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E-Buyur Market: Fruit and Vegetable Quality Detection Platform Using On-Device Hybrid Artificial Intelligence Method to Reduce Food Loss in MSMEs

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Abstract

Indonesia produces large volumes of fruits and vegetables yet faces high food loss and waste (FLW), with studies estimating 23-48 million tons of food waste annually. Observations in Grobogan Regency show traders discarding around 30-40% of daily stock, often produce that is edible but visually imperfect (grade B/C). This study designs and evaluates E-Buyur Market, a digital marketplace embedding an on-device hybrid AI pipeline to automatically signal fruit-vegetable quality. The system combines a YOLO-TFLite commodity detector with a multitask MobileNetV3-Small TFLite grader to predict type, edibility, and a quality score derived from freshness probability. The model was trained on approximately 115,000 images compiled from publicly available Kaggle fruit-vegetable repositories, processed using data augmentation and post-training quantization for TensorFlow Lite deployment; a separate small set of real seller-captured photos was used to qualitatively test the deployed model under real usage conditions. On a held-out test set, the model achieves a type-classification accuracy of 0.91, freshness ROC-AUC of 0.94, PR-AUC of 0.92, and inference latency of tens of milliseconds on mid-range phones. Based on the system's design and signaling-theory rationale, on-device hybrid AI is expected to improve sell-through, reduce shrinkage, and shorten time-to-list for MSME sellers; empirical validation of these business-level outcomes through a live field trial remains future work.

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INTRODUCTION

Indonesia is an agrarian country with a significant contribution of the agricultural sector to the national economy. However, various studies indicate that Indonesia still faces serious problems of food loss and waste (FLW), particularly for perishable fruit and vegetable commodities. A study by the National Development Planning Agency (Bappenas) estimated that FLW generation in Indonesia during the 2000-2019 period reached approximately 23-48 million tons per year, equivalent to 115-184 kg per capita per year, with economic losses of around IDR 213-551 trillion per year or 4-5% of Indonesia's GDP (Kementerian PPN/Bappenas, 2021). Most of this FLW originates from the horticultural product supply chain, indicating that fruit and vegetable management is still far from efficient. Field studies and observations in Grobogan Regency, Central Java Province, known as Central Java's food barn, illustrate this problem concretely. Interviews with traders indicate that they discard approximately 30-40% of their daily fruit and vegetable stock. per capita per year, with economic losses of around IDR 213-551 trillion per year or 4-5% of Indonesia's GDP (Kementerian PPN/Bappenas, 2021). Most of this FLW originates from the horticultural product supply chain, indicating that fruit and vegetable management is still far from efficient. Field studies and observations in Grobogan Regency, Central Java Province, known as Central Java's food barn, illustrate this problem concretely. Interviews with traders indicate that they discard approximately 30-40% of their daily fruit and vegetable stock.

These discarded products are generally still fit for consumption but have cosmetic defects, classified as grade B and C, making them less attractive than grade A. On the other hand, many consumers, especially in e-commerce channels, still equate perfect appearance with freshness, thus reluctant to purchase products with minor cosmetic defects. Consequently, grade B/C products are difficult to sell and end up as waste, reducing the income of MSME traders in traditional markets and online stores. From an environmental Perspective, rotting fruit and vegetable waste contributes to methane gas emissions that exacerbate global warming, consistent with findings that FLW contributes a significant portion of national greenhouse gas emissions (Kementerian PPN/Bappenas, 2021). From a policy perspective, the government actually has a mandate to reduce food waste, evidenced by Food Law No. 18 of 2012 emphasizing sustainable food utilization and waste prevention. Indonesia is also committed to SDG Target 12.3, which aims to halve per capita food waste at the retail and consumer levels by 2030 and reduce food loss along production and supply chains, including post-harvest (United Nations, 2015; United Nations, 2024). Additionally, the National Food Agency initiated movements such as the Save Food Movement and the Food Rescue program to save excess food from being wasted (Badan Pangan Nasional, 2023).

Recent research on fruit and vegetable ranking based on deep learning shows that computer vision systems can accurately classify external product quality and potentially reduce waste through better quality management (Fu, Nguyen, & Yan, 2022; Hayat et al., 2024; Yuan & Chen, 2024; Zárate & Cáceres Hernández, 2024). E-Buyur Market is a marketplace that embeds an on-device hybrid AI pipeline to perform fruit-vegetable grading and automatically display quality badges on product pages. The objectives of this activity are to design an efficient on-device pipeline architecture for fruit-vegetable grading cases in Indonesian marketplaces, evaluate the technical performance of models on real-world data, and measure business impact indications on sell-through, conversion rate, shrinkage, and time-to-list for MSME sellers.

In the realm of digital marketing, the above situation can be explained through information asymmetry theory that online buyers cannot touch or smell products, resulting in high quality uncertainty and potentially causing the lemons problem phenomenon, where buyers cannot distinguish between high and low quality, and they tend only to be willing to pay average prices. High-quality products are pushed out of the market because they are considered too expensive compared to perceived risk, resulting in markets filled with low-quality products (lemons). To reduce asymmetry, signaling theory emphasizes the importance of credible, easily understood, and difficult-to-manipulate quality signals, such as verified labels or clear quality scores. In the E-Buyur Market context, verified scores are interpreted as 0-100 scores produced consistently by AI models based on training datasets, not sellers' unilateral claims, and accompanied by brief explanations so buyers understand the reasoning behind the scores. This approach aligns with research findings on risk and trust in agricultural products in e-commerce, showing that quality information clarity can reduce perceived risk and increase purchase intention (Zhang et al., 2020).

The development of edge computing technology and on-device machine learning opens opportunities to build such quality signals directly on sellers' devices. TensorFlow Lite and its ecosystem are designed to run deep learning models on resource-constrained devices (David et al., 2021; Rashidi, 2022). Efficient CNN architectures, such as MobileNetV3-Small, enable lightweight yet accurate computer vision models for mobile devices (Howard et al., 2019). On the other hand, the YOLO family represented by YOLOv4, YOLOX, and YOLOv7 shows superior object detection performance on real- world images with diverse backgrounds (Bochkovskiy et al., 2020; Ge et al., 2021; Wang et al., 2023).

Several recent studies apply CNN and these detection models for fruit-vegetable grading and sorting, but most are still limited to testing in laboratory environments or controlled datasets and have not been integrated with real e-commerce flows or assessed for business impact on MSMEs (Mirwansyah & Wibowo, 2022; Rajmohan et al., 2023; Chen et al., 2020).

The main remaining challenge is translating these various policies and initiatives into concrete solutions that MSME actors in real markets can use, thereby narrowing the gap between regulation and practice. Based on this background, this article presents E-Buyur Market as an innovative work aimed at MSME fruit and vegetable traders who have been bearing losses due to unsold grade B and C stock. Visually imperfect products often must be heavily discounted or even discarded, causing profit margins to drop and loss risks to increase even though consumption quality is actually still suitable. Consequently, this application aims to serve as a solution to the problem of food waste in Indonesia, specifically regarding fruit and vegetable waste.

RESEARCH METHODS

A. System Architecture

The system design adopts an on-device first approach comprising three main integrated components to ensure efficiency and privacy. The first component is the YOLO-TFLite commodity detector, which functions to produce bounding boxes and initial commodity labels from the camera feed. The detected areas are subsequently cropped as regions of interest (ROI) to be processed by the next stage. The second component is the MobileNetV3-Small TFLite multitask grader. This module receives the ROI and simultaneously produces two outputs: a commodity type probability vector via a softmax layer covering 54 classes, and a freshness probability via a sigmoid layer in the range of 0-1. The third component is the quality score module and application interface. This component converts the raw freshness probability into a user-friendly 0-100 score and determines whether to display a "Layak" (Suitable) badge. The quality score is calculated using the following formula:

$$\mathrm{quality}_{\mathrm{score}} = \lfloor 100 \times \mathrm{p}_{\mathrm{fresh}} \rfloor \qquad (1)$$

Caption of the formula:

$\mathrm{p}_{\mathrm{fresh}}$	=	Predicted freshness probability from the model (0-1)
$\mathrm{quality}_{\mathrm{score}}$	=	Final quality assessment score (0-100)

Products are considered suitable for sale $\mathrm{quality}_{\mathrm{score}} \geq 70\%$. This threshold value was determined through a calibration process aimed at balancing precision and recall, ensuring that only truly sellable items receive the badge.

For clarity, four related terms are used throughout this paper with distinct meanings. Freshness denotes the raw model output $\mathrm{p}_{\mathrm{fresh}}$ (0-1), the sigmoid probability that the produce is in fresh condition. Quality score is this same value rescaled to a 0-100 range for display to users. Edibility is used descriptively to refer to produce that remains safe and acceptable for consumption despite cosmetic imperfections (grade B/C); it is not a separate model output but is inferred from the freshness/quality score. Suitability for sale is the binary outcome (the "Layak"/"Tidak Layak" badge) obtained by thresholding the quality score at 70%, as described above.

B. Dataset and Preprocessing

To ensure model robustness, the training dataset was compiled entirely from several publicly available fruit and vegetable image sets on Kaggle, totaling 115,012 images covering 54 commodity classes with variations in freshness labels (fresh vs. rotten). The dataset was split into training (78,207 images), validation (13,802 images), and testing (23,003 images) sets, stratified by commodity type using a fixed random seed. Separately, a small set of real-world photos captured through the E-Buyur Market seller application was used to qualitatively test the deployed model's behavior under real usage conditions (see Figure 3); these photos were not included in the training, validation, or test splits, and were not used to compute any of the quantitative metrics reported in this study. Prior to training, images are resized to 224×224 pixels for classification and to the appropriate input resolution for detection. Pixel values are normalized to the range , and color channels are adjusted to match the model backbone format. Furthermore, data augmentation is applied to the training set, including random crops, horizontal flips, brightness and contrast adjustments, small rotations, and the addition of light compression noise. The primary purpose of this preprocessing pipeline is to increase the model's robustness against the high variance of lighting and angles found in sellers' photos.

C. Training Process

The training procedure is conducted in two distinct stages. The first stage involves fine-tuning the MobileNetV3-Small architecture using a combined loss function defined as:

$$\mathcal{L} = \mathcal{L}_{\text{type}} + \lambda\, \mathcal{L}_{\text{fresh}} \quad (2)$$

Caption of the formula:

$\mathcal{L}$	=	Total combined loss value
$\mathcal{L}_{\text{type}}$	=	Categorical cross-entropy loss for commodity classification
$\mathcal{L}_{\text{fresh}}$	=	Binary cross-entropy loss for freshness prediction
$\boldsymbol{\lambda}$	=	Weighting parameter to balance the two tasks

In this equation, $\mathcal{L}_{\text{type}}$ represents the categorical cross-entropy loss for commodity type classification, while $\mathcal{L}_{\text{fresh}}$ denotes the binary cross-entropy loss for freshness prediction. The parameter λ is used to balance the contributions of both tasks to the total loss (set to equal weights of 1.0 in this study). Training was conducted using the Adam optimizer with a batch size of 32 across two phases: a warm-up phase (3 epochs, initial learning rate of 1 × 10^(-3)) with the MobileNetV3-Small backbone frozen, followed by a fine-tuning phase (up to 12 further epochs, learning rate reduced to 1×10^(-5)) in which the last 30 backbone layers were unfrozen. To prevent overfitting, an Early Stopping callback (patience of 4 epochs, monitoring the validation freshness AUC) and a ReduceLROnPlateau callback (factor 0.2, patience 2) were applied to prevent overfitting. The second stage focuses on model deployment, where the trained model is converted to TensorFlow Lite format using post-training quantization techniques (FP16/INT8). This step is crucial to significantly reducing the model size and accelerating inference speed. The TFLite interpreter on the target devices utilizes XNNPACK and, where available, the NNAPI or GPU delegate for hardware acceleration.

D. Application Development and Process Flow

The AI module is seamlessly integrated into the E-Buyur Market seller application, which is built upon the Flutter framework with a Laravel backend. The process flow initiates when sellers log into the application and access the dashboard, which displays a summary of stock value, product count, total units, and average freshness. To list a product, sellers select the "Scan Product" menu, directing the phone camera to capture photos of fruits or vegetables within a guided green frame. Upon capture, the application executes the YOLO-TFLite model to detect commodities and crop the ROI. This ROI is then fed into the MobileNetV3-Small TFLite model to predict type, freshness probability, and quality score. The results are displayed instantaneously on the screen, featuring the commodity name, suitability percentage, an expression icon (happy/neutral/sad), and a decision badge ("Layak" if score ≥ 70 or "Tidak Layak" if < 70). If declared suitable, quality information is automatically populated into the listing form, thereby reducing time-to-list. Conversely, if declared unsuitable, the app suggests redirecting the product for personal consumption or donation, helping to suppress shrinkage. A similar flow is applied to the buyer side, where freshness badges allow for transparent quality comparison.

E. Evaluation Metrics

The model evaluation relies on several key metrics. First, type classification accuracy measures the proportion of correct label predictions across the 54 classes. Second, for the freshness task, precision, recall, and F1-score are calculated, with the F1-score defined as:

$$\text{F1} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (3)$$

Caption of the formula:

F1	=	The harmonic mean of precision and recall
precision	=	The ratio of correctly predicted positive observations to the total predicted positives
recall	=	The ratio of correctly predicted positive observations to the all observations in actual class

Third, the Area Under the ROC Curve (ROC-AUC) and Precision-Recall Curve (PR-AUC) are used to assess discrimination ability on imbalanced data. Fourth, technical performance is measured by median inference latency (p50) and 95th-percentile latency (p95) on mid-range devices, along with power consumption estimates. At the business level, the study monitors changes in sell-through rates, conversion rates (CVR), shrinkage (discarded products), and time-to-list to gauge the practical impact of AI integration on MSME income and food loss reduction.

RESULT AND DISCUSSION

A. Model Performance and Efficiency

The technical evaluation of the E-Buyur Market platform demonstrates that the proposed hybrid AI architecture achieves a high degree of accuracy suitable for commercial deployment. As shown in the learning curves in Figure 1.

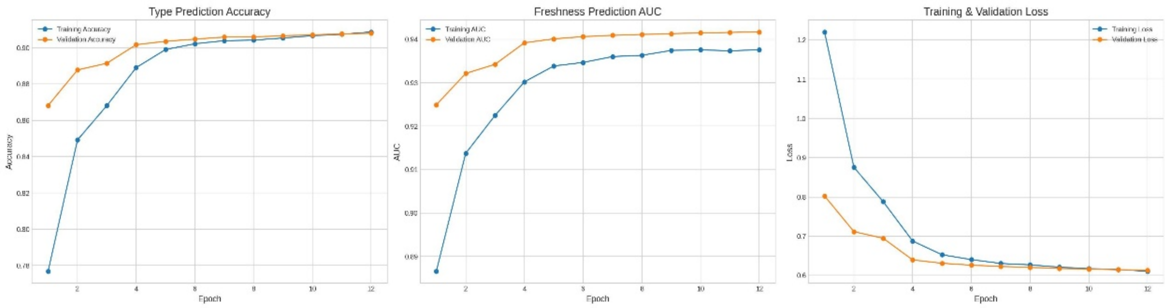

Figure 1. Training and validation curves showing accuracy and loss over epochs for both type classification and freshness prediction tasks.

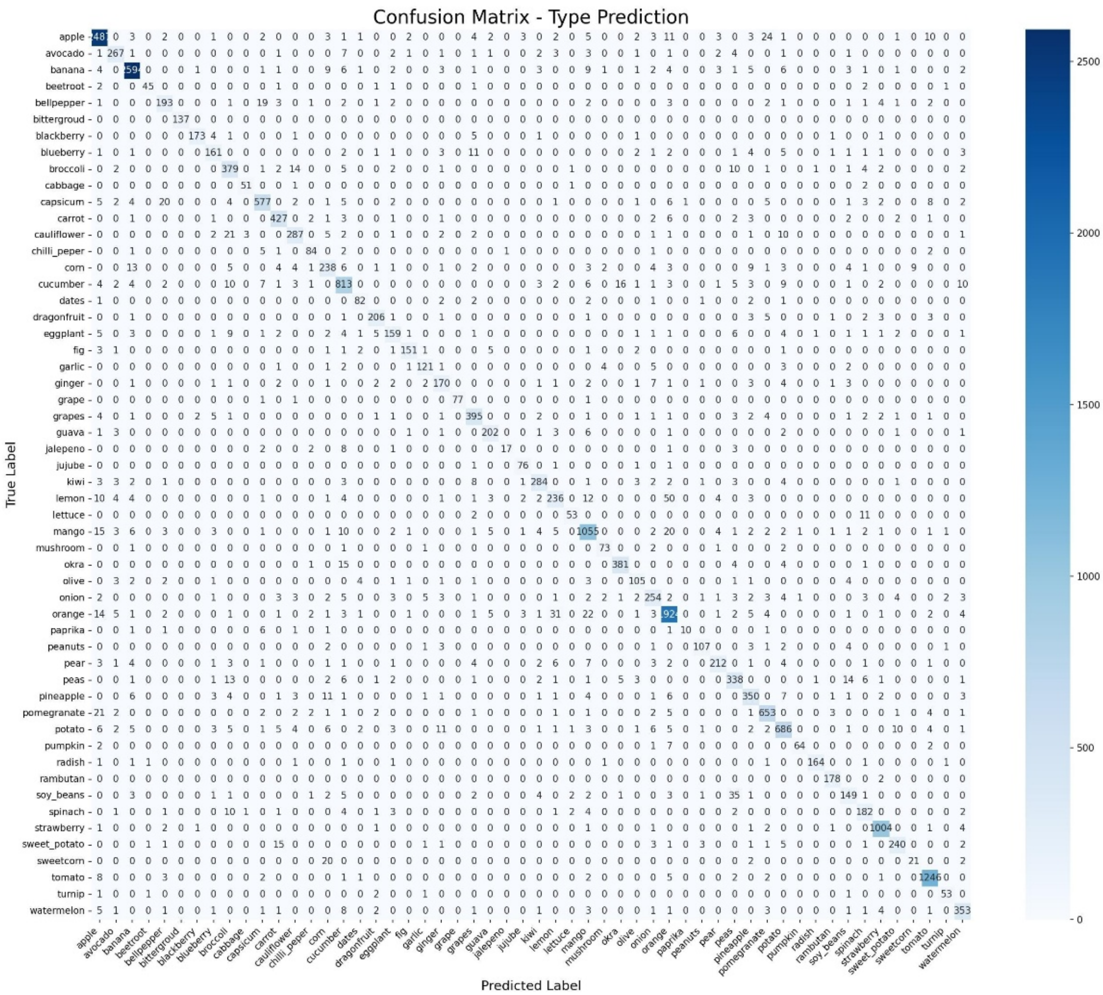

Figure 2. Confusion matrix for commodity type classification on the held-out test set (23,001 images)

The training and validation performance for both type classification and freshness tasks shows consistent improvement. Specifically, type classification accuracy increases sharply in the first few epochs, exceeding 90%, and stabilizes without significant symptoms of overfitting. This stability indicates that the fine-tuning and augmentation strategy effectively handles the heterogeneity of the 54 commodity classes. Further analysis using the Confusion Matrix as shown in Figure 2, reveals that the majority of probability mass is concentrated on the main diagonal, confirming good class separation. Remaining errors are primarily confined to visually similar commodity pairs, such as differentiating between Red Apple and Fuji Apple, or amongst distinct chili varieties. These errors are reasonable given the high visual variance and the occasional ambiguity in field labels.

The quantitative evaluation results on the 23,003-image held-out test set are summarized in Table 1. Instead of presenting per-class metrics for all 54 commodities, which is space-prohibitive, we report the macro-averaged metrics to demonstrate the model's balanced capability across the imbalanced dataset.

Table 1. Overall Technical Performance Metrics on Held-out Test Set

Evaluation Taks	**Performance Metric**	**Score/ Value**
Commodity Type Classification	Overall Accuracy	91.06%
	MacroAveraged Precision	0.888
	MacroAveraged Recall	0.856
	MacroAveraged F1-score	0.869
Freshness Prediction (Raw)	ROC-AUC	0.940
	PR-AUC	0.920
Suitability Decision (Score ≥ 70%)	Binary Accuracy	83.90%
	Recall (Fresh Class)	0.630
	Recall (Rotten Class)	0.970
On Device Efficiency	Inference Latency	$\sim 30 - 50ms$
	Quantized Model Size (FP16)	2.3MB

As shown in Table 1, the model achieves an overall type-classification accuracy of 91.06%, with a macro-averaged F1-score of 0.869, reflecting consistently strong performance. Regarding freshness assessment, the model achieves an ROC-AUC of approximately 0.94 and a PR-AUC of 0.92. At the deployed decision threshold (quality_score ≥ 70%), the model reaches an overall freshness accuracy of 83.9%, with a recall of 0.97 for the rotten class but only 0.63 for the fresh class. This asymmetry is a deliberate consequence of the calibrated threshold, which prioritizes avoiding false "suitable for sale" badges on unsellable stock over maximizing the recall of fresh items. From an efficiency perspective, the quantized TFLite FP16 model (2.3 MB) yields an inference latency of tens of milliseconds per image, ensuring a fluid user experience suitable for commercial deployment on standard smartphones, consistent with recent findings on TinyML applications (David et al., 2021; Rashidi, 2022).

B. Application Interface and User Experience

The integration of the AI pipeline into the application interface translates technical metrics into actionable business insights. Qualitative analysis demonstrates that under sufficient lighting, the model reliably recognizes type and freshness even when fruits are stacked. However, confidence drops when objects are partially obstructed or photographed from extreme angles. To mitigate this, the User Interface (UI) provides clear feedback.

Figure 3. Qualitative prediction examples showing successful cases and common failure patterns

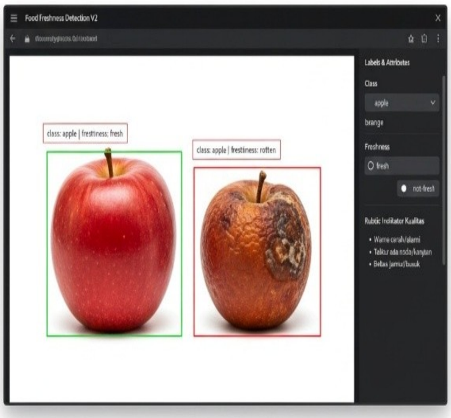

Figure 4. User interface showing grading results for a fresh apple (high score, green badge) versus a not-fresh apple (low score, red badge)

Figure 4 illustrates that the grading interface of fresh apples with smooth surfaces yields high scores and a green "Layak dijual" (Suitable for sale) badge, whereas apples with spots trigger a "Tidak Layak" (Unsuitable) warning. This binary distinction allows sellers to immediately segregate products, streamlining their inventory management.

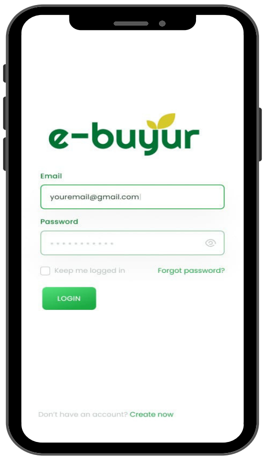

Figure 5. E-Buyur market login screen for sellers

The implementation extends to the seller dashboard as seen in Figures 5 and Figure 6 which aggregates these scores into a portfolio view, displaying total stock value alongside average freshness percentage. This feature shifts the seller's focus from mere quantity to quality management.

Figure 6. Seller dashboard showing stock summary, product count, total units, and average freshness percentage

On the buyer side, the freshness percentage badge serves as a standardized quality signal. By displaying "84% Freshness" on a product card, the platform reduces the information asymmetry that typically plagues online fresh food sales, as shown in Figure 7. This mechanism supports the signaling theory discussed earlier, where credible, verifiable scores increase purchase intention by reducing perceived risk (Zhang et al., 2020).

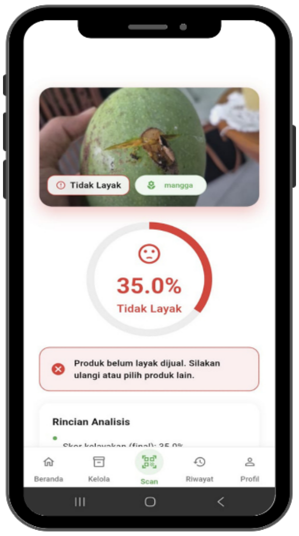

Figure 7. Buyer catalog view showing product cards with freshness percentage badges

Meanwhile, the scanning process itself is designed to be educational. Figure 8 demonstrates this workflow; when a mango receives a 35% score, the accompanying message explicitly guides the seller to retry or choose another product. This feature effectively connects algorithmic predictions with operational actions.

Figure 8. Scanning process showing the AI analysis screen with a progress bar and the final result, including the score and decision label

C. Discussion and Practical Implications

The results of this study confirm that an edge-first pipeline utilizing YOLO and MobileNetV3 is not only technically viable but also operationally beneficial for MSME marketplaces. The use of YOLO as an ROI detector significantly reduces background bias, increasing system robustness against amateur photography common among MSME sellers (Bochkovskiy et al., 2020; Wang et al., 2023). Meanwhile, the lightweight MobileNetV3 architecture enables the deployment of sophisticated grading logic without the need for expensive cloud computing resources, preserving user privacy and reducing operational costs (Howard et al., 2019; Chen et al., 2020). Practically, this technology accelerates the digital transformation of MSMEs, enhancing operational efficiency, expanding market access, and optimizing business strategies through appropriate technological solutions; by adopting the e-buyur market platform, fruit and vegetable MSMEs can automate business processes, expedite market distribution, reduce operational costs, and reach customers in a broader market. This aligns with research by Hendrawan et al (2024), which indicates that the use of analysis and detection tools enables MSMEs to understand consumer behavior, measure the effectiveness of marketing campaigns, and make data-driven decisions.

However, several limitations must be acknowledged. The system's performance is heavily dependent on image capture conditions; low-resolution cameras or poor lighting can degrade prediction reliability. Furthermore, there is a potential for "gaming" the system, where sellers might intentionally photograph only the good side of a rotting fruit. While the current AI can detect visible defects, it cannot inspect the internal state of the fruit. This limitation highlights the need for continuous user education and potentially integrating multi-view analysis in future updates. Additionally, the domain shift between the training dataset (often studio-quality) and real-world market photos remains a challenge, necessitating the continuous expansion of a localized Indonesian fruit and vegetable dataset (Mirwansyah & Wibowo, 2022). Despite these challenges, the technical results support the underlying premise of signaling theory discussed earlier: a credible, AI-verified quality score is expected to increase sell-through and reduce shrinkage by lowering buyers' perceived risk toward grade B/C produce. Quantifying these business-level outcomes, however, requires a live field trial with participating MSME sellers tracking actual sell-through, conversion, and shrinkage figures over time; this remains an important direction for future work, and the projected benefits discussed here should be read as design rationale rather than measured results (Kementerian PPN/Bappenas, 2021; United Nations, 2024).

CONCLUSION

The design and evaluation of E-Buyur Market demonstrate that implementing an on-device hybrid AI pipeline is a technically viable and strategically effective solution to mitigate the prevalence of grade B and C food loss within the Indonesian MSME sector. By integrating a YOLO-based detector and MobileNetV3 grader directly into the seller's workflow, the platform successfully bridges the gap between high-level sustainability policies and the operational realities of traditional markets, providing a reliable, privacy-preserving, and instant quality assessment mechanism. The system demonstrates robust technical performance in terms of classification accuracy and freshness discrimination suitable for real-time deployment, and its design is intended to translate these capabilities into tangible business benefits, including reduced shrinkage, decreased time-to-list, and enhanced buyer trust through transparent quality signaling; confirming these business outcomes empirically through a live MSME field trial is identified as a priority for future work.

The system not only demonstrates robust technical performance in terms of classification accuracy and freshness discrimination suitable for real-time deployment, but also translates these capabilities into tangible business benefits, including reduced shrinkage, decreased time-to-list, and enhanced buyer trust through transparent quality signaling. However, the system faces limitations regarding detection bias; because it focuses exclusively on fruits and vegetables, there is a risk of generating inaccurate detections. Consequently, future work should involve expanding the dataset to include greater variety and specificity, as well as enabling analysis through 3D-CNN (Three-Dimensional Convolutional Neural Network) models which is consistent with the findings of Hasibuan & Hendrik (2025), who noted that 3D-CNNs are highly effective at handling variations in viewing angles and lighting when trained on diverse datasets.

Ultimately, this research confirms that accessible edge intelligence empowers small-scale traders to monetize visually imperfect yet edible produce, thereby contributing to the national circular economy and the achievement of Sustainable Development Goal 12.3 regarding responsible consumption and production.

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