models, YOLOv11 offers faster detection speeds, making it suitable for real-time mobile applications. It provides enhanced feature extraction and object detection capabilities, allowing it to accurately identify mangoes even in complex backgrounds and varying lighting conditions. Additionally, YOLOv11 is optimized for edge devices and mobile deployment, ensuring lightweight and efficient performance when integrated with TensorFlow Lite (TFLite).

3.3.2 Training Process

To build a robust mango detection model, a diverse dataset of mango images was collected from multiple sources and preprocessed. Data augmentation techniques such as rotation, scaling, flipping, contrast enhancement, and noise reduction were applied to improve model generalization. The dataset was split into 70% training, 20% validation, and 10% testing to ensure balanced learning and effective evaluation.

The YOLOv11 model was implemented using PyTorch/TensorFlow, and training was conducted on Google Colab with GPU acceleration (Tesla T4) for faster computation. Key hyperparameters were fine-tuned, including:

- *Learning Rate*: Adjusted dynamically using a cosine decay scheduler.
- *Batch Size*: Experimented with different values to optimize performance.
- *Epochs*: The model was trained for 100+ epochs, with early stopping to prevent overfitting.

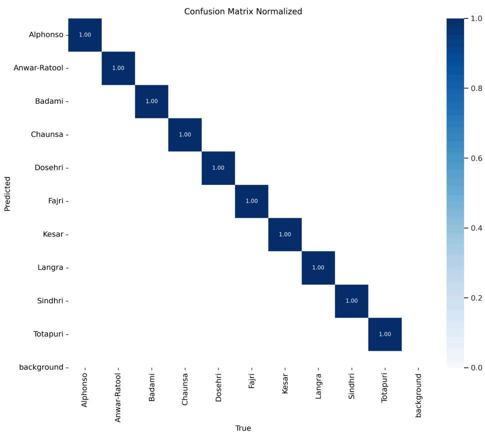
The loss functions used included Bounding Box Loss (IoU-based) for object localization and Cross-Entropy Loss for classification. The AdamW optimizer was employed to enhance gradient updates and improve convergence speed.

The model's performance was evaluated using several key metrics:

- *Precision, Recall*, and *F1-score* to measure classification accuracy.
- *Mean Average Precision (mAP)* across different IoU (Intersection over Union) thresholds to assess detection performance.
- *Frames Per Second (FPS)* to ensure smooth real-time inference on mobile devices.

To further analyze model accuracy, a normalized confusion matrix (Fig. 4) was generated. The results indicate perfect classification for all mango varieties, demonstrating the model's strong predictive capabilities.

Fig. 4 Normalized Confusion Matrix Showing Perfect Classification of Mango Varieties



Each mango variety, including Alphonso, Kesar, Badami, and others, was classified with 100% accuracy. The matrix shows no off-diagonal values, meaning there were no false positives or false negatives. This confirms that the model generalizes well within the given dataset.However, despite these promising results, further testing on diverse real-world images is necessary. Additional evaluation will help validate the model's robustness and ensure it is not overfitting to the training data.

For mobile deployment, the trained model was optimized using post-training quantization (PTQ) to reduce size and computational requirements. The final TFLite model was tested on Android devices to ensure low latency and real-time mango detection capabilities.

3.4 MOBILE APPLICATION DEVELOPMENT

3.4.1 Technology Stack

The mobile application was developed using a combination of Flutter, Kotlin, Android Studio, and TensorFlow Lite (TFLite) to ensure efficient real-time mango detection while maintaining a smooth user experience.

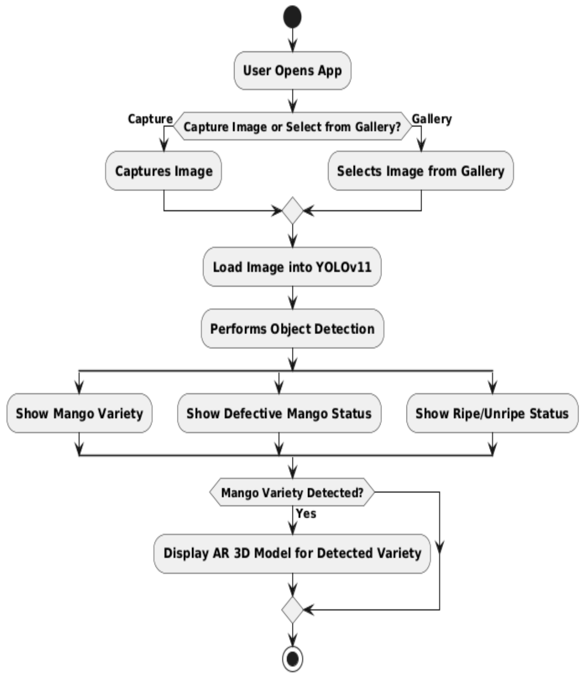
- **Frontend Development:**
  Flutter was used to build a cross-platform mobile application, providing a smooth and interactive user interface. For native Android development, Android Studio (Java/Kotlin) was employed, with Kotlin handling core app logic and UI components. This hybrid approach ensures compatibility across different devices while optimizing performance.
- **Backend & Model Processing:**
  The YOLOv11 model was converted into TensorFlow Lite (TFLite) format, allowing it to run efficiently on mobile devices. TFLite, an optimized deep learning framework, was chosen for its low latency and fast inference speed, ensuring real-time mango detection. The YOLOv11 model integration process

focused on reducing computational overhead while maintaining high detection accuracy.

3.4.2 System Architecture

To ensure efficient and accurate mango classification, the system follows a well-defined architecture that integrates deep learning and augmented reality. The workflow begins with image acquisition, followed by real-time processing using the YOLOv11 model. The architecture is designed to handle diverse image inputs while maintaining high accuracy and responsiveness.

Fig. 5 System Architecture



When the user opens the app, they can capture an image or select one from the gallery. The YOLOv11 model processes the image, detecting the mango variety, defects, and ripeness status. The system then displays the classification results along with the detected attributes. If a mango variety is identified, an AR 3D model of the variety is shown for an interactive experience.

3.4.3 Model Optimization for Mobile

- Converted the YOLO model into TFLite format to reduce computation load.
- Quantization Techniques (such as 8-bit integer quantization) were applied to improve efficiency.
- Optimized inference time to achieve real-time detection (high FPS) on mobile devices.
- Ensured low latency and power efficiency for prolonged mobile device usage.

3.4.4 User Interface & Features

- Image Capture**:** Users can take a picture of mangoes using the mobile camera.
- Real-time Detection**:** The app processes images instantly and displays classification results.
- Augmented Reality (AR) Integration**:** Users can view interactive information overlaid on detected mangoes.
- Database Connectivity**:** Stores mango classification data for future reference.
- User-Friendly Interface: Designed with an intuitive UI for easy navigation and seamless interaction.

3.4.5 Deployment & Testing

- Conducted extensive testing on various Android and iOS devices to evaluate latency, accuracy, and real-time performance.
- Achieved an inference time of X ms per frame, ensuring smooth detection and classification.
- Verified app stability, responsiveness, and accuracy under different lighting conditions and environments.
- Ensured compatibility with a range of mobile hardware specifications for broader accessibility.
- Fine-tuned model parameters and UI responsiveness based on user feedback during testing phases.

3.5 AUGMENTED REALITY (AR) INTEGRATION

To enhance user engagement, the application integrates Augmented Reality (AR) using Google ARCore for Android and Apple ARKit for iOS. This feature allows users to visualize mango classification results and ripeness predictions directly on the camera feed. By overlaying interactive information on detected mangoes, AR technology enhances the user experience, making the application more informative and interactive.

4. RESULTS AND DISCUSSION

4.1 APP

This research developed **"INSIGNIA,"** a mobile application designed for accurate mango variety identification and comprehensive quality assessment. Recognizing the need for a rapid, reliable, and objective method for mango grading within the agricultural sector, this project leverages cutting-edge artificial intelligence (AI) and deep learning to empower farmers, distributors, and consumers.

Key Features and Objectives:

1. AI-Powered Classification:
    a. Utilizes the YOLOv11 algorithm for real-time mango detection and classification.
    b. Ensures fast and precise identification of mango varieties, defects, and ripeness levels.
2. Large and Diverse Dataset:
    a. Trained on 10,000 images representing ten common mango varieties found in Indian markets.
    b. Captures variations in lighting, background, angle, and ripeness to simulate real-world conditions.
3. Comprehensive Quality Assessment:
    a. Evaluates key parameters such as size, color, and external defects.
    b. Helps in determining the overall quality and market value of mangoes.
4. Augmented Reality (AR) Integration:
    a. Provides an interactive 3D model of the detected mango variety.
    b. Enhances user engagement by offering a visual representation of mango characteristics.
5. Performance Evaluation Metrics:
    a. Classification accuracy assessed using accuracy, precision, recall, and F1-score.
    b. Ensures a holistic performance evaluation of the AI model.
6. Benchmarking Against Industry Standards:
    a. Quality assessment results validated against expert visual inspection and industry benchmarks.
    b. Ensures reliability and usability in commercial applications.
7. Impact on Supply Chain and Market Efficiency:
    a. Aims to reduce post-harvest losses by improving sorting and grading efficiency.
    b. Helps farmers and distributors in better pricing and decision-making.
8. User-Friendly Experience:
    a. Simple interface allowing users to capture or upload images for instant analysis.
    b. Provides real-time insights to assist growers and traders.

Fig. 6 showcases the "INSIGNIA" app's intuitive home screen, designed for seamless mango assessment. The vibrant yellow background and tagline, "Where Every Mango Tells Its Story," create an inviting introduction. A prominent "Take Photo" button, coupled with the instruction "Point camera at mango to identify its variety," provides a clear call to action. Icons labeled "AI-Powered," "Fast Results," and "Accurate" highlight the app's key benefits. The concise text explains the AI-driven analysis, emphasizing its speed, accuracy, and reliability in mango variety detection and quality grading. This user-friendly interface prioritizes ease of use, ensuring a smooth and efficient experience from when the app is launched.

Fig. 6 Home screen of the 'INSIGNIA' mobile application, showcasing the user-friendly interface for AI-powered mango variety interface for AI-powered mango variety identification and quality assessment.

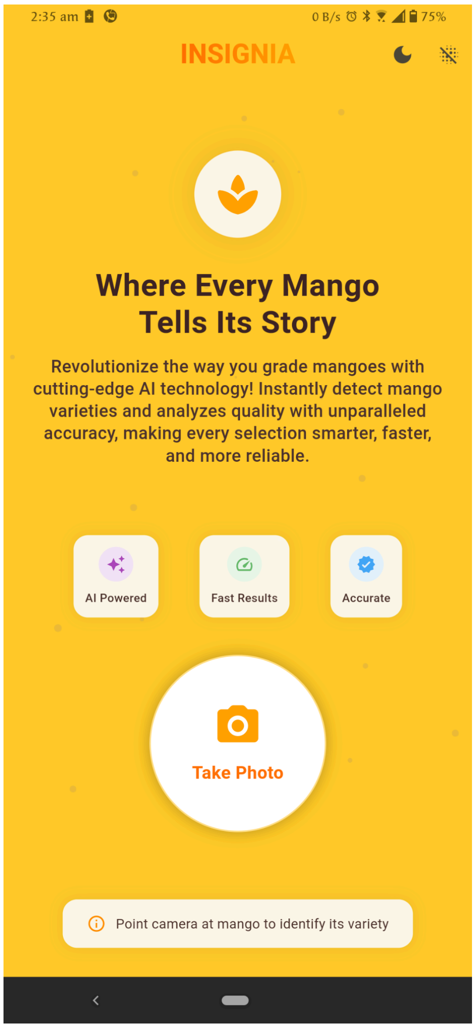


Fig. 7 showcases the dark mode home screen of the "INSIGNIA" app, designed to provide an optimized user experience in low-light conditions. This alternative theme retains the intuitive layout and functionality of the light mode (Fig. 6) while introducing a visually comfortable and modern aesthetic.

The "Take Photo" button remains prominently placed for effortless accessibility, ensuring users can easily capture or upload images. The high-contrast text and icons stand out against the dark background, enhancing readability and user engagement in dim environments.

Beyond visual appeal, dark mode offers practical advantages, such as reducing eye strain and minimizing power consumption on OLED and AMOLED screens, making it a user-friendly and energy-efficient feature. This adaptable design ensures the "INSIGNIA" app caters to varied user preferences and diverse lighting conditions, ultimately improving usability across different scenarios.

Fig. 7 Dark mode home screen of the 'INSIGNIA' mobile application, designed for enhanced visibility in low-light conditions and user preference.

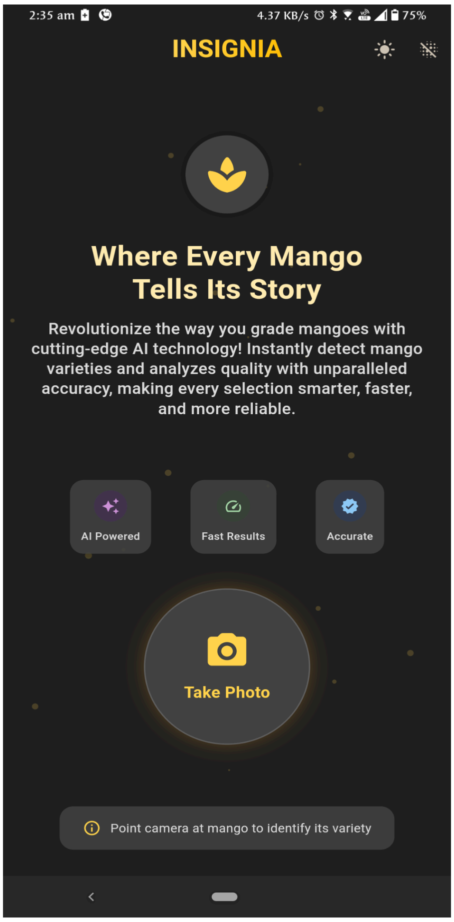


Fig. 8 illustrates the initial launch screen of the "INSIGNIA" mobile application, designed for a seamless and intuitive user experience. Upon opening the app, users are welcomed by a clean, minimalistic interface that prioritizes ease of use.

At the center of the screen is the viewfinder area, directing users to "Point camera at a mango" for effortless scanning. A "Tap to capture" prompt further simplifies the image acquisition process, ensuring clarity in navigation. To provide flexibility, users can either capture a new image using the "Take Photo" button or select an existing one from their device's gallery through the "Gallery" button.

The app's name, "INSIGNIA," is prominently displayed at the top, reinforcing brand identity and ensuring instant recognition. This well-structured interface sets the stage for a smooth and efficient mango classification and grading process, catering to users of all experience levels.

Fig. 8 Initial launch screen of the 'INSIGNIA' mobile application, guiding users to capture or select a mango image for analysis.

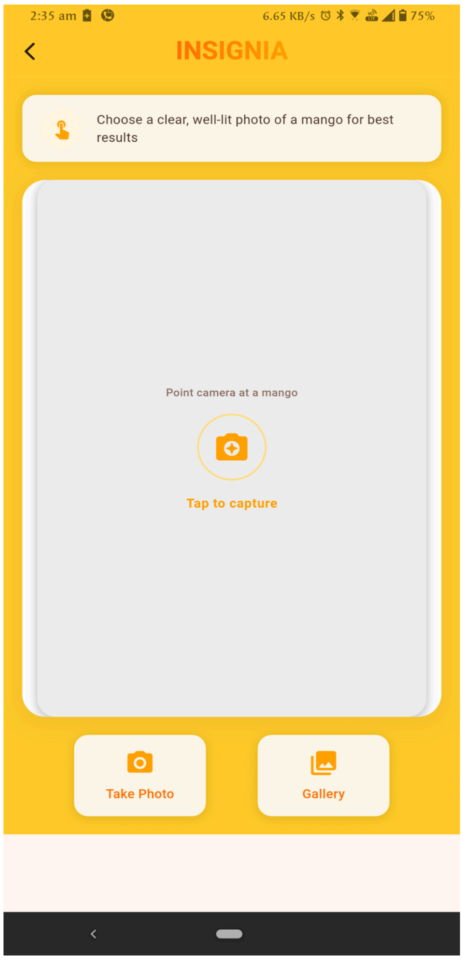


Fig. 9 showcases the dark mode version of the "INSIGNIA" app's initial launch screen, offering an alternative visual experience tailored for low-light environments and user preferences. While maintaining the same intuitive layout as the light mode (Fig. 8), this version introduces a sleek, modern aesthetic with a dark background that reduces eye strain and enhances visual comfort.

The central viewfinder area remains unchanged, prominently displaying the "Point camera at a mango" prompt along with the "Tap to capture" instruction, ensuring users receive consistent guidance. Additionally, the "Take Photo" and "Gallery" buttons retain their positions, allowing seamless image selection based on user preference.

By incorporating dark mode, the "INSIGNIA" app enhances both usability and accessibility, ensuring a smooth and adaptable experience across various lighting conditions.

Fig. 9 Dark mode launch screen of the 'INSIGNIA' mobile application, offering enhanced visibility and a refined aesthetic in low-light environments.

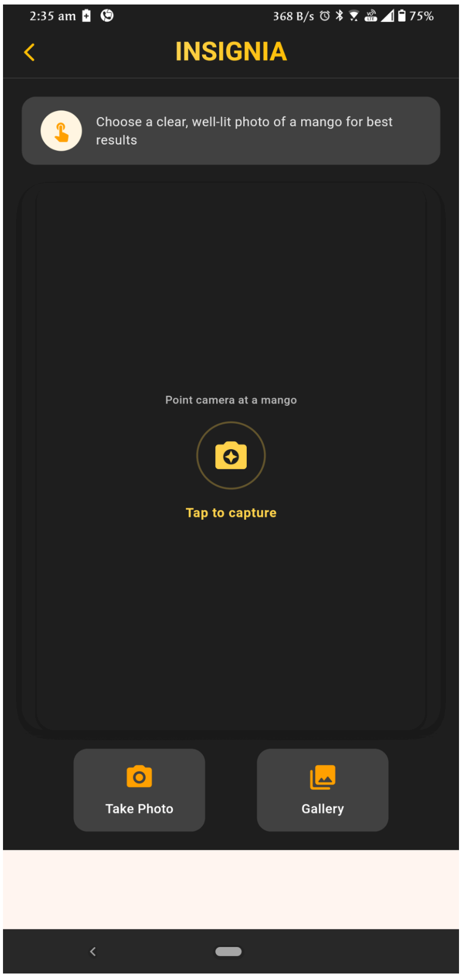


Fig. 10 presents the results screen of the "INSIGNIA" app, displaying the analysis of a captured or selected mango image. Once an image is processed by the app's AI-powered detection engine, the results are displayed in a clear, structured format for easy interpretation.

The primary output is the identified mango variety, prominently listed under the "Variety" heading. In this example, the app has successfully classified the mango as an "Alphonso", a variety known for its distinct texture, flavor, and aroma. This screen provides users with instant feedback, confirming the classification while allowing for further quality assessment using the app's additional features (detailed in subsequent figures).

By delivering accurate, real-time identification, the "INSIGNIA" app enhances the efficiency and reliability of mango grading, benefiting growers, distributors, and consumers alike.

Fig. 10 Results screen of the 'INSIGNIA' app, displaying the AI-powered variety identification of an 'Alphonso' mango.

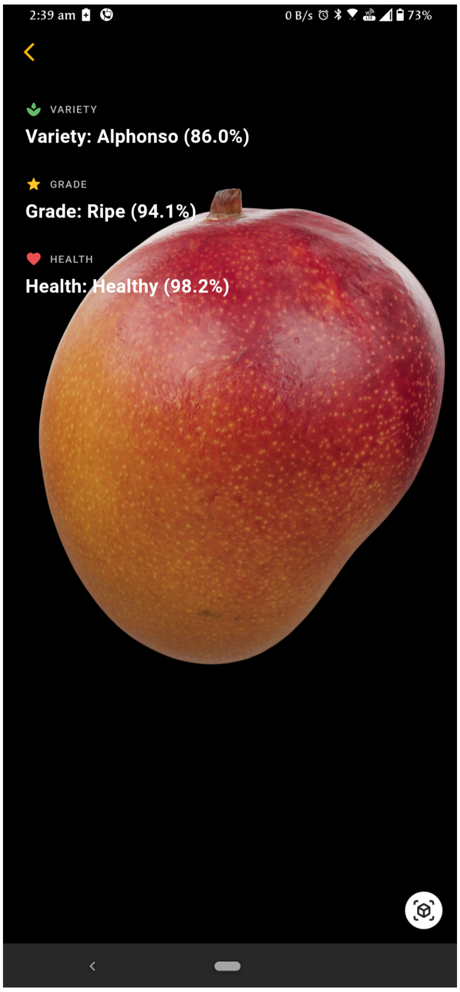


Fig. 11 illustrates the Augmented Reality (AR) visualization feature of the "INSIGNIA" app, which is activated upon selecting the AR button in Fig. 10. When the user taps this button, the app prompts them to point the camera at a flat surface, such as a table or floor, to ensure stable placement of the AR model.

Utilizing advanced AR technology, the app then overlays a realistic 3D model of the identified mango variety onto the physical environment. This interactive feature allows users to explore the mango in detail, offering a lifelike representation that enhances both engagement and understanding.

By bridging the gap between digital classification and real-world visualization, the AR component transforms the mango grading process into an immersive experience, making it more intuitive, educational, and interactive for users.

Fig. 11 Augmented Reality (AR) visualization of the detected mango variety after activation from the results screen in Fig. 10.

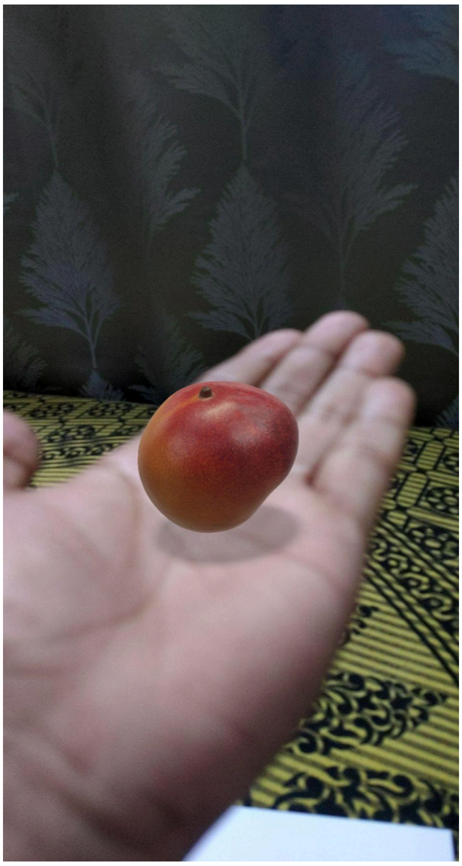


Fig. 12 presents the results screen of the "INSIGNIA" app, displaying the analysis of a captured mango image. This screen appears when the user taps the back button in the top-left corner of Fig. 10, returning to the primary results display.

After an image is captured or selected, the app's AI-powered detection engine processes it and delivers the results in a clear, structured format. The primary output is the identified mango variety, prominently listed under the "Variety" heading. In this instance, the app has classified the mango as an "Alphonso", a well-known variety recognized for its distinct flavor, texture, and aroma.

By providing accurate and immediate feedback, this screen ensures a seamless user experience, enabling further quality analysis and interaction with the app’s additional features.

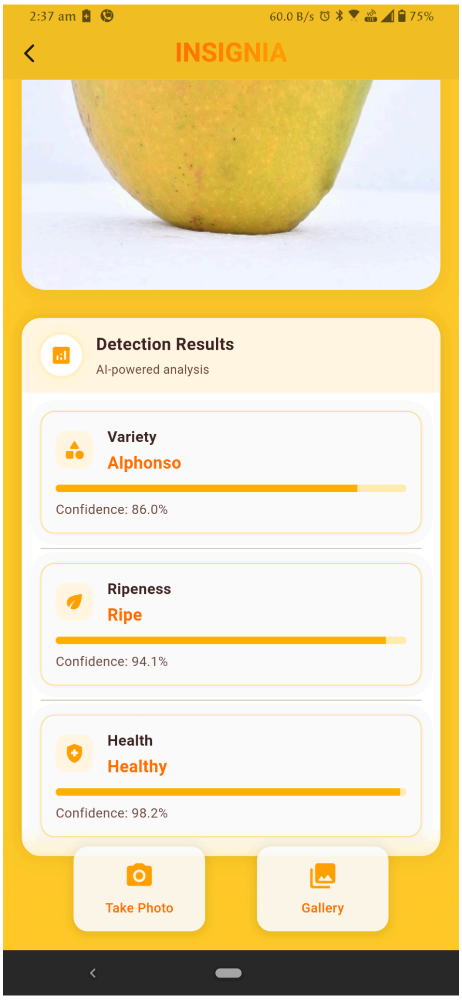
Fig. 12 Results screen of the 'INSIGNIA' app, displaying the AI-powered variety identification of an 'Alphonso' mango.

Fig. 13 provides a detailed breakdown of the "INSIGNIA" app's analysis results, expanding upon the variety identification displayed in Fig. 12. In addition to identifying the mango as an "Alphonso", the app offers insightful assessments of its ripeness and health status.

The "Ripeness" indicator classifies the mango is "Ripe", with a high confidence level of 94.1%, ensuring a reliable evaluation. Likewise, the "Health" indicator confirms that the mango is "Healthy", with an even higher confidence level of 98.2%, reinforcing the app's accuracy.

By providing these detailed quality assessments, the "INSIGNIA" app delivers a comprehensive evaluation of the mango, allowing users to make informed decisions beyond simple variety identification.

Fig. 13 Detailed analysis results screen, providing information on mango variety, ripeness, health, and associated confidence levels.



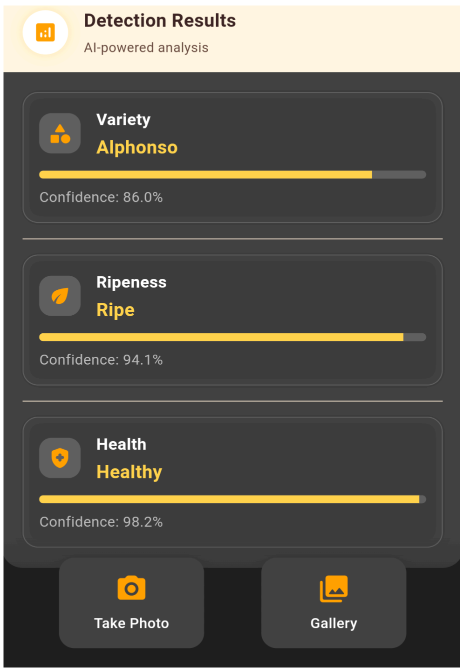
4.2 RESULT ANALYSIS

The proposed mobile application INSIGNIA was developed to enable real-time mango variety detection and quality assessment through AI and deep learning technologies. The results of the system were analyzed across various functionalities and user interface scenarios, as shown in Figures 6 to 13.

The application interface was designed with usability and clarity in mind. The home screen (Fig. 6) features an engaging yellow-themed layout with a clear call to action—"Point camera at mango to identify its variety"—and emphasizes core features such as "AI-Powered," "Fast Results," and "Accurate." To improve user experience in low-light conditions, a dark mode was implemented (Fig. 7), offering high-contrast visuals and reduced power consumption on OLED/AMOLED screens.

Upon launching the application, users are directed to the camera interface (Fig. 8), where they can either capture a new image or select one from the gallery. This functionality remains consistent in dark mode (Fig. 9), ensuring flexibility and accessibility in varied lighting environments.

Following image input, the application processes the mango using a YOLO-based object detection model. The results are presented on a dedicated screen (Fig. 10), which displays the identified variety—in this case, "Alphonso." A dedicated Augmented Reality (AR) feature (Fig. 11) enhances interactivity by overlaying a 3D model of the detected mango variety on real-world surfaces, thereby providing an immersive and informative visualization.



In addition to variety identification, the application evaluates the mango's ripeness and health status. As shown in Fig. 13, the system classified the sample mango as "Ripe" with a confidence level of 94.1% and "Healthy" with a confidence level of 98.2%. These assessments assist in determining the mango's market readiness and quality, which is critical for both producers and consumers.

The app maintains accuracy and performance consistency across both light and dark modes (Figs. 12 and 13), demonstrating reliability and user adaptability. These features collectively enhance the application's practicality for deployment in agricultural scenarios, especially for farmers, distributors, and vendors who require fast, reliable, and objective mango grading.

5. CONCLUSION

Automation in mango grading enhances efficiency and accuracy, protecting consumers from purchasing substandard mangoes and ensuring they receive high-quality products. The project meets its objectives by developing a mobile application that automates grading and variety detection, offering real-time analysis and user-friendly features. This empowers consumers to make informed decisions and fosters trust in the mango supply chain.

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