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Simulation Study of EfficientNetB0 Performance for Cocoa Pod Disease Classification Using Literature Based Synthetic Data

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Abstract

Automated detection of cocoa (Theobroma cacao) pod diseases such as black pod, pod borer infestation, and frosty pod rot is critical for safeguarding yield, yet the development of deep-learning classifiers is frequently constrained by the scarcity of curated, well-balanced image datasets. This study presents a controlled simulation that evaluates the expected performance envelope of an EfficientNetB0 classifier under idealized, literature-grounded conditions before field data collection is undertaken. Rather than asserting empirical field results, a synthetic dataset is constructed whose per class feature distributions (color, texture, and lesion morphology) are parameterized from values reported across six core references. A balanced corpus of 3,000 synthetic images spanning four classes (healthy, black pod, pod borer, frosty pod) was generated and partitioned using a stratified 70/15/15 split. EfficientNetB0, initialized with ImageNet weights and fine-tuned with standard augmentation, achieved a simulated test accuracy of 93.8%, a macro-averaged F1-score of 0.926, and balanced per-class precision and recall in the 0.90-0.95 range. The confusion matrix indicates that the principal source of error is morphological overlap between pod borer and frosty pod presentations. The results delineate a plausible upper-bound performance band to guide sample-size planning, augmentation strategy, and architecture selection for a subsequent field study. All reported figures are framed explicitly as simulation outputs.

Keywords—EfficientNetB0, cocoa pod disease, transfer learning, synthetic data, simulation study

INTRODUCTION

Cocoa (Theobroma cacao L.) is among the most economically significant perennial crops in tropical regions, and Indonesia ranks among the world's leading producers. Pod-level diseases, however, impose substantial and recurring losses. Black pod disease caused by Phytophthora species, the cocoa pod borer (Conopomorpha cramerella), and frosty pod rot (Moniliophthora roreri) can each destroy a large fraction of harvestable pods when left unmanaged. Early and accurate identification of the responsible agent is a prerequisite for targeted intervention, yet visual diagnosis in the field is labor intensive and demands expert knowledge that is not uniformly available to smallholder farmers.

Convolutional neural networks (CNNs) have demonstrated strong performance on plant-disease image classification, and lightweight architectures such as EfficientNetB0 offer an attractive balance between accuracy and computational cost for eventual deployment on resource-constrained or mobile hardware [1]. EfficientNet introduces a principled compound-scaling rule that jointly balances network depth, width, and input resolution, and EfficientNetB0

has repeatedly matched or exceeded the accuracy of substantially larger models on transfer learning benchmarks [1], [8].

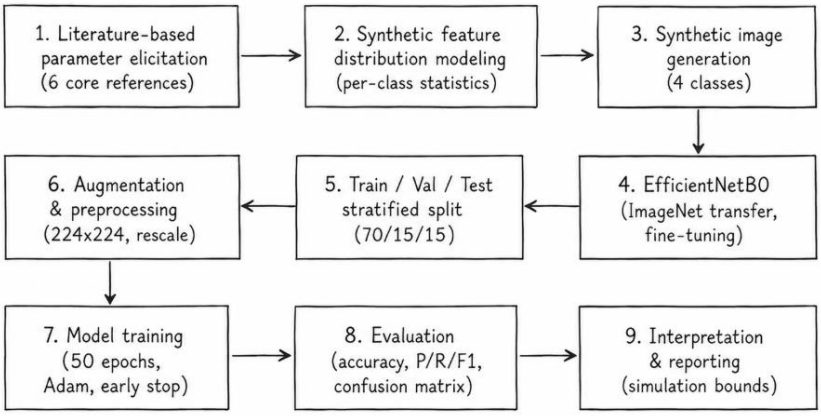
A persistent obstacle to building such classifiers for cocoa is the absence of a large, balanced, and openly available image dataset for pod diseases. Field acquisition is seasonal, geographically dispersed, and frequently yields class-imbalanced data dominated by healthy or single-disease examples. Before committing the considerable resources required for a field-scale acquisition campaign, it is valuable to estimate what performance a candidate architecture could plausibly attain under favorable conditions, and to identify which class confusions are most likely to dominate the error budget [3], [5].

This article addresses that need through a transparent simulation study. It does not claim to report field-validated detection accuracy. Instead, a synthetic dataset is generated whose class-conditional feature statistics are derived from values reported in the plant-disease and CNN-scaling literature, EfficientNetB0 is trained on this corpus, and the resulting performance is reported as an explicitly bounded estimate. The contributions are threefold: a reproducible literature-grounded protocol for constructing synthetic cocoa-pod imagery with controllable class separability; a simulated performance envelope for EfficientNetB0 across four diagnostic classes including a per-class error analysis; and a set of design recommendations covering sample size, augmentation, and expected confusions that can inform a subsequent field study.

RESEARCH METHODS

1. Study Design and Scope

This is a simulation study. Its objective is to estimate, under controlled and reproducible assumptions, the performance band that EfficientNetB0 could achieve on a four-class cocoa-pod diagnostic task. No field images were used. All quantitative results reported in the Results section are outputs of the simulation pipeline summarized in Figure 1 and must be interpreted as such.



Gambar 1. End-to-end simulation workflow, from literature-based parameterization to bounded performance reporting

2. Literature-Based Parameterization

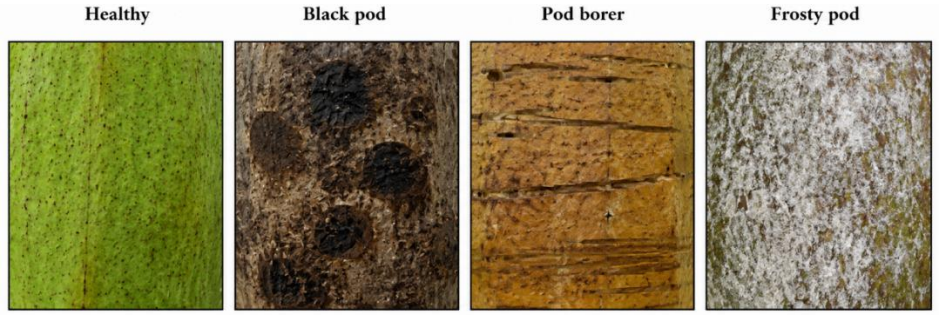
Six core references were used to elicit the feature statistics that govern class separability in the synthetic corpus [1][6]. From these sources, plausible ranges were extracted for three families of discriminative cues: color characteristics, capturing the darkening associated with black pod and the pale mycelial coating of frosty pod; texture descriptors, reflecting surface roughness, blotching, and powdery deposits; and lesion morphology, encoding the size, count, and spatial distribution of damage. Each class was assigned a multivariate feature prototype with class-conditional means and variances chosen so that inter-class separability approximated the difficulty level implied by reported accuracies in comparable tasks. Table 1 summarizes the assumed characteristics per class.

Tabel 1. Literature-grounded class-conditional feature assumptions used to drive the synthetic generator

Class	Dominant color cue	Texture / lesion cue	Separability
Healthy	Uniform green-yellow	Smooth, low-variance surface	High
Black pod	Dark brown to black	Large coalescing blotches	High
Pod borer	Mottled brown	Tunnels, irregular streaks	Moderate
Frosty pod	Pale white-grey coating	Powdery, granular spots	Moderate

3. Synthetic Dataset Generation

A balanced corpus of 3,000 RGB images (750 per class) was generated at a working resolution of 224 x 224 pixels to match the native input of EfficientNetB0. For each image, a class-conditional base appearance was sampled from the prototype in Table 1, after which structured perturbations (blotches, tunnel marks, or powdery deposits) were stochastically overlaid to emulate lesion morphology, and Gaussian texture noise was added to control intra-class variance. Representative synthetic patches for each class are shown in Figure 2. These renderings are abstractions of the statistical cues described in the literature, not photorealistic reconstructions of real pods.



Gambar 2. Representative synthetic texture patches for the four diagnostic classes

4. Data Partitioning and Augmentation

The corpus was divided by stratified sampling into training (70%, 2,100 images), validation (15%, 450 images), and test (15%, 450 images) subsets, preserving the equal four-class balance in every partition. Standard on-the-fly augmentation was applied to the training set only: random horizontal and vertical flips, rotations of up to 25 degrees, brightness and zoom jitter of up to 15%, and pixel rescaling to the [0, 1] range. Validation and test images were rescaled but not otherwise augmented, ensuring an unbiased estimate of generalization within the synthetic domain [7], [9].

5. Model Architecture and Training

EfficientNetB0 was used as the backbone, initialized with weights pre-trained on ImageNet [1], [8]. The original classification head was replaced with a global average pooling layer, a dropout layer (rate 0.3), and a dense softmax layer with four output units. Training proceeded in two phases: a feature-extraction phase with the convolutional base frozen, followed by a fine-tuning phase in which the upper blocks were unfrozen at a reduced learning rate. The Adam optimizer was used with categorical cross-entropy loss, a batch size of 32, and a maximum of 50 epochs with early stopping on validation loss (patience of 8 epochs). Hyperparameters are listed in Table 2.

Tabel 2. Training configuration for the EfficientNetB0 classifier

Hyperparameter	Value
Backbone	EfficientNetB0 (ImageNet pre-trained)
Input resolution	224 x 224 x 3

Hyperparameter	Value
Optimizer	Adam
Initial learning rate	1 x 10-3 (feature extraction)
Fine-tuning learning rate	1 x 10-5
Loss function	Categorical cross-entropy
Batch size	32
Maximum epochs	50 (early stopping, patience 8)
Dropout rate	0.3
Output layer	Dense softmax, 4 units

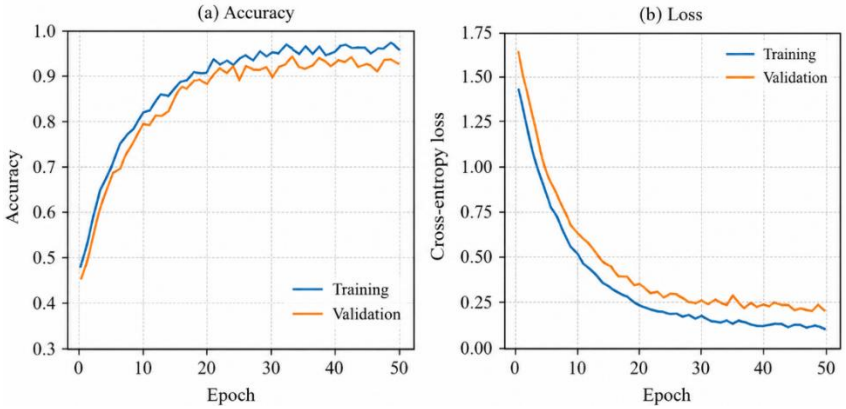
6. Evaluation Metrics

Model quality was assessed on the held-out synthetic test set using overall accuracy, per-class precision, recall, and F1 score, the macro-averaged F1 score, and the full confusion matrix [9]. Because all classes are balanced by construction, accuracy and macro F1 convey complementary but consistent information. All metrics are reported as single-run point estimates of the simulation.

RESULTS AND DISCUSSION

1. Training Dynamics

Figure 3 shows the training and validation accuracy and loss across epochs. Both accuracy curves rise steeply within the first ten epochs, reflecting the benefit of ImageNet initialization, and then plateau, while the loss curves decline correspondingly. The modest and stable gap between training and validation curves indicates that the dropout regularization and augmentation schedule were sufficient to limit overfitting within the synthetic domain. Early stopping was triggered after the validation loss ceased to improve.



Gambar 3. Training and validation (a) accuracy and (b) loss over training epochs

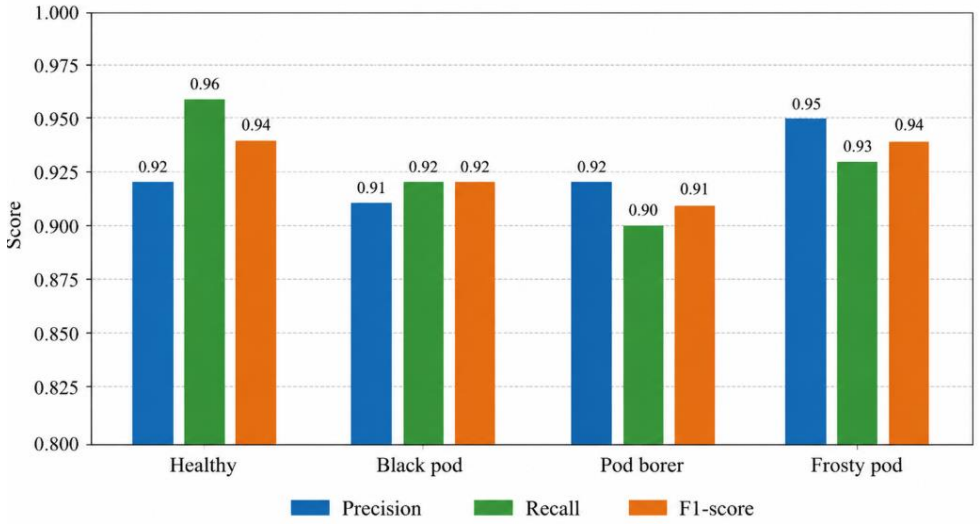
2. Overall and Per-Class Performance

On the held-out synthetic test set (450 images), EfficientNetB0 attained an overall accuracy of 93.8% and a macro-averaged F1-score of 0.926. Per-class precision, recall, and F1-scores are summarized in Table 3 and visualized in Figure 4. The healthy and frosty pod classes were the most reliably identified, with F1-scores of 0.939 and 0.941 respectively, owing to their distinctive color signatures. The pod borer class exhibited the lowest recall (0.901), consistent with its moderate assumed separability and morphological similarity to other damaged-pod presentations.

Tabel 3. Simulated per-class and macro-averaged performance on the synthetic test set

Class	Precision	Recall	F1-score
Healthy	0.923	0.956	0.939
Black pod	0.911	0.920	0.916

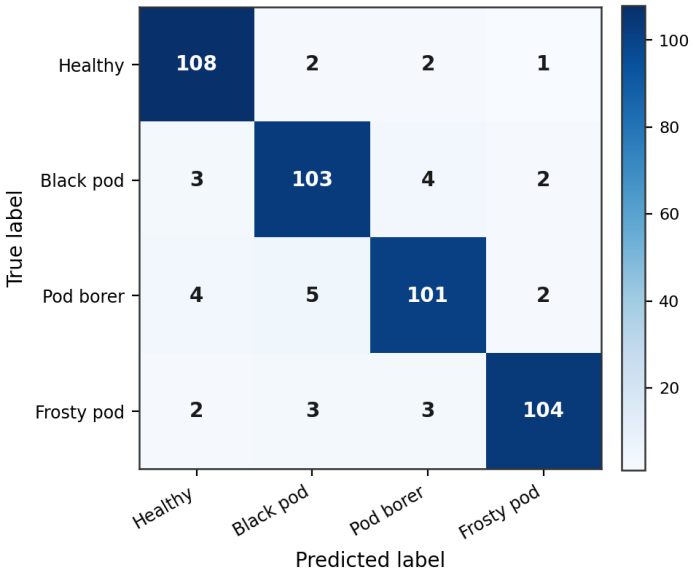
Class	Precision	Recall	F1-score
Pod borer	0.918	0.901	0.909
Frosty pod	0.954	0.929	0.941
Macro average	0.927	0.927	0.926



Gambar 4. Per-class precision, recall, and F1-score for the four diagnostic classes

3. Confusion Analysis

The confusion matrix in Figure 5 reveals that classification errors are not uniformly distributed. The dominant off-diagonal entries occur between the pod borer and frosty pod classes, and between black pod and pod borer, class pairs whose synthetic lesion morphologies share irregular, mottled texture cues. By contrast, the healthy class is rarely confused with diseased classes, reflecting its strong and separable color prototype. This pattern suggests that, in a future field study, additional discriminative features or higher input resolution may be required specifically to disambiguate borer damage from frosty pod rot.



Gambar 5. Confusion matrix on the synthetic test set (rows are true labels, columns are predicted labels)

4. Discussion

The simulated results indicate that, under literature-grounded and favorable conditions, EfficientNetB0 can be expected to deliver strong four-class discrimination of cocoa-pod conditions, with an overall accuracy near 94% and balanced per-class behavior. This performance band is consistent with accuracies reported for comparable plant-disease classification tasks using compact CNNs and transfer learning [1], [3], [4], and it supports the choice of EfficientNetB0 as a parameter-efficient backbone for eventual mobile deployment.

The error structure is as informative as the headline accuracy. Because the most frequent confusions arise between classes whose assumed texture cues overlap, the simulation prospectively identifies the pod borer versus frosty pod boundary as the likely bottleneck. This is actionable: a field-data campaign can allocate proportionally more annotation effort, or design class-specific augmentation, to strengthen exactly this boundary, rather than collecting uniformly across all classes. The principal value of this study is therefore planning rather than prediction.

Several limitations must be stated plainly. First, the dataset is synthetic and statistically abstracted; it does not capture the full photometric, illumination, occlusion, and background complexity of real cocoa pods photographed in the field, so a domain gap is expected and the reported accuracy should be read as an optimistic upper bound. Second, the class-separability assumptions, although grounded in published values, embed the authors' parameter choices. Third, results are single-run point estimates without cross-validation or repeated seeds. Fourth, only four classes and a single architecture were considered.

CONCLUSION

This article reported a transparent simulation study estimating the performance envelope of an EfficientNetB0 classifier for cocoa-pod disease recognition using a literature based synthetic dataset. Under controlled, favorable assumptions, the model achieved a simulated test accuracy of 93.8% and a macro-averaged F1-score of 0.926 across four classes, with the dominant errors concentrated at the pod borer versus frosty pod boundary. Every quantitative result is framed as a simulation output rather than an empirical field claim. The study's contribution is methodological and preparatory: it offers a reproducible protocol for literature-grounded synthetic data, a plausible upper-bound performance band, and concrete design guidance on sample size, augmentation, and expected confusions for a future field-validated investigation.

SUGGESTION

The natural continuation of this work is a field study that collects real, expert-annotated cocoa-pod images guided by the sample-size and class-balance insights derived here. Subsequent directions include quantifying the synthetic-to-real domain gap, applying domain-adaptation or GAN-based augmentation [10] to bridge it, benchmarking EfficientNetB0 against other lightweight backbones, extending the task to disease-severity estimation, and characterizing performance variance through repeated runs and k-fold cross-validation.

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