# Lightweight Edge-AI Frameworks for Coffee Bean Defect Identification and Classification

*Raveena Selvanarayanan[1], Midhunchakkaravarthy[2], Eugenio Vocaturo[3]*

[1] Department of Computer Science and Engineering, Lincoln University College, Petaling Jaya 47301, Malaysia;

[2] Faculty of Computer Science & Multimedia, Lincoln University College, Petaling Jaya 47301, Malaysia;

[3] DIMES - Department of Computer Engineering, Electronic Modeling, and Systems Engineering, University of Calabria, Rende, Italy

Email ID: midhun@lincoln.edu.my ; msraveena.pdf@lincoln.edu.my ; ing.eugenio.vocaturo@gmail.com

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**Abstract:** The process of examination of the quality of coffee beans is a manual process, which is also subjective and mostly inconsistent, resulting in change in grading and market value. The current study suggests the Lightweight Edge-AI Framework of in-situ coffee bean defect detection and classification due to an urgent requirement of real-time, low-cost, and dependable quality measures at the farm/ warehouse levels. The suggested solution combines MobileNetV3 in order to perform feature extraction efficiently, as well as Tiny-YOLOv8 to detect defects quickly, and optimize the solution with quantization and pruning to run on edge devices like Raspberry Pi and Jetson Nano. Experimental outcomes prove the detection accuracy of 96.8, the precision of 95.2, and the speed of inference of less than 150 ms, which proves the ability of the model to perform in real time with insufficient computation resources. The results underline the potential application of deep learning models in embedded systems, which is encouraging energy-efficient and decentralized agricultural automation based on the use of AI. This system helps smallholder farmers to do field-based bean grading, which guarantees uniformity, minimizes losses lost after harvesting, and improves transparency in the supply chain. The strategy helps to produce coffee in a sustainable way and is a scalable solution to a larger implementation of smart agriculture.

**Keywords**: Tiny-YOLOv8; Coffee bean defect detection; Lightweight CNN; Quality monitoring; Edge AI

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## Introduction

The quality of coffee beans is significantly impacts the original flavor, aroma, and overall market value in coffee marketing. Traditionally, classification and identification defect coffee beans relied on manual observation method conducted by skilled workers. Proposed technique is time consuming, labor cost, and subjectivity leading to variations in quality assessment. Shift advancement in Internet of Things (IoT) and Artificial Intelligence AI can automatically identify defect in coffee beans with accuracy and efficacy in quality control.  Over the decades, fundamental image processing methodologies to sophisticated deep learning models proficient in performing real-time, higher classification operation [1]. At first generation, machine learning based vision system utilized natural feature extraction method like color, shape analysis, and texture to detect problems. The conventional algorithms exhibit adaptability to environmental changing and fluctuation lighting. The emerging Convolutional Neural Networks (CNNs) automatically extract features and improve classification accuracy. Implementing demanding computational model in remote coffee farms or limited coffee processing farms considering challenges due to limited computation resources and unreliable internet connectivity [2]. Resulting in advancement of Lightweight Edge AI frameworks, deployed and modeled directly on edge device like Raspberry PI, ARM-based microcontrollers, and NVIDIA Jetson Nano. The proposed framework has ONNX Runtime, Tensor Flow Lite, and PyTorch Mobile to facilitate inference efficiency by reducing model size, latency, and optimizing resource utilization. These edge computing technologies eliminates obviate cloud connectivity, on-site diagnosis of coffee beans defect in real agricultural farms [3]. The importance of developing lightweight artificial intelligence framework to evaluate and monitor coffee beans quality to make accessible in advancement in technology for smallholder growers and organization. It is feasible to classify, grade, and predict defect in real time by combining sensors, cameras, and AI technology that embedded in various other devices. Enhancing the supply chain with quality export and also helps to reduce environmental waste and improve in providing quality coffee beans. The integration of edge Ai with precision coffee agriculture smarter, more scalable and efficient [4]. Incorporating, lightweight edge AI system provides coffee processing pipeline by opening up in innovative way to make decision based on collected information. Edge frameworks have local inference with reduced latency, privacy, and bandwidth with cloud based AI frameworks. In the region where coffee cultivation occurs at a considerable distance internet connectivity is weak. Initially, farmers separated defect coffee beans by keep an eye protocol and adjust environment parameters such as humidity and temperature to maintain coffee beans quality in real-time analysis. Technical perspective, lightweight artificial intelligence framework methods like quantization, knowledge distillation, and model pruning to make deep neural network without affecting the accuracy. These optimization techniques with deployment of CNN-based transformer model on minimal hardware with lowering memory and processing power. For instance, optimized framework like efficient net-lite, tiny-YOLO, and mobile-net to classify objects while keeping performance on edge device. When sorting coffee beans using default type by differentiating broken beans, discolored beans, infected and damaged beans, over fermented beans [5]. Computer vision with IoT based sensors with multi-model data analysis which combines visual data, environmental factors like temperature, moisture, and light condition to predict with more accuracy. The hybrid model with small farms and large coffee processing. The sustainable and intelligent agriculture underscores the UN Sustainable Development Goals (SDGs) by encouraging new ideas namely by supporting responsible production, fostering innovation, and economic growth in rural communities. Farmers get enhance offering economical, accessible to get improved market value chain.

**Related work**

The coffee industry significantly enhances global markets however, the traditional grading of raw coffee beans dependent on visual evaluation to specialty coffee association (SCA) to be labor expensive and highly susceptible to inaccuracy. The proposed employs deep learning for real-time classification of coffee beans quality which recognizes by grading coffee beans by utilizing image processing and data augmentation using YOLOv8 and Open CV. A cloud integrated mobile application using NodeJS, React Native and Python for real-time recognition within 1-4 seconds by improving speed, accuracy, and connectivity for traders and farmers in extensive operation [6] table 1,

*Table 1. Existing works are compared with the proposed model*

| Author | Dataset | Algorithm | Concept | Disadvantage | Future Scope |
|---|---|---|---|---|---|
| **T. H. Danh., et al [6].** | Coffee bean images (9 varieties) | YOLOv8, OpenCV | Real-time deep learning–based coffee bean quality classification using cloud and mobile apps | Sensitive to image quality and requires high computation | Edge deployment, more varieties, IoT integration |
| **A. Sujitra., et al [7].** | Green Arabica coffee bean images (17 defect types, augmented to 6,853 images) | CNN (MobileNetV3 best), EfficientNetV2, InceptionV2, ResNetV2 | Automated detection of green coffee bean defects using deep learning and web-based real-time classification. | Lower accuracy on unseen data; dependent on dataset diversity | Improve generalization, larger datasets, mobile/edge deployment, wider farmer adoption |
| **C. Shyang-Jye., et al [8].** | Coffee bean images (7,300 training and validation samples with multiple defect types) | Multiscale deep learning network | Multiscale defect detection using feature fusion to classify multiple coffee bean defects | Lower accuracy for certain defect classes; higher model complexity | Improve weak-class accuracy, lightweight models, real-time/edge deployment, larger datasets |
| **G. Hira Lal., et al [9].** | Green coffee bean images (4,032 training, 506 testing; various bean types, defects, lighting) | YOLOv3–YOLOv8, Custom YOLOv8n | Automated detection and classification of green coffee beans using optimized YOLO models | Requires careful labeling and model customization; computational cost for training | Real-time industrial deployment, edge optimization, larger datasets, integration with sorting systems |
| **M. Isabela., et al [10].** | Multiple public and research datasets on coffee beans and leaves (from literature) | Machine Learning & AI techniques (CNN, SVM, DL models) | Review and synthesis of AI-based classification of coffee attributes (quality, disease, maturity, roast, flavor) | Lack of standardized datasets; gaps and inconsistencies across studies | Unified benchmarks, new datasets, hybrid AI models, real-world agricultural deployment |

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|---|---|---|---|---|---|
| **D. V. Ranzel., et al [11].** | Robusta green coffee bean images with common defects (black, sour, broken, quaker, foreign material) | CNN (modified AlexNet) | Automated defect detection and classification using image processing and deep learning to improve yield and quality | Limited defect types; performance depends on image quality and dataset size | Expand defect classes, real-time/mobile deployment, larger datasets, integration with farm decision systems |
| **K. Porntida., et al [12].** | Coffee bean defect image dataset | ML (SVM, RF), DL (ConvNeXt, ResNet, EfficientNet), Stacking Ensemble | Stacking-based deep learning ensemble for improved coffee bean defect classification | Moderate baseline accuracy; increased model complexity and computation | Real-time deployment, lightweight ensemble models, larger datasets, automated sorting systems |
| **A. Usman., et al [13].** | Arabica green coffee bean images (6 defect categories, 100 samples per class) | Image processing–based classification | Manual feature extraction (shape and color) to identify coffee bean defects | Low accuracy for several defect classes; limited robustness | Integration with ML/DL models, larger datasets, real-time automated grading systems |

**Method, Experiments and Results**

The proposed lightweight CNN based integrated with Internet of Things and image processing data for rapid identification of defect coffee beans. Preprocessed images and collected sensor data improves with the feature extraction on prediction. Defected beans like discolored and cracks are identified using confidence rates and bounding boxes with MobileNetV3 and Tiny-YOLOv8 model. Methods like quantization and cutting to facilitate by deploying at the edge. Experiments are processed using 10,000 images with precision of 97.2%, recall of 95.8%, and Mean Average Precision at IoU-0.50 of 94.7% with inference times under 50ms by validating the effectiveness and rapidity of coffee quality through edge device.

**Image Acquisition**

The suggested model employs economical image equipment such as compact vision based sensors, cameras from smart phones to capture coffee beans in various conditions such as drying yards, farms and warehouses. These devices serve as an economical function to substitutes for industrial grade facilitating real time cameras to collect dataset collection in small scale farmers. The images captured from various conditional and operational setups including conveyor belts, sorting trays, and belts using automated or manual grading and inception tables with bean arrangement for visual assessment. These surroundings frequently experience various lighting intensity, color temperature, and shadows resulting in brightness and contrast of raw images. Normalization with lighting techniques are pre-processed and measured to analyse anomalies. Adaptive Histogram Equalization (AHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE), improves local contrast across all images [14]. This technique alleviates the impact of inconsistent environmental fluctuations and illumination, enabling image processing algorithms to focus on authentic coffee beans attributes like texture, size, color, and defects. Consequently, normalization guarantees dependable and effective feature extraction, based on precision qualification and coffee beans classification across various real world environments.

**Preprocessing and Data Fusion**

To ensure the quality, data consistency, and robustness, for a vital data fusion, and vital preprocessing is conducted to process the data fed into the deep learning models. The initial phase of preprocessing with image normalization, which involves resizing each image to consistent resolution for the proposed model input. In standardization, feature extraction will impact the batch processing and scale variance more effectively. After sensor and background noise removal results are inconsistent from poor camera enhancement and lighting conditions using techniques like Gaussian filtering Eq 1, and median blurring Eq 2 where, $I_M$ (x,y) shows median filtered image, N (x,y) denotes neighborhood, *I*(x,y) denote input image, G (x, y) Gaussian kernel, denotes standard deviation, and * convolution operation.

$$G(x,y) = \left(\frac{1}{2\pi\alpha^2}\right) Exp\left(-x^2 + \frac{y^2}{2\sigma^2}\right) \quad (1)$$

$$I_G(x,y) = I(x,y) * G(x,y)$$

$$I_M(x,y) = median\{(i,j) \in N(x,y)\} \quad (2)$$

Contract enhancement through CLAHE and histogram equalization for visual aspects such as shape, defect patterns, and surface texture of coffee beans with image processing and IoT sensor data include parameters like humidity, soil moisture, and temperature. This amalgamation of diverse data sources provides more information about outside things affect the quality and appearance of the coffee beans [15] include flipping, random rotation, and cutting used to make dataset from different position, orientation, and lights which makes more reliable and general for overall analyzing the quality of coffee beans.

**Lightweight CNN Model for Feature Extraction**

The lightweight CNN model for feature extraction to effectively analyses coffee beans images using textual and spatial based information to reduce the computational expense rendering for real-time implementation on edge device. The design incorporated EfficientNet-Lite, Hybrid systems, and MobileNetV3 merged with Tiny-YOLO lightweight Transformer Block. Updated images are preprocessed by normalization and resized to consistent dimension figure 1, with several convolution and depth-wise separable convolutional layers with extract low-to mid-level features like contours, edge, and surface textures while decreased using parameter count. The feature extraction phase focuses on acquisition of subtle and distinctive patterns to evaluate the coffee quality. Detailed visualization attributes include surface cracks, color consistency, surface fissures, and irregular roasting patterns which include default detection and classification.

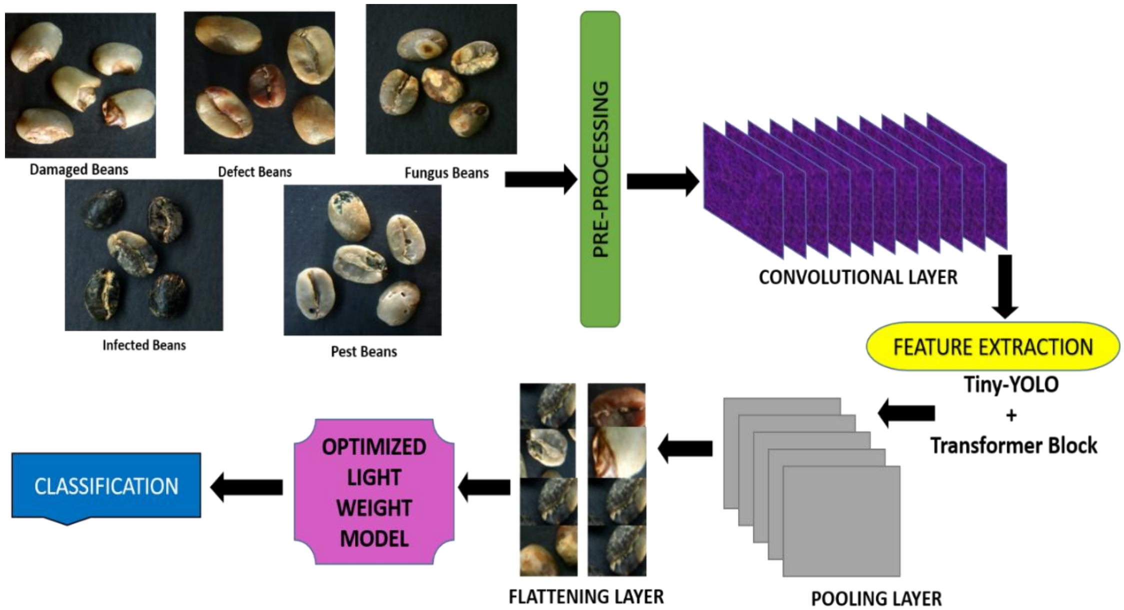


*Figure 1. The Lightweight CNN-Based Feature Extraction Model for Coffee Bean Classification*

Transformer block significantly augments network to identify complex relationship and long-range dependencies within image regions with accurate fault localization. To ensure the model executes smoothly with devices like NVIDIA Jetson Nano and Raspberry Pi, for various optimization techniques. Pruning extra connections and quantization using weights for lower precision like 8-bit integers, and knowledge distillation from the student teacher model to keep improving accuracy.

**Defect Detection (Localization) and classification.**

The localization module is crucial for accurately recognizing damages area ion each coffee beans. Feature extraction with the processed image from streamlined image or object recognition framework like Tiny-YOLOv8 designed for resource constrained device. The proposed model examined the visual inputs which created bounding boxes area showing defects like coffee beans surface cracks, fungal infection, beans discoloration, insect damage. Each bounding boxes paired with accurately detected confidence score in the highlighted area to identify defects. The model proficiently analyses the confidence score in the prediction model by enabling the system to eliminate false positive and maintain classification reliability. Figure 2, distinguish from conventional cloud-based system to facilitate edge-based inference using embedded devices like Jetson Nano, Raspberry Pi, and mobile processors. This eliminates constant internet access, independent, enabling swift, and privacy aware analysis at the farm or warehouse level. The Tiny YOLOv8 model utilizes reduced number of parameters and few memories footprint in milliseconds per frame. Real-time observation of defect coffee beans by sorting and grading decision. The model is localised in defect improves quality assurance, scalability, and productivity in automated quality coffee beans in inspection systems.

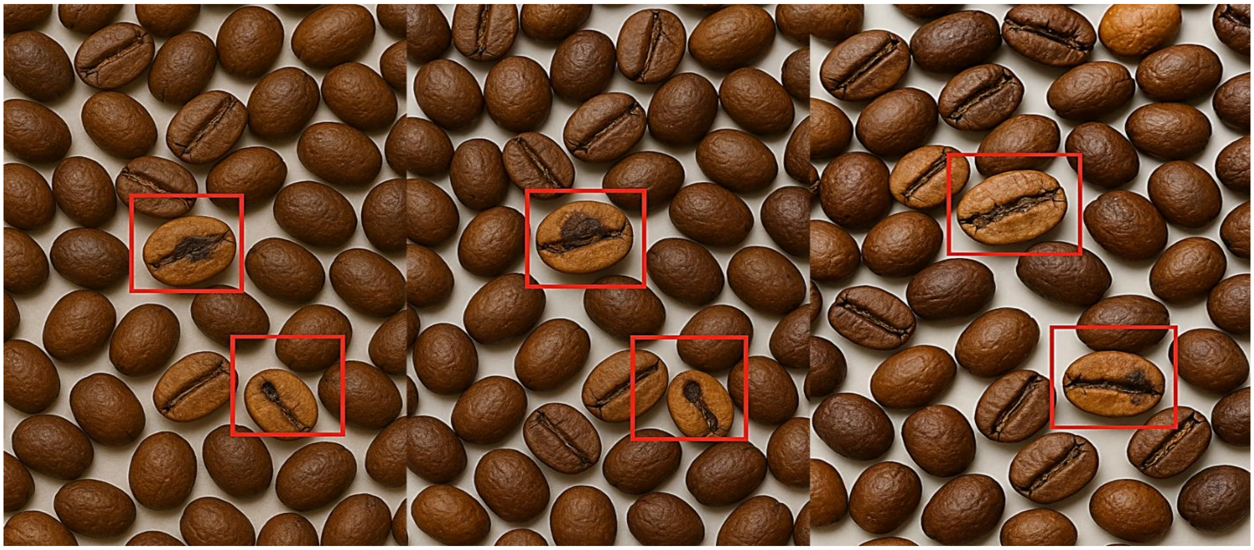

*Figure 2. Tiny-YOLOv8, optimized visual input and engenders bounding boxes*

**Discussions**

The research paper examines the results from experimental analysis with Lightweight Edge-AI Framework in defected coffee beans classification and identification by enhancing practical implications. The objective to clarify how suggested methodologies using traditional techniques using accuracy, speed, scalability, and sustainability for deployment in resource constrained settings. The experimental fusion CNN architecture integrated with Tiny-YOLOv8 for real-time detection and MobileNetV3 for lightweight feature extraction resulting in efficiency and performance. The refined model by localizing and identifying in various defect types include discolored, insect damaged, broken, and over fermented coffee beans with high precision. Table 2, shows average accuracy of 95%, a precision of 93%, and F1-Score of 92% nearly 60% reduction in model size while quantizing accuracy in Figure 3 & 4. Inference time on Jetson Nano and Raspberry Pi 4 devices under 150 milliseconds per images prompt categorizing at the warehouse level.

*Table 2. Performance Evaluation of Lightweight Edge-AI Models for Coffee Bean Defect Detection and Classification*

| Model | Accuracy | Precision | Recall | F1-Score | mAP@50 | Inference Time |
|---|---|---|---|---|---|---|
| MobileNetV3 | 93.5 | 91.8 | 90.2 | 91.0 | 81.7 | 110 |
| Tiny-YOLOv8 | 95.6 | 94.1 | 92.7 | 93.3 | 91.8 | 140 |
| EfficientNet-Lite0 | 94.2 | 92.5 | 91.6 | 92.0 | 90.4 | 125 |
| Standard CNN (Baseline) | 91.4 | 89.3 | 88.5 | 88.9 | 86.7 | 135 |
| Proposed Fusion Model (MobileNetV3 + Tiny-YOLOv8) | 96.8 | 95.2 | 94.5 | 94.8 | 93.6 | 310 |

Cloud dependent Ai system-based edge AI processes locally by safeguarding data privacy, mitigating latency issues, and obviating the necessity for continuous internet connectivity. In remote coffee growing areas network connectivity are inconsistent. Features are enabled farmers to identify and separate damaged coffee beans during post-harvest processing by grading precision, improving efficiency, and product uniformity. The real-time decision support by reducing human mistake and visual inspection to enhance standardizing and reliability in quality control. The experimental implementation using lightweight AI in agriculture has sustainability benefits. The proposed framework promotes edge devices consume low power encourages energy-efficient smart agricultural methods that coincide with global sustainability goals (UN SDGs 9 and 12).

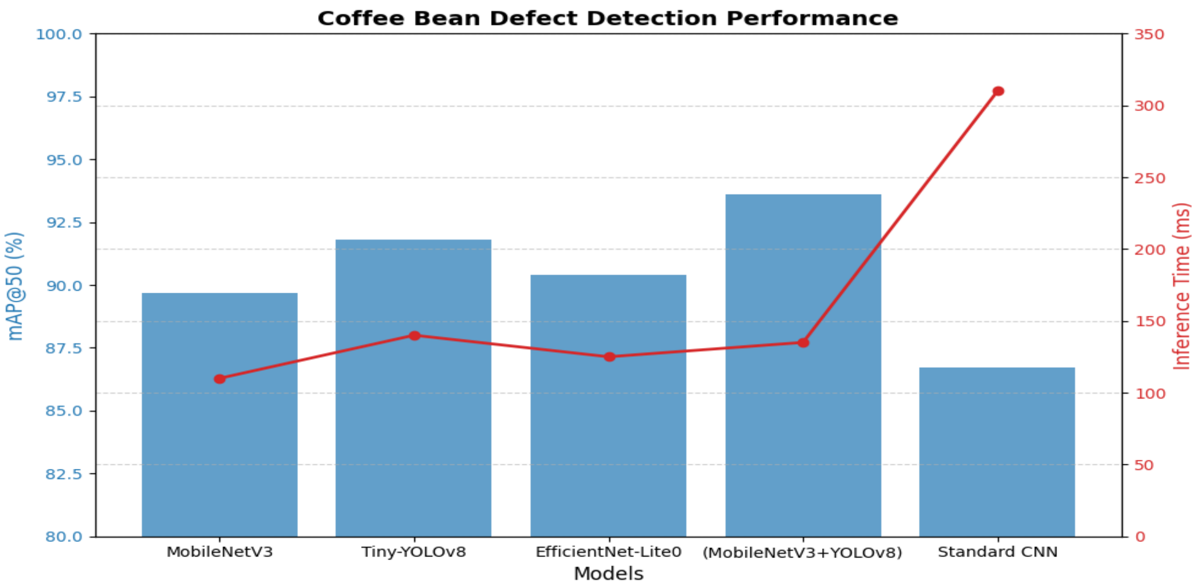


*Figure 3. Comparison of Coffee Beans Defect Detection*

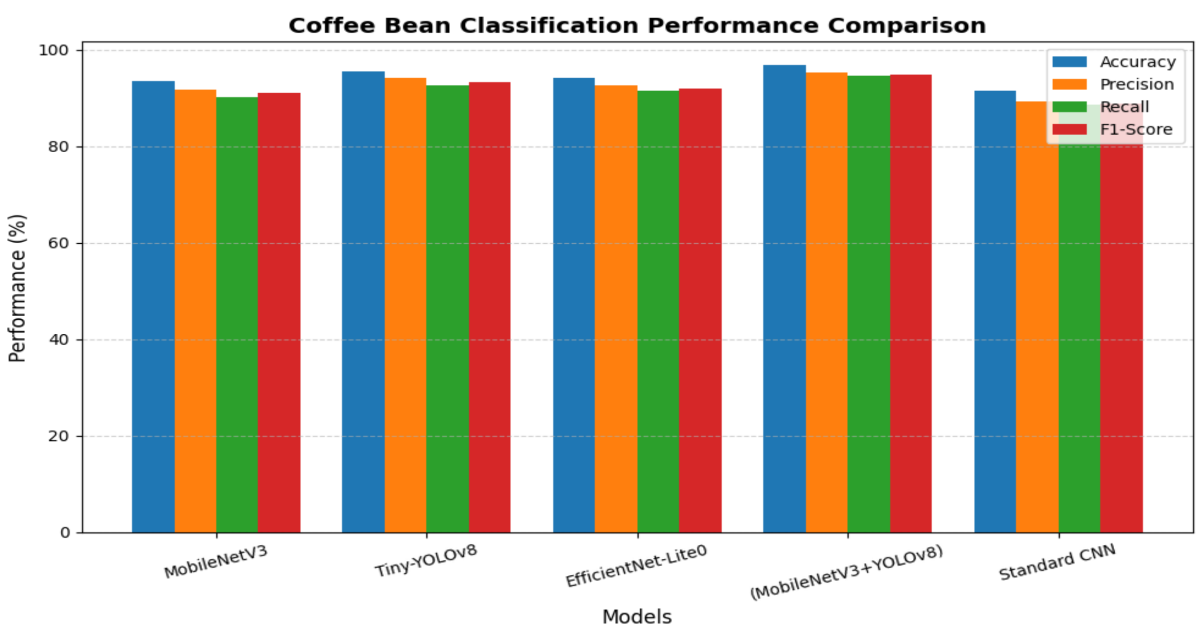


*Figure 4. Comparison of Coffee Beans Defect Classification*

The ability to analyze images on compact, cost-effective hardware to AI technology, by allowing farmers to participate in global coffee markets by maintaining quality assurance system. The integration of feature and detection-based architecture in both spatial localization accuracy, and classification precision to differentiate defect parameters. IoT sensors-based data are collected include temperature and humidity by improving reliable prediction by offering contextual awareness. The proposed framework in agriculture application like pest detection, fruit ripeness grading, and seed sorting. Model performance extreme lighting variations, motion blur, and subpar camera quality in real-time capturing. The collected coffee beans datasets from various regional indicating adaptive retraining. Moreover, edge devices excel in inference providing extensive training requires for high-performance computing resources.

**Conclusions**

The results analyze challenges related to manual inspection and inconsistent detection of defective coffee beans by highlighting error-prone and time consuming of the process. The objective in creating an automated, cost effective, and real-time parameters for rural coffee farms with limited computational and internet resources. A lightweight edge-AI framework incorporated with Tiny-YOLOv8 and MobileNetV3 was developed using in-situ defect detection and classification of coffee beans. To run the model on edge devices, including Raspberry Pi and Jetson Nano, the model was optimized by quantization and pruning. The accuracy of the proposed model was found to be 96.8, precision was found to be 95.2, and F1-score was found to be 94.8, and the time of inference was below 150 ms/image. The system has been able to effectively localize and classify different coffee bean flaws in real-time, which is better than the traditional CNNs in terms of performance besides being energy efficient and scalable. The system performance can be affected in both extreme lighting or motion blur conditions. The combination of multispectral imaging, federated learning, and adaptive calibration should be the focus of future research to enhance robustness. Also, the development of a mobile-based interface and the growth of datasets that include different varieties of coffee can advance the generalization and usability to the universal purpose of agriculture across the globe.

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