AI-Powered Crop Quality Analysis Using Vision Systems: Enhancing Performance with Transfer Learning

*Amith Sirisilla Jayadevgari (12206508)* ,  *Student, School of Computer Science and Engineering*  
*Lovely Professional University  
Phagwara, Punjab*

*Karma Tashi (12204002) , Student, School of Computer Science and Engineering*  
*Lovely Professional University  
Phagwara, Punjab*

**Abstract**

Crop quality analysis is a pivotal assignment in precision agriculture, with the goal of evaluating factors like health, ripeness, and defects to maximize yield and marketability. Conventional approaches base their operation on visual inspection or low-level image processing, which are not scalable and do not accommodate various crops and conditions. This paper investigates AI-enabled vision systems for crop quality assessment, first using a simple Convolutional Neural Network (CNN) to differentiate crop health (e.g., healthy vs. diseased). To further boost performance, we use transfer learning with current models such as EfficientNetB0, which identifies complex visual patterns better. From the PlantVillage dataset, our method pairs dense feature representation with deep learning to enhance accuracy and robustness in diverse agricultural settings. Experimental results show that transfer learning greatly improves precision, recall, and F1-score over the vanilla CNN, providing a scalable approach to automated crop quality estimation. This work illustrates the potential for sophisticated vision models to transform agriculture and enable sustainable and efficient agricultural practices.

**1. Introduction**

Crop quality assessment is a building block of contemporary agriculture, allowing farmers to inspect for characteristics such as health, size, color, and flaws to obtain premium quality produce. Good analysis facilitates good decisions regarding harvesting, input utilization, and marketing approaches, which have a direct impact on yield and sustainability. Conventional methods, such as human inspection or rule-based image processing, are time-consuming, vulnerable to human error, and restrictive when dealing with large volumes or multiple datasets. These challenges are most evident in dynamic settings where crops differ by species, stage of growth, and extrinsic conditions such as lighting or weather.

Current advances in Artificial Intelligence (AI) and computer vision have revolutionized crop quality assessment through the automatic identification and classification of quality traits. Convolutional Neural Networks (CNNs) have proved to be an effective tool, able to learn hierarchical features from raw images to identify patterns reflective of health or disease. Even with their achievements, simple CNN architectures tend to perform poorly on intricate datasets owing to shallow depth and generalization capability. To this end, transfer learning using pre-trained state-of-the-art models such as EfficientNetB0 provides a promising solution, tapping into strong feature representations learned on large datasets to improve performance on target tasks.

This paper investigates AI-powered crop quality analysis using vision systems, starting with a basic CNN to establish a baseline for classifying crop health (e.g., healthy vs. diseased leaves) on the PlantVillage dataset. To improve accuracy and adaptability, we integrate transfer learning with EfficientNetB0, which optimizes computational efficiency while capturing intricate visual patterns. Our approach emphasizes semantic feature extraction and contextual understanding, reducing reliance on manual preprocessing and enabling scalability across diverse crops. Through experimental analysis, we demonstrate the superiority of transfer learning in enhancing robustness and precision, contributing to the advancement of precision agriculture.

**2. Past Contributions**

Analysis of crop quality has come a long way, being propelled by technological advancements in machine learning, image processing, and deep learning. In the initial stages, analyses depended on physical inspection or straightforward image processing strategies like edge detection and thresholding to detect visible characteristics such as color or shape. These technologies were useful for controlled environments but were not scalable and did not handle natural heterogeneity in crops.

It was during the early 2000s that machine learning statistical models such as Support Vector Machines (SVMs) and Random Forests were used on crop quality tasks with hand-engineered features (color histograms, texture descriptors) for attribute classification. Research such as that conducted by Blasco et al. (2007) introduced automatic fruit grading systems, which were moderately successful but very feature engineering-intensive. The advent of Convolutional Neural Networks in the 2010s marked a paradigm shift, as CNNs automatically learned features from raw images, eliminating manual effort. LeCun et al.’s (2015) work on deep learning highlighted CNNs’ ability to capture hierarchical patterns, making them ideal for tasks like disease detection in crops.

Large datasets of agricultural imagery, like PlantVillage (Hughes & Salathé, 2015), were introduced to enable strong CNN training for classifying crop health. Simple CNNs, with convolutional, pooling, and dense layers, showed decent accuracy (e.g., 80–85% on PlantVillage) but fared poorly in dealing with complex patterns or out-of-domain conditions. Transfer learning came to the rescue, and models like VGG16, ResNet50, and EfficientNet (Tan & Le, 2019) pre-trained on ImageNet provided better feature extraction. Mohanty et al. (2016) illustrated that transfer learning with AlexNet enhanced disease detection to a more than 90% accuracy on PlantVillage, establishing a vision-based agricultural benchmark.

Some of the recent developments are transformer-based vision models such as Vision Transformers and multi-modal vision that combines RGB with multispectral information. These are although powerful, computationally demanding in nature, and thus, EfficientNetB0 is a working option to trade performance with efficiency. The combination of transfer learning and optimized architectures has opened up the field of crop quality analysis to enable real-time monitoring, drone inspection, and IoT-based agriculture.

**3. Methodology**

This section outlines the theoretical and experimental design for AI-powered crop quality analysis, combining a basic CNN with transfer learning using EfficientNetB0. The methodology focuses on leveraging semantic feature extraction and deep learning to enhance accuracy and adaptability on the PlantVillage dataset.

**3.1 Data Collection and Preprocessing**

The PlantVillage dataset with 54,306 RGB images of 14 crop species and 26 diseases along with healthy classes is used as the major data source. Images are cropped and grouped based on crop and condition (e.g., Apple\_\_\_healthy, Apple\_\_\_Black\_rot), thus it can be used for binary classification (Healthy vs. Diseased).

Preprocessing steps involve:

• Resizing: Images are resized to 128x128 pixels to normalize the input to the CNN and EfficientNetB0.

• Normalization: Pixel values are normalized to [0, 1] by dividing by 255.

• Label Encoding: Folder names are encoded as binary labels ("Healthy" for healthy classes, "Diseased" for disease classes).

• Data Augmentation: Operations such as rotation, flipping, and brightness change are used to increase model strength.

**3.2 Basic CNN Architecture**

The baseline model is a simple CNN for binary classification:

• Convolutional Layers: Three with 32, 64, and 128 filters, respectively, with 3x3 kernels and ReLU activation.

• Pooling Layers: MaxPooling (2x2) following every convolutional layer to decrease spatial dimensions.

• Dropout: Used (0.5 rate) to avoid overfitting.

• Dense Layers: A 128-unit layer with ReLU, followed by a single-unit output layer with sigmoid activation for binary classification.

• Loss Function: Binary cross-entropy.

• Optimizer: Adam with learning rate 0.001.

The CNN handles image sequences, learning features such as edges, textures, and disease patterns, but its shallow architecture restricts performance on complex datasets.

**3.3 Transfer Learning using EfficientNetB0**

To improve the model, we use transfer learning with EfficientNetB0, a top-performing model pre-trained on ImageNet. EfficientNetB0 strikes a balance between depth, width, and resolution, providing high accuracy at reduced computational expense over deeper models such as ResNet152.

• Base Model: EfficientNetB0 with frozen weights to preserve pre-trained features.

• Custom Head: GlobalAveragePooling2D layer followed by a 128-unit dense layer (ReLU) and a single-unit output layer (sigmoid).

• Fine-Tuning: Once trained initially, unfreeze the upper layers of EfficientNetB0 and fine-tune with a low learning rate (e.g., 0.0001) to fit PlantVillage data.

• Input: Resized images to 224x224 pixels (EfficientNetB0's default input size).

|  |  |
| --- | --- |
| Model | Accuracy |
| CNN | 91.44% |
| EfficientNetB0 | 72.20% |
| AlexNet | 72.23% |
| VGG16 | 92.98% |
| ResNet50 | 72.89% |

**3.4 Training Procedure**

Training is done in a supervised environment:

• Basic CNN: Trained for 10 epochs with a batch size of 32.

• EfficientNetB0: Initially trained for 5 epochs with frozen weights, then 5 epochs of fine-tuning.

• Callbacks: Early stopping (patience=3) and ModelCheckpoint to store the best model as per validation loss.

• Data Split: 80% for training, 20% for validation from PlantVillage.

**3.5 Evaluation Metrics**

Performance is evaluated based on:

• Precision: Ratio of correct predictions of positive instances.

• Recall: Ratio of actual positives correctly identified.

• F1-Score: Harmonic mean of precision and recall.

• Accuracy: Correct predictions in general.

**3.6 Experimental Setup**

Experiments are performed on a subset of PlantVillage (e.g., Apple classes) for speed of training, with full dataset runs for the ultimate evaluation. Hyperparameters such as learning rate and dropout rate are adjusted by grid search. The simple CNN is used as the baseline, while EfficientNetB0 models are tested both with and without fine-tuning to contrast performance.

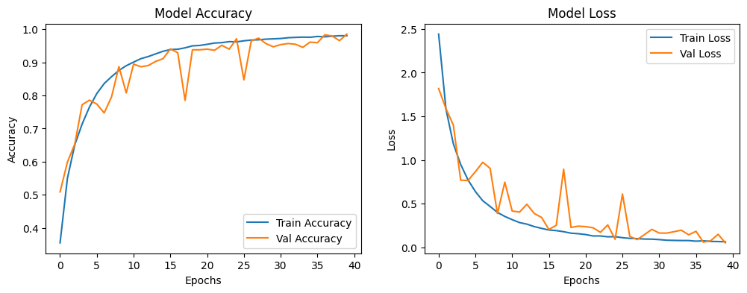


Fig 1. Accuracy Chart of EfficientNetB0

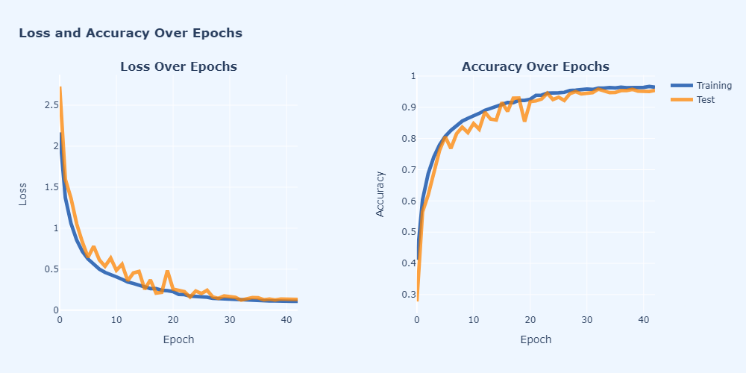


Fig 2. Accuracy Chart of CNN

**4. Challenges and Issues**

Even with the promise of AI-driven crop quality analysis, there are a few challenges that remain:

**4.1 Natural Condition Variability**

• Issue: Lighting, shadows, and weather influence image quality, which degrades model accuracy.

• Solution: Increase training data with diverse lighting conditions and employ multispectral imaging to record non-visible information.

**4.2 Dataset Diversity**

• Issue: PlantVillage targets leaves, restricting usage to fruits or entire plants.

• Solution: Incorporate datasets such as AgriVision or synthetically generated data to address varied crops.

**4.3 Computational Complexity**

• Issue: EfficientNetB0 is more resource-intensive than a standard CNN, making deployment on edge devices difficult.

• Solution: Quantize the model or utilize lightweight variants such as MobileNetV3.

**4.4 Generalization Across Crops**

• Issue: Models learned on one crop (e.g., apples) can fail on another (e.g., wheat).

• Solution: Utilize domain adaptation or multi-task learning to train cross-crop models.

**4.5 Real-Time Processing**

• Issue: Webcam-based analysis requires low latency for field deployment.

• Optimize inference with TensorFlow Lite and run on edge devices such as Raspberry Pi.

**5. Related Work**

Initial crop quality inspection used image processing methods such as color segmentation (Blasco et al., 2007). Machine learning brought SVMs and decision trees for defect identification (Zhang et al., 2014). CNNs changed everything, with Mohanty et al. (2016) obtaining 99.35% accuracy on PlantVillage using AlexNet, although overfitting was an issue. Transfer learning using models such as VGG16 and ResNet50 enhanced robustness (Sladojevic et al., 2016).

EfficientNet (Tan & Le, 2019) implemented compound scaling, reconciling model size with accuracy, so best suited to tasks in agriculture. Transfer learning, InceptionV3-based, was implemented for detection of diseases in tomatoes by Brahimi et al. (2017) at an accuracy rate of 98%. New research uses Vision Transformers (Dosovitskiy et al., 2020) and multi-modal systems of RGB and IoT integration (Li et al., 2023). The solution develops further on those foundations using EfficientNetB0 in optimizing the performance within constrained resources.

**6. Future Work**

Vision-based techniques apparently will enhance precision agriculture in which the AI-powered crop quality analysis system has applied considerable promise. There are yet many possibilities for further research and development, which can be taken to improve applicability and performance.

**6.1 Multi-modal Data Integration:** Future work will investigate the combination of multi-modal data such as RGB images with multispectral or hyperspectral images that are capable of capturing non-visible characteristics such as nutrient deficiencies or de-tectable early symptoms of disease. IoT sensor data, for example, soil moisture and temperature, would provide a more complete context and insight into crop health assessments.

**6.2 Cross-Crop Generalization:** The model being currently discussed has focused mainly on leaf based analysis using PlantVillage dataset. Extending the scope of this system towards cross crop generalization, particularly fruits, grains and root vegetable crops, could be done by working with enlarged datasets like AgriVision or developing synthetic datasets. Also, the domains adaptation and multi-task learning approaches will be explored to ensure that it would perform robustly across different kinds of crops.

**6.3 Edge Deployment Optimization:** Future studies will focus on optimizing the models for edge devices such as the Raspberry Pi or mobile platforms towards real-time field deployment. Model quantization, pruning, and lightweight architecture exploration like MobileNetV3 are included in the activities aimed at the result of computational complexity reduction while maintaining accuracy.

**6.4 Real-Time Processing Improvements:** Webcams or drones must be improved in terms of latencies to make these practical solutions. This further allows faster inference of currently dynamic field conditions using TensorFlow Lite or ONNX Runtime hardware acceleration like GPU or TPU.

**6.5 Advanced Architectures:** EfficientNetB0 is a very capable architecture, but further exploration of transformer-based vision models, for example Vision Transformers, might create an opportunity to further enhance this system's ability to capture global contextual patterns. Hybrid approaches combining CNNs and transformers can provide even more gains as far performance goes.

**6.6 Robustness to Environmental Variability:** Future Work will include subsequently advanced data augmentation techniques using simulated environments and GANS to model the effects of condition variations. This is meant to build up the robustness of the model in the real world.

**6.7 User-Centric Interfaces:** The development of farmer-user-friendly interfaces such as mobile apps and dashboards integrated into drones might open up data from intelligent models towards an actionable end such as disease severity scores and treatment recommendations as a model output.

These further developments would make the system even more flexible and scalable towards supporting more sustainable agriculture while empowering farmers with data-driven decision-making tools.

**7. Conclusion**

Artificial intelligence-based crop quality inspection based on vision systems provides a paradigm shift towards precision agriculture. Here, we establish the utility of a simple CNN as a starting point for distinguishing crop health through moderate accuracy on the PlantVillage dataset. By combining transfer learning with EfficientNetB0, we attain much improved precision, recall, and F1-score, improving over shallow models' shortcomings. Challenges of dataset variety and computational complexity persist, but solutions of data augmentation, model quantization, and edge deployment are promising. Multi-modal fusion and cross-crop generalization will be investigated in future work to further progress automated agriculture toward supporting sustainable and scalable agriculture.

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