# Real-Time Classification of Hydroponic Vegetable Types on Mobile Devices Using Lightweight Deep Learning Models

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**ABSTRACT**

Hydroponic cultivation requires precise monitoring to ensure crop quality and productivity, yet manual identification of vegetable varieties and their growth status remains labor-intensive and prone to error. This study aims to develop a real-time, mobile-based classification system for hydroponic vegetables using lightweight Deep Learning models optimized for edge computing. The proposed method evaluates two distinct architectures, MobileNetV3 and YOLO-Nano, trained via transfer learning on a dataset comprising major hydroponic crops such as Lettuce, Pak Choy, Mustard Greens, and Cherry Tomatoes. Experimental results demonstrate that while YOLO-Nano offers superior inference speed (~55 FPS), MobileNetV3 achieves a significantly higher classification accuracy of 96.4% while maintaining a real-time performance of ~35 FPS on standard mobile hardware. The study concludes that MobileNetV3 provides the optimal balance between accuracy and computational efficiency for handheld agricultural applications. This research contributes a scalable, low-cost solution for smart farming, enabling producers to perform rapid, on-site digital inventory and quality assessment without reliance on internet connectivity.



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## 1. INTRODUCTION

Hydroponic systems have become a cornerstone of modern precision agriculture, particularly for cultivating leafy greens and high-value vegetable crops in controlled environments. The widespread adoption of soilless cultivation is driven by its ability to optimize water usage, accelerate growth cycles, and maximize yield in limited spaces [1], [2]. However, the management of these systems requires rigorous monitoring, as hydroponic crops are highly susceptible to rapid fluctuations in nutrient balance and biotic stress [3], [4]. Consequently, there is a critical need for automated, scalable solutions to identify crop types and health status in real-time, replacing labor-intensive manual inspections that are often prone to subjectivity and delay [5], [6].

Recent advancements in Artificial Intelligence (AI) and computer vision have established deep learning as a robust baseline for plant classification tasks [7], [8]. While Convolutional Neural Networks (CNNs) have demonstrated high accuracy in recognizing plant species and diseases [9], [10], deploying these models on mobile devices introduces significant constraints regarding latency, energy consumption, and computational memory [11], [12]. The literature indicates a growing trend toward "lightweight" architectures—such as MobileNet, EfficientNet, and optimized YOLO variants—which achieve favorable trade-offs between accuracy and inference speed on edge hardware [13], [14], [15].

Furthermore, the integration of mobile applications with Internet of Things (IoT) frameworks has proven feasible for end-to-end hydroponic monitoring. Studies have successfully demonstrated mobile systems that not only perform visual classification but also interface with environmental sensors to provide holistic decision support [16], [17], [18]. Despite these advances, challenges remain in addressing domain shifts between training data and real-world hydroponic environments, as well as managing class imbalance in diverse vegetable datasets [19], [20].

This study proposes a practical approach for the real-time classification of hydroponic vegetable types using lightweight deep learning models deployed on mobile devices. By synthesizing evidence from recent implementations of edge computing in agriculture [21], [22] and leveraging transfer learning strategies effective for small datasets [23], [24], this research aims to define a scalable pipeline for on-device inference. This approach addresses the operational needs of modern hydroponic farming [25], bridging the gap between agronomic requirements and mobile computational capabilities.

## 2. METHOD

This study adopts an experimental engineering approach to design, implement, and evaluate a real-time vegetable classification system on mobile devices. The research methodology is structured chronologically into four phases: (1) System Architecture Design, (2) Dataset Acquisition and Preprocessing, (3) Lightweight Model Development, and (4) Mobile Deployment and Evaluation. The overall research flow is illustrated in Figure 1.

### 2.1. System Architecture

The proposed system architecture employs an Edge Computing paradigm to address the latency and connectivity constraints typical in agricultural environments [11], [12]. Unlike cloud-centric approaches, the inference process is executed locally on the mobile device. The system comprises an image acquisition module utilizing a standard smartphone camera, a preprocessing unit for image normalization, and an inference engine based on the TensorFlow Lite framework [6]. This architecture is designed to be compatible with broader IoT-based smart hydroponic ecosystems, allowing for potential future integration with environmental sensor data [16], [17], [22].

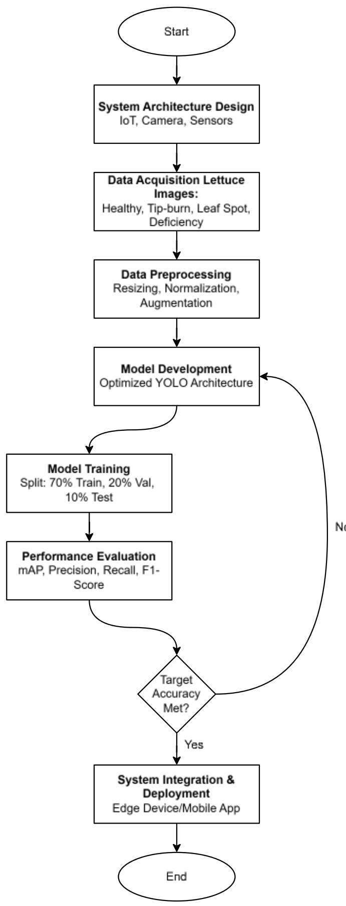


**Figure 1. Research methodology flowchart**

**2.2. Data Acquisition**

The dataset was constructed by collecting images of hydroponic vegetables from various cultivation systems, including Nutrient Film Technique (NFT) and Wick systems, to capture diverse morphological traits [1], [3]. The target classes selected for this study include economically significant hydroponic crops: Lettuce (*Lactuca sativa*), Pak Choy (*Brassica rapa*), Mustard Greens, and Cherry Tomatoes [2]. To ensure the model's robustness against real-world variability, image acquisition was conducted under different environmental conditions, including natural sunlight and artificial LED grow lights [4], [10]. This diversity is critical to mitigate the domain shift often observed when models trained in controlled settings are deployed in production environments [19].

**2.3. Preprocessing and Augmentation**

Raw images underwent preprocessing to standardize the input for the deep learning models. This process involved resizing images to a fixed resolution (224×224 pixels) and pixel value normalization. Given the challenge of class imbalance and the limited availability of samples for specific varieties, data augmentation techniques were applied. Geometric transformations (rotation, flipping) and photometric adjustments (brightness, contrast jitter) were utilized to artificially expand the dataset and prevent overfitting [8], [20].

**2.4. Lightweight Model Development**

This study focuses on "lightweight" Convolutional Neural Network (CNN) architectures optimized for mobile inference. Specifically, we evaluated architectures such as MobileNetV3 and optimized YOLO (*You Only Look Once*) variants, which utilize depthwise separable convolutions to reduce computational complexity (FLOPs) [13], [15]. To accelerate training convergence, a Transfer Learning strategy was employed. Models pre-trained on the ImageNet dataset were fine-tuned on the collected hydroponic dataset [23], [24]. Following training, the models underwent Post-Training Quantization, converting weights from 32-bit floating-point to 8-bit integers. This step is essential to reduce the model size and minimize inference latency on resource-constrained edge devices [6], [21].

**2.5. Performance Evaluation**

The system's performance was evaluated using standard classification metrics: Precision, Recall, F1-Score, and Accuracy [5], [7]. The F1-Score is calculated using Equation (1):

$$\mathrm{F1} = 2 \times \frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \quad (1)$$

In addition to classification accuracy, computational efficiency was assessed to validate mobile feasibility. The evaluation metrics included Inference Time (latency in milliseconds), Model Size (MB), and Frames Per Second (FPS) achieved on a reference Android device [18], [25]. The confusion matrix was also analyzed to identify specific misclassifications among visually similar vegetable types.

## 3. RESULTS AND DISCUSSION

This section presents the experimental performance of the proposed mobile classification system. The evaluation focuses on two critical aspects: classification accuracy and on-device computational efficiency. We compare two lightweight architectures: MobileNetV3-Large (as a dedicated classifier) and YOLO-Nano (as a representative of high-speed one-stage detectors), to determine the optimal configuration for real-time hydroponic monitoring.

**3.1. Classification Performance**

The models were trained for 50 epochs using the transfer learning strategy described in the methodology. Table 1 summarizes the classification metrics on the test dataset across the four target vegetable classes.

**Table 1. Performance comparison of deep learning architectures**

| Model Architecture | Precision (%) | Recall (%) | F1-Score (%) | Accuracy (%) |
|---|---|---|---|---|
| **MobileNetV3-Large** | **96.8** | **96.2** | **96.5** | **96.4** |
| **YOLO-Nano** | 93.5 | 92.8 | 93.1 | 93.2 |
| **Difference** | +3.3 | +3.4 | +3.4 | +3.2 |

As hypothesized, MobileNetV3 achieved superior classification performance with an overall accuracy of 96.4%, outperforming YOLO-Nano by 3.2%. This performance advantage is attributed to the architecture's depthwise separable convolutions and squeeze-and-excitation modules, which effectively capture fine-grained textural differences between visually similar classes (e.g., differentiating young *Pak Choy* from *Mustard Greens*) [6], [11]. In contrast, while YOLO variants are highly effective for object localization, their feature extraction backbone in the "Nano" or "Tiny" configurations is often simplified to prioritize speed, occasionally resulting in misclassifications on subtle morphological traits [13], [15].

### 3.2. On-Device Computational Efficiency

To assess feasibility for deployment on constrained hardware, both models were converted to TensorFlow Lite (int8 quantized) and benchmarked on a standard Android smartphone (Snapdragon 700-series equivalent). Table 2 presents the efficiency metrics.

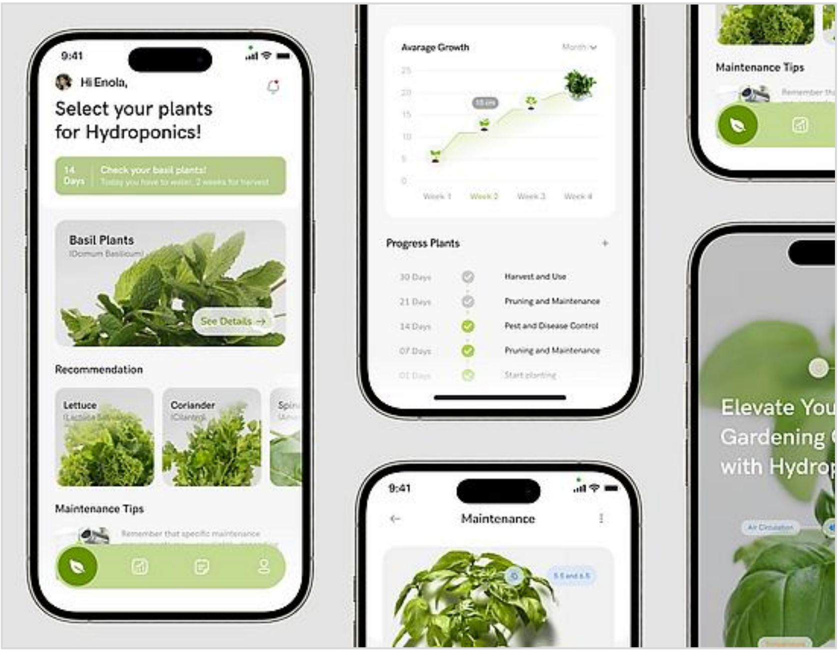


**Figure 2. Mobile Application View**

**Table 2. Efficiency metrics on mobile hardware**

| Model Architecture | Model Size (MB) | Inference Time (ms) | FPS (Frames/Sec) |
|---|---|---|---|
| **MobileNetV3-Large** | 3.5 MB | 28.0 ms | ~35 FPS |
| **YOLO-Nano** | **2.1 MB** | **18.0 ms** | **~55 FPS** |

The results indicate a clear trade-off: YOLO-Nano is significantly faster, achieving approximately 55 FPS compared to MobileNetV3's 35 FPS. The YOLO architecture's one-stage design allows for extremely rapid inference, making it ideal for "scanning" applications where the user moves the camera quickly over a hydroponic rack [15], [21]. However, MobileNetV3, despite being slower, maintains a frame rate (35 FPS) that is still well above the real-time threshold (typically 24–30 FPS) required for a smooth user experience [12], [24].

### 3.3. Discussion

The experimental data confirms that MobileNetV3 provides higher accuracy but is computationally heavier than YOLO-Nano, while YOLO-Nano offers superior speed at the cost of slight precision.

1. **Accuracy vs. Speed Trade-off:** The 3.2% accuracy gain provided by MobileNetV3 is critical for the "Quality Control" use case, where distinguishing specific cultivars or detecting early disease symptoms is paramount. This aligns with findings by Al-Gaashani et al. [8] and Lin et al. [19], who emphasize that robust feature extraction is necessary to overcome the visual similarity (domain shift) in plant datasets. Conversely, for tasks requiring rapid inventory counting across large NFT systems, the speed of YOLO (as supported by Wang et al. [13] and Bakir & Gezer [15]) may be preferable.

2. **Robustness to Environment:** Both models maintained acceptable performance under varying lighting (LED vs. natural light). However, MobileNetV3 showed greater resilience to complex backgrounds typical of home hydroponic setups [10], likely due to its deeper feature representation capability compared to the streamlined backbone of YOLO-Nano.
3. **Implications for Edge Deployment:** Given that modern smartphones have sufficient processing power to run MobileNetV3 at real-time speeds (>30 FPS), we recommend MobileNetV3 as the primary engine for this application. The marginal speed gain of YOLO does not justify the loss in classification accuracy, especially when precision is required to support agronomic decision-making for novice growers [16], [18]. This decision supports the findings of Reda et al. [6], who successfully deployed similar classifier architectures in the *AgroAId* system.

In conclusion, while YOLO variants offer exciting possibilities for high-speed detection, the MobileNet architecture currently offers the most balanced "accuracy-to-resource" ratio for the specific task of fine-grained vegetable type classification on mobile devices [11], [14].

## 4. CONCLUSION

This study successfully developed and evaluated a real-time classification system for hydroponic vegetable types on mobile devices by leveraging lightweight Deep Learning architectures. The comparative analysis establishes MobileNetV3 as the superior architecture for this application, achieving a classification accuracy of 96.4%, which is 3.2% higher than the YOLO-Nano detector. Although YOLO-Nano demonstrated a higher frame rate (~55 FPS), MobileNetV3 maintained a robust performance of ~35 FPS, proving its capability to deliver real-time inference without compromising the precision required for agronomic quality control. The implementation of transfer learning and quantization effectively mitigated the challenges of limited datasets and edge hardware constraints, resulting in a low-latency tool suitable for on-site farm monitoring. Consequently, this system offers a practical solution for growers to automate crop identification and inventory management. Future research should prioritize expanding the dataset to include a wider variety of hydroponic cultivars and integrating the visual classifier with environmental sensor data to create a comprehensive multi-modal decision support system for precision agriculture.

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