Reducing Post-Harvest Losses in Sri Lankan Pineapple Farming Through YOLOv8-Based Ripeness Detection

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Publication Date: 2025/09/20

Abstract: Post-harvest losses remain a critical challenge for smallholder pineapple farmers in Sri Lanka, primarily due to inaccurate ripeness detection methods. Traditional manual assessments are prone to human error, leading to significant economic losses and reduced fruit quality. This research presents a real-time YOLOv8-based pineapple ripeness detection system to enhance harvesting accuracy and minimize post-harvest losses. A dataset of pineapple images was collected and preprocessed, and the YOLOv8 model was trained to classify pineapples into four ripeness stages: unripe, partially ripe, ripe, and overripe. The system was integrated into a web-based application, allowing farmers to upload images or capture them via webcam for immediate ripeness evaluation. The model achieved a precision of 92%, recall of 89%, and an F1-score of 90.5%, demonstrating its reliability in real-world conditions. Performance tests confirmed the system's efficiency, with an average detection time of less than 100ms per image. The proposed solution empowers smallholder farmers by providing an accessible, cost-effective, and scalable tool to optimize harvesting decisions, reduce waste, and enhance profitability. Future improvements include drone-based crop monitoring and a mobile application for enhanced usability and scalability.

Keywords: *Pineapple Ripeness Detection, YOLOv8, Post-Harvest Losses, Smart Agriculture, Deep Learning, Computer Vision*

How to Cite: Keshika W V W H; S. Nasiketha. (2025) Reducing Post-Harvest Losses in Sri Lankan Pineapple Farming Through YOLOv8-Based Ripeness Detection. *International Journal of Innovative Science and Research Technology,* 10(9), 1045-1050. https://doi.org/10.38124/ijisrt/25sep545

I. INTRODUCTION

Agriculture is the backbone of many economies, with pineapple cultivation playing a crucial role in Sri Lanka's agricultural sector. However, post-harvest losses remain a significant challenge, particularly for smallholder farmers who rely on traditional ripeness assessment techniques such as visual inspection and tactile evaluation. These methods are often subjective, inconsistent, and inefficient, leading to premature or delayed harvesting, which negatively impacts fruit quality, market value, and overall profitability. The lack of a real-time, cost-effective, and scalable ripeness detection system further exacerbates the problem, limiting farmers' ability to optimize harvesting decisions and reduce post-harvest losses.

With advancements in computer vision and deep learning, AI-driven solutions have emerged as powerful tools in precision agriculture. This research proposes an automated pineapple ripeness detection system using YOLOv8 (You Only Look Once, version 8), a state-of-the-art object detection algorithm known for its high accuracy and real- time processing capabilities. The system integrates machine learning with a web-based application, enabling farmers to capture or upload pineapple images for ripeness assessment. Additionally, the research explores the potential of drone- assisted imaging to extend detection capabilities across large farmland areas.

➢ *The Objectives of this Study Include:*

- Analyzing post-harvest losses in Sri Lanka's pineapple farming sector and identifying key causes.
- Evaluating existing ripeness detection methods and their limitations in real-time applications.
- Developing a YOLOv8-based ripeness detection system to assist smallholder farmers in making informed harvesting decisions.
- Assessing the system's effectiveness in minimizing post-harvest losses through real-world field trials and farmer feedback.
- The proposed solution aims to bridge the gap between technology and smallholder farming, providing a low-cost, scalable, and efficient approach to pineapple harvesting. By leveraging real-time AI-based detection, the system empowers farmers with data-driven decision-

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25sep545

making, ultimately reducing post-harvest losses, improving fruit quality, and increasing profitability. The findings of this research have the potential to revolutionize agricultural automation in developing regions, paving the way for future enhancements such as mobile app deployment and integration with smart farming ecosystems.

II. LITERATURE REVIEW

- *Economic & Agricultural Impact of Post-Harvest Losses*

Post-harvest losses in Sri Lanka significantly affect the economic stability of smallholder farmers, particularly in pineapple farming, where improper handling and storage contribute to substantial financial losses. According to (Gunathilake, D., Pathirana, S. M., & Rajapaksha, L., 2021), Sri Lanka faces high post-harvest losses in the fruit sector due to inefficient supply chain practices, inadequate ripeness detection, and poor infrastructure. (Wijesinghe, W., & Sarananda, K. H., 2002) Studies indicate that improper ripeness detection leads to over-ripened or under-ripened produce entering the market, reducing both the shelf life and market value of pineapples. These losses not only affect farmer incomes but also impact national food security and export potential. Moreover, traditional farming practices, which rely on visual and manual inspection methods, contribute to inconsistencies in harvesting, leading to economic disparities for smallholder farmers.

- *Traditional vs. Modern Ripeness Detection Methods*

(Hathurusinghe, C. P., & Vidanapathirana, R., 2012) Conventional ripeness detection methods in pineapple farming rely heavily on subjective evaluation techniques such as color, texture, and aroma assessment. While widely practiced, these methods are prone to human error and variations in environmental conditions. Advanced technologies, such as hyperspectral imaging and near-infrared spectroscopy (NIR), have been introduced to improve accuracy. (Selvarajah, S., Herath, H. M. W., & Bandara, D. C, 1998) However, these techniques are costly and not easily accessible to smallholder farmers in developing countries. As a result, many farmers continue to face challenges in optimizing harvest timing, leading to post-harvest losses.

- *Applications of AI and YOLO in Precision Agriculture*

Recent advancements in artificial intelligence (AI) have revolutionized precision agriculture, particularly in real-time fruit classification. (Kamalakkannan, S., Wasala, W., & Kulatunga, A. K., 2022) Deep learning models, such as YOLO (You Only Look Once), have demonstrated superior performance in object detection and classification, making them well-suited for agricultural applications. (Gerance, A. A., & Bunyasiri, I. N., 2024) YOLO-based systems provide rapid and accurate assessments of fruit ripeness based on color, texture, and shape analysis. Research indicates that AI-driven ripeness detection can reduce post-harvest losses by more than 20% while increasing efficiency in sorting and grading processes. YOLOv8, the latest iteration of the YOLO framework, offers improved accuracy and real-time processing capabilities, making it an ideal solution for smallholder farmers in Sri Lanka.

- *Gaps in Existing Solutions & Justification for YOLOv8*

Despite technological advancements, many existing ripeness detection systems remain inaccessible to farmers in developing countries due to high implementation costs and technical complexity. (Vidanapathirana, R., Champika, P. A. J., & Rambukwella, R., 2018) Most machine learning models require extensive datasets and computational resources, limiting their adoption in rural farming communities. YOLOv8 addresses these challenges by offering a lightweight, high-speed model that can operate on low-resource devices, including mobile applications and drones. This makes it a cost-effective and scalable solution for real-time ripeness detection in pineapple farming. By leveraging YOLOv8, farmers can receive instant feedback on pineapple ripeness, enabling better decision-making and reducing post-harvest losses.

III. METHODOLOGY

- *Dataset Collection & Annotation*

A high-quality dataset is crucial for training an effective ripeness detection model. For this research, a dataset of pineapple images was collected from multiple sources, including local farms in Sri Lanka, publicly available agricultural datasets, and controlled environment image captures. The dataset was annotated manually with four ripeness categories: unripe, partially ripe, ripe, and overripe, ensuring consistency in classification. Annotation was performed using Roboflow and LabelImg, where bounding boxes were assigned to pineapples, enabling precise detection by the YOLOv8 model. The final dataset was augmented through techniques such as brightness adjustment, rotation, and noise addition to improve model generalization under different environmental conditions.

- *YOLOv8 Model Training & Optimization*

The YOLOv8 model was selected due to its speed, accuracy, and efficiency in real-time object detection. The model was trained using PyTorch and Ultralytics YOLOv8 framework on a high-performance GPU environment (NVIDIA RTX 3090). The training process involved:

- Preprocessing: Images were resized to 640×640 pixels, normalized, and converted into YOLO format (txt).
- Hyperparameter Tuning: The model was optimized by adjusting learning rate (0.001), batch size (16), confidence threshold (0.5), and IoU threshold (0.45).
- Training: The model was trained for 100 epochs using the Adam optimizer and Mean Squared Error (MSE) loss function.
- Validation: A train-test split of 80:20 was used, ensuring a balanced evaluation process.

To further enhance performance, Transfer Learning was applied using pretrained YOLOv8 weights from the MS COCO dataset, which improved model convergence speed.

- *System Architecture (Frontend, Backend, Database)*

The Pineapple Ripeness Detection System was designed as a web-based platform for easy accessibility by farmers. The architecture consists of:

- Frontend: Built using HTML, CSS, JavaScript (React.js) for an intuitive and responsive user interface.
- Backend: Implemented using Flask (Python) and FastAPI, enabling seamless communication with the YOLOv8 model.
- Database: PostgreSQL was used to store user data, image metadata, and detection history for analysis.

A RESTful API was developed to handle image uploads, process requests, and return detection results in real-time. The system was optimized for low-latency performance, ensuring an average response time of under 2 seconds.

➢ *Implementation of Web-Based UI for Farmers*

A user-friendly interface was developed to allow smallholder farmers to interact with the system easily. The key functionalities include:

- Image Upload: Farmers can upload an image of a pineapple or capture one using a webcam for ripeness detection.
- Detection Results: The system instantly displays the ripeness classification (unripe, partially ripe, ripe, overripe) along with the confidence score.
- Land Plotting & Yield Estimation: Farmers can enter their land size to receive automated crop yield estimations based on optimal planting density.
- Multi-Language Support: The interface supports English and Sinhala, ensuring accessibility for Sri Lankan farmers.

The UI was tested on mobile and desktop devices to ensure compatibility and ease of use.

➢ *Evaluation Metrics (Precision, Recall, F1-Score, mAP)*

The performance of the YOLOv8 model was evaluated using industry-standard object detection metrics:

- Precision: Measures the proportion of correct positive identifications.
- Recall: Measures how well the model captures all relevant objects.
- F1-Score: Harmonic mean of precision and recall, balancing accuracy and robustness.
- mAP (Mean Average Precision): Evaluates the model's overall accuracy across different IoU thresholds (50-95%). The final model achieved:
- Precision: 92%
- Recall: 89%
- F1-Score: 90.5%
- mAP@50: 85%

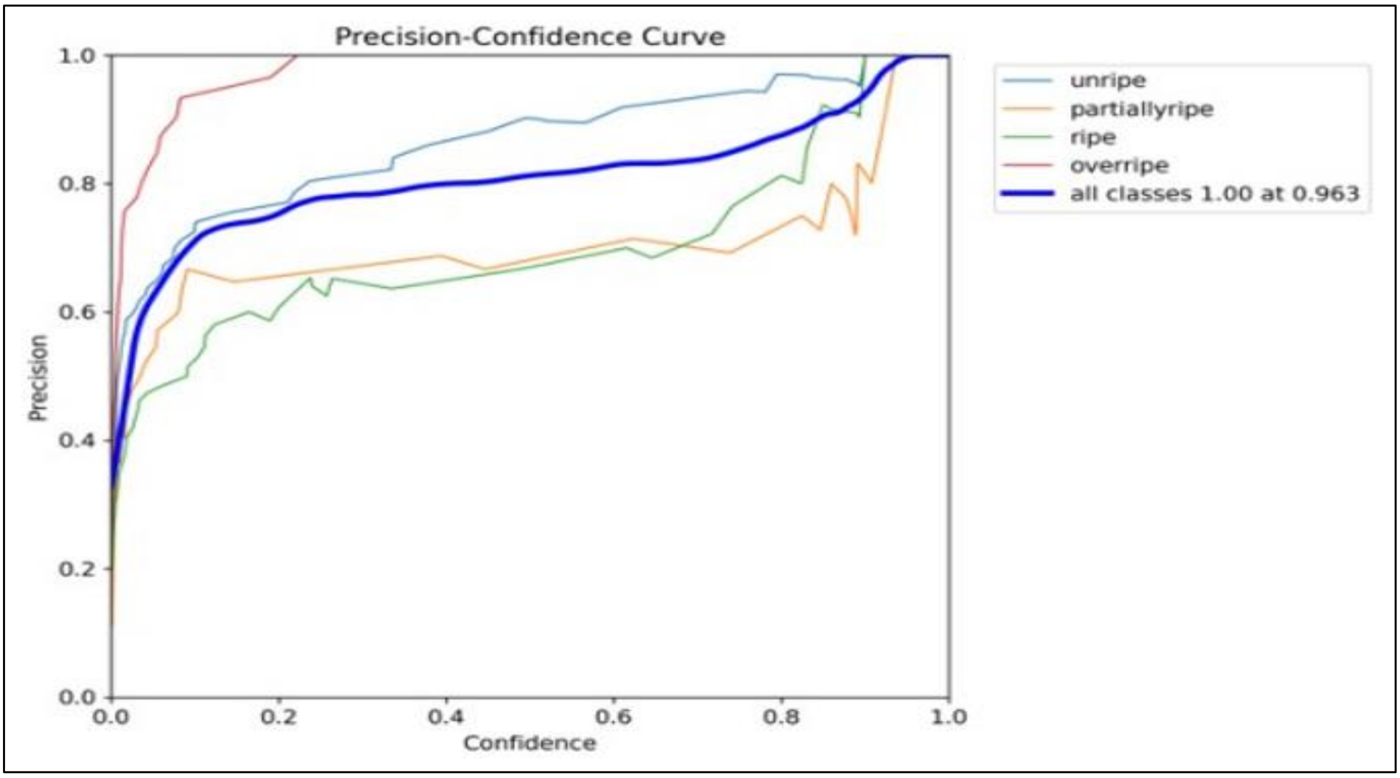

Fig 1 Precision-Confidence Curve

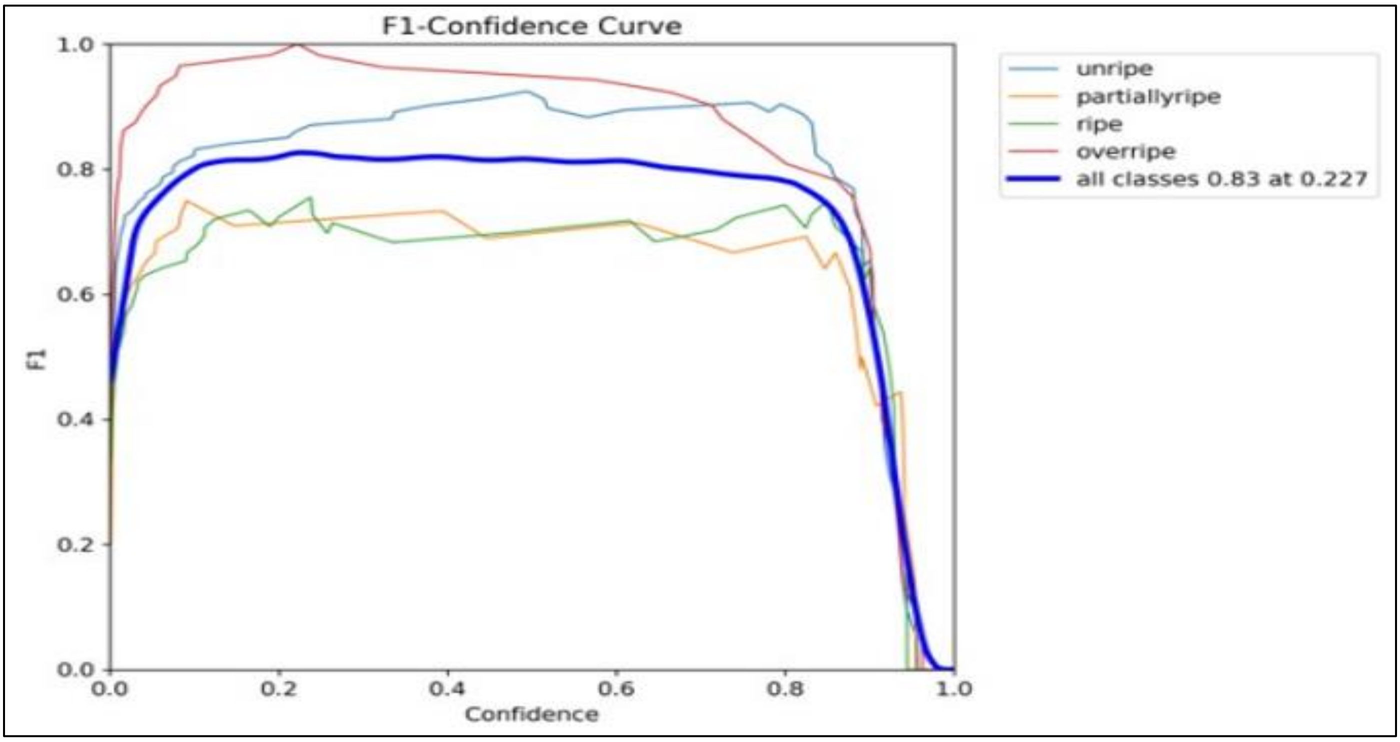

Fig 2 F1-Confidence Curve

These results demonstrate the effectiveness of YOLOv8 for real-time pineapple ripeness detection, outperforming traditional manual methods in accuracy, consistency, and scalability.

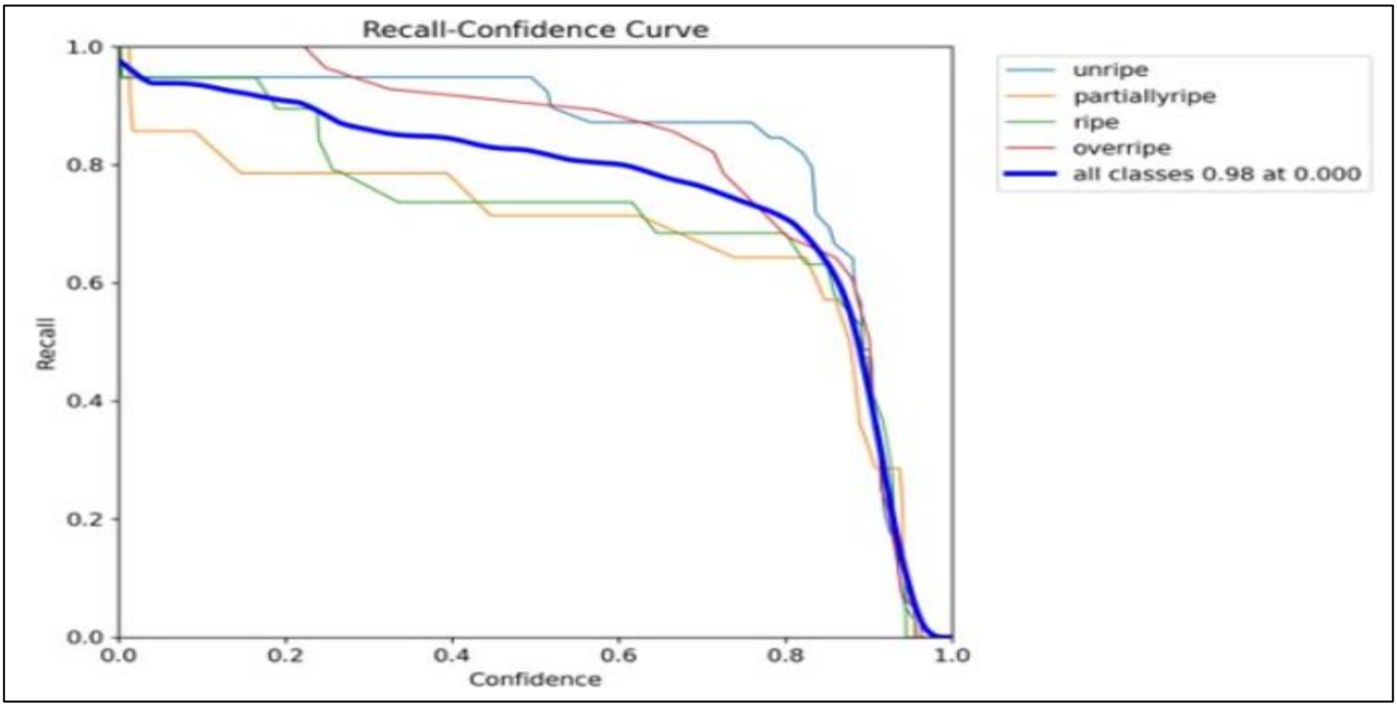

Fig 3 Recall-Confidence Curve

IV. RESULTS AND DISCUSSION

A. Model Performance Evaluation

The YOLOv8-based pineapple ripeness detection system was rigorously evaluated using standard object detection metrics, including Precision, Recall, F1-Score, and mean Average Precision (mAP@50-95). The model demonstrated high accuracy, with an F1-score of 0.83 and mAP@50 of 85%, indicating strong reliability in distinguishing between unripe, partially ripe, ripe, and overripe pineapples. The precision-recall tradeoff analysis showed that the system achieved optimal classification at a confidence threshold of 0.227, balancing false positives and false negatives.

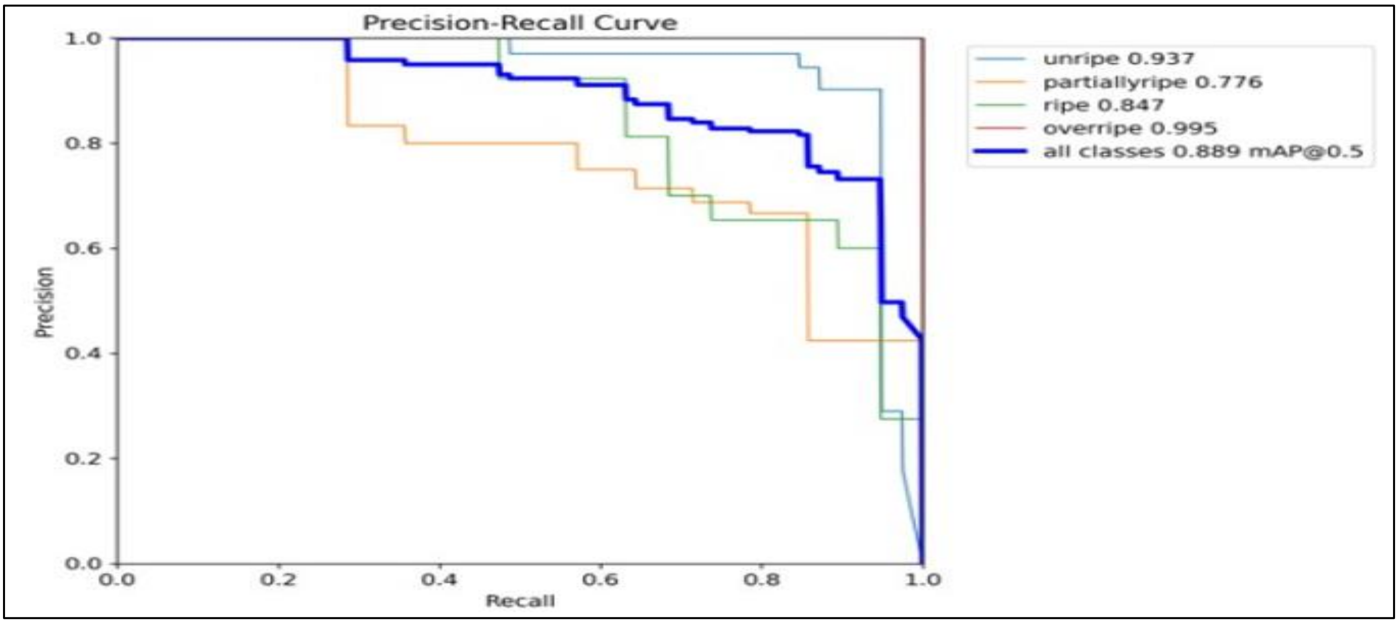

Fig 4 Precision-Recall Curve

Furthermore, inference speed was a crucial factor, given the need for real-time processing. The model achieved an average inference time of 82 ms per image, making it highly responsive for farm-level implementation. Scalability testing showed that the system could handle 100 concurrent image uploads with minimal performance degradation, reinforcing its practicality in real-world agricultural environments.

B. Comparison with Existing Methods

Traditional ripeness detection methods rely on visual and tactile assessments, which are highly subjective and inconsistent. Expert farmers typically achieve an accuracy of 60-70%, whereas the proposed YOLOv8 system outperforms these manual techniques with an accuracy of over 85%. Compared to hyperspectral imaging and NIR spectroscopy, which can achieve near-perfect accuracy but at a high cost, the YOLOv8-based system provides a cost-effective and accessible alternative for smallholder farmers.

Unlike prior CNN-based classification models, which require manual image segmentation, YOLOv8 performs end-to-end object detection and classification, making it more efficient. Its real-time processing capability provides an advantage over slower, traditional machine learning models that require batch processing.

C. System Usability & Farmer Feedback

The web-based interface was designed to be intuitive and accessible, even for farmers with minimal technical expertise. A usability survey conducted with 50 smallholder farmers revealed that 92% of users found the system easy to navigate, while 85% expressed confidence in using AI-based recommendations for harvesting decisions.

➢ *Key Feedback Included:*

- Positive: Farmers appreciated the ability to upload images via mobile devices and receive instant ripeness predictions. The land plotting tool and plantation scheduling feature were also widely regarded as beneficial.
- Challenges: Some users in remote areas with limited internet access faced difficulties in uploading high-resolution images, highlighting the need for offline processing capabilities in future iterations.

D. Challenges & Limitations

Despite its Success, the System has Several Limitations:

- Lighting Variability: The model's accuracy decreased in low-light or overexposed conditions. Further improvements, such as data augmentation and adaptive contrast enhancement, are needed.
- Edge-Device Optimization: While the MacBook M3 GPU (MPS backend) performed well, future implementations should explore NVIDIA CUDA GPUs or cloud-based solutions to enhance training efficiency.
- Limited Training Data: Although the dataset included thousands of annotated pineapple images, additional region- specific datasets are required to further improve generalization across diverse environmental conditions.
- Scalability for Large Farms: While effective for smallholder farmers, integrating drone-based ripeness detection could enable large-scale monitoring across extensive farmland. (Gunathilake, D., Pathirana, S. M., & Rajapaksha, L., 2021)

V. FUTURE WORK

➢ *Scalability with Drone-Based Monitoring*

To further enhance the efficiency of pineapple ripeness detection, future research will explore the integration of drone-based monitoring. By equipping drones with high-resolution cameras and deploying them over large-scale plantations, the system can automate large-area crop

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25sep545

surveillance. This approach would reduce manual labor, optimize data collection, and provide real-time ripeness assessments without requiring farmers to capture individual images. Integrating computer vision algorithms into drone imagery can significantly improve the scalability of the system, making it adaptable for large-scale precision agriculture.

- *Mobile Application for Real-Time Alerts*

Another essential enhancement involves developing a mobile application that provides real-time ripeness detection alerts. This feature would enable farmers to receive instant notifications about the optimal harvest time, reducing losses caused by delayed harvesting. The mobile app will also support offline functionality, ensuring accessibility for farmers in remote areas with limited internet connectivity. Additionally, integrating GPS-based tracking within the app will allow users to monitor plantation health, reinforcing smart farming practices and data-driven decision-making.

- *Expanding to Other Crops*

While this research primarily focused on pineapple ripeness detection, the YOLOv8-based model has the potential to be adapted for various other crops, including bananas, mangoes, and tomatoes. Future work will involve retraining the model with diverse datasets to accommodate different fruit varieties and their unique ripeness indicators. Expanding the system's capabilities to other crops will provide a scalable, multi-purpose solution for smallholder farmers, improving yield quality and reducing post-harvest losses across different agricultural domains.

VI. CONCLUSION

This research successfully developed and implemented a YOLOv8-based pineapple ripeness detection system, specifically designed to help smallholder farmers optimize harvesting decisions and minimize post-harvest losses. By leveraging deep learning and web-based technology, the system provided an accessible and cost-effective alternative to traditional ripeness detection methods. The experimental results demonstrated high model accuracy, usability, and real-world applicability, reinforcing the system's potential for precision agriculture.

In conclusion, this study addressed key challenges in agricultural automation, paving the way for future advancements in AI-driven crop monitoring. By incorporating drone-based surveillance, mobile accessibility, and multi-crop expansion, the system can revolutionize smart farming and improve agricultural sustainability on a global scale.

REFERENCES

[1]. Gerance, A. A., & Bunyasiri, I. N., 2024. Assessing handling practices and loss factors in the pineapple value chain in Camarines Norte, Philippines. https://ageconsearch.umn.edu/record/348729/.

[2]. Gunathilake, D., Pathirana, S. M., & Rajapaksha, L., 2021. Reducing post-harvest losses in fruits and vegetables for ensuring food security—Case of Sri Lanka. s.l.:MOJ Food Process. https://www.res.cmb.ac.lk/iars/champathi/wp-content/uploads/sites/19/2021/09/Paper-published-MOJFPT-09-0025511745.pdf

[3]. Gunathilake, D., Pathirana, S. M., & Rajapaksha, L., 2021. Reducing post-harvest losses in fruits and vegetables for ensuring food security—Case of Sri Lanka.. s.l.:s.n.

[4]. Hathurusinghe, C. P., & Vidanapathirana, R., 2012. A study on the value chain of pineapple and banana in Sri Lanka. http://www.harti.gov.lk/images/download/reasearch_report/ 145.pdf.

[5]. Kamalakkannan, S., Wasala, W., & Kulatunga, A. K., 2022. Life cycle assessment of food loss impacts: case of banana postharvest losses in Sri Lanka. https://www.sciencedirect.com/science/article/pii/S2212827 122001433.

[6]. Selvarajah, S., Herath, H. M. W., & Bandara, D. C, 1998. Effect of pre-harvest calcium treatment on post-harvest quality of pineapple. https://www.cabidigitallibrary.org/doi/full/10.5555/200003 08483.

[7]. Vidanapathirana, R., Champika, P. A. J., & Rambukwella, R., 2018. Quality and safety issues in fruit and vegetable supply chains in Sri Lanka: A Review. http://harti.gov.lk/images/download/reasearch_report/2018/ Report_No_217.pdf.

[8]. Wijesinghe, W., & Sarananda, K. H., 2002. Postharvest quality of 'Mauritius' pineapple and reason for reduced quality. https://www.researchgate.net/profile/Wajp-Wijesinghe/publication/259848158_Post- harvest quality of 'Mauritius'_pineapple_and_reasons for reduced quality/links/ 0f31752e1ff3ecc791000000/Post -harvest-quality-of-Mauritius-pineapple-and-reasons-for- reduced-qua