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AI-Based Smart Farming Implementation: A Comparative Analysis of EfficientNet-B0-SVM and ResNet-50-SVM for Cacao Leaf Disease Detection

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Abstract

Cacao productivity in West Sulawesi remains suboptimal, primarily due to leaf diseases such as Vascular Streak Dieback (VSD) and Leaf Blight**,** which negatively affect plant growth. Manual disease identification performed by farmers still has several limitations, particularly in terms of subjectivity and accuracy. These limitations become more apparent when distinguishing early-stage disease symptoms that share similar visual characteristics, often leading to misidentification and reduced crop quality. Therefore, this study aimed to develop a more accurate and objective system for cacao leaf disease classification. The dataset consisted of 549 images divided into three classes: Leaf Blight, Healthy, and Vascular Streak Dieback (VSD)**.** The training process was conducted in two stages, namely transfer learning and fine-tuning, while Grid Search was employed to optimize the SVM hyperparameters. The results showed that the EfficientNet-B0-SVM model achieved a validation accuracy of 95.45% and a final test accuracy of 91.82%**,** whereas the ResNet-50-SVM model achieved a validation accuracy of 93.18% and a final test accuracy of 92.73%**.** These findings indicate that both models were able to classify cacao leaf diseases with a high level of accuracy. In addition, the application of Principal Component Analysis (PCA) significantly reduced the number of extracted features while preserving more than **95%** of the original information. Therefore, the proposed CNN-PCA-SVM approach can be considered an effective method for supporting image-based cacao leaf disease identification.

Keywords: EfficientNet-B0, hybrid method, PCA, ResNet-50, support vector machine

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1. INTRODUCTION

Cacao (*Theobroma cacao*) is one of Indonesia's strategic plantation commodities [1], contributing significantly to the national economy as both a source of income for farmers and a contributor to state foreign exchange earnings [2]. According to a 2023 report by the International Cocoa Organization (ICCO), Indonesia ranks among the world's top four cacao producers and is the largest producer in Asia. This indicates that the cacao sector holds substantial potential for further development in support of national economic growth.

One region with significant potential for cacao development is West Sulawesi, particularly Polewali Mandar Regency. This region is a major cacao plantation center, where the majority of the local population depends on the sector for their livelihood. In addition to cultivation activities, farmers also play a role in the production and distribution of cacao seedlings, giving the region a strategic position within the national cacao supply chain. Given this potential, West Sulawesi has a significant opportunity to be developed into a leading and productive cacao production center.

However, national cacao productivity declined by 2.84% in 2023 [2], and productivity in West Sulawesi continues to fluctuate and remains suboptimal. One of the primary factors contributing to this condition is pest and disease infestation, particularly affecting the leaves, which play a critical role in the photosynthesis process. Diseases such as Vascular Streak Dieback (VSD) and Leaf Blight are known to hinder plant growth from the seedling stage through to the production stage, and have the potential to significantly reduce productivity.

This issue is further exacerbated by the conventional method of disease identification, which relies on manual visual observation by farmers. This approach has notable limitations in terms of subjectivity and accuracy, particularly in distinguishing early-stage disease symptoms that exhibit similar visual characteristics [3],[4]. As a result, misidentification frequently occurs, leading to inappropriate treatment, increased risk of loss, and reduced harvest quality.

With advancements in technology, Artificial Intelligence (AI)-based approaches, particularly deep learning [5]–[9], have been widely adopted for the classification of cacao diseases. Several previous studies have reported promising results using direct CNN architectures, such as NASNet-Mobile, which achieved 94.88% accuracy [10], and mobile-based CNN models with an accuracy of approximately 88% [11]. On the other hand, a previous study indicates that performance can be further enhanced through hybrid approaches. Specifically, in cocoa pod disease detection, fusing deep features from CNNs stabilized with the exponential moving average method with classical descriptors (color, texture, and shape), followed by PCA-based dimensionality reduction, achieved 91.48% accuracy with an SVM classifier, while a stacking-based ensemble applied to the same features reached 93.73% [12]. This aligns with other findings reporting that combining CNN-based feature extraction with classifiers such as SVM can improve plant disease detection performance, particularly in scenarios characterized by high intra-class variation and limited training data [13]. However, lightweight CNN architectures such as MobileNet still face limitations in capturing complex features within cacao disease images, and prior studies applying PCA have generally relied on a fixed number of principal components without systematic tuning, alongside limited exploration of classifier hyperparameters, which compromise the discriminative power and generalization ability of the resulting model.

Therefore, this study proposes a hybrid CNN-PCA-SVM framework that integrates EfficientNet and ResNet as feature extractors, PCA as a dimensionality reduction technique, and Support Vector Machines (SVM) as the classification algorithm. The application of PCA aims to reduce feature redundancy while preserving the most informative features, thereby improving computational efficiency and classification performance.

The main contributions of this study are as follows: (1) implementing a hybrid CNN-PCA-SVM framework for cacao leaf disease classification, (2) comparing the performance of two different CNN architectures, namely EfficientNet and ResNet, and (3) evaluating the effect of PCA on the feature representations generated by both architectures. This study is expected to provide a more accurate and computationally efficient model that can support the development of AI-based smart farming systems and contribute to improving cacao productivity in West Sulawesi.

2. RESEARCH METHOD

This research uses cacao leaf image data divided into three classes, namely healthy, Vascular Streak Dieback (VSD), and Leaf Blight. The method used in this research is a hybrid approach that combines a Convolutional Neural Network (CNN) architecture as a feature extractor with a Support Vector Machine (SVM) algorithm as the classifier. Two pretrained CNN architectures, namely EfficientNet-B0 and ResNet-50, are used. The features extracted from both architectures are then used to train an SVM model with a Radial Basis Function (RBF) kernel, resulting in two classification models, namely EfficientNet-SVM and ResNet-SVM, which are subsequently compared in terms of performance based on accuracy, precision, recall, F1-score, and confusion matrix metrics. The workflow of the cacao leaf classification is shown in Figure 1 below.

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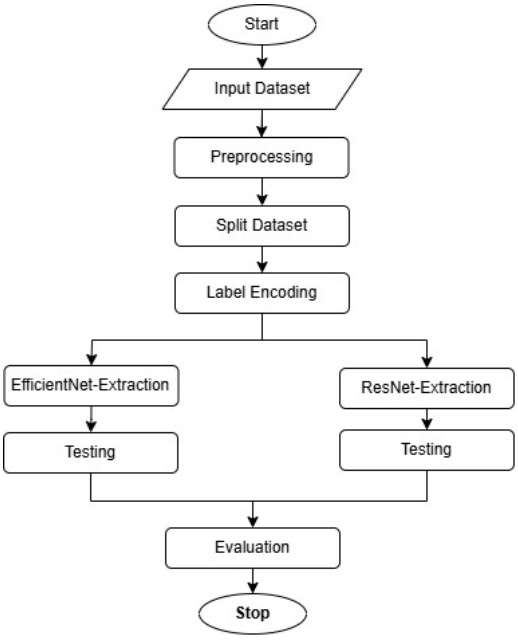


Figure 1. Cacao Leaf Classification Workflow

2.1. Input Dataset

The dataset used as input was collected directly from cacao plantations in Riso Village, Tapango Subdistrict, Polewali Mandar Regency, West Sulawesi Province. It consists of 549 cacao leaf images representing three conditions, with 183 images each for Vascular Streak Dieback (VSD), Leaf Blight, and healthy leaves. The images were captured from different cacao plants under natural field conditions, with varying backgrounds such as surrounding foliage, soil, and other plant parts. Each leaf was photographed only once, and no duplicate or near-duplicate images were included in the dataset. Because the images originate from different plants and were taken against diverse backgrounds, the dataset captures real-world variability in leaf appearance and image context, which helps reduce the risk of the model learning background-specific or plant-specific cues. Sample input images are shown in Figure 2.



Healthy Leaf Blight Vascular Streak Dieback

Figure 2. Input Images of cacao Leaf Data

2.2. Preprocessing

Each input image was resized to 224×224 pixels to ensure that all data share consistent dimensions before being processed by the convolutional layers during feature extraction and model training. Furthermore, data augmentation was applied during the training process to enhance data diversity and improve the model's ability to recognize various characteristics of cacao leaf images. The dataset used in this research consisted of 549 images. Augmentation was performed dynamically during

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model training, meaning no new image files were generated and the physical size of the dataset remained unchanged. The augmentation techniques employed included horizontal flipping, rotation, zooming, and contrast adjustment. Horizontal flipping generated image variations by mirroring images horizontally, while rotation created different object orientations. Additionally, zooming introduced variations in object scale, and contrast adjustment simulated different lighting conditions. These augmentation techniques are expected to enhance the model's ability to extract more representative features, thereby improving overall classification performance.

2.3. Split Dataset

To maintain balanced class proportions across all data partitions, stratified sampling was employed to divide the dataset of 549 images into training, validation, and testing subsets. The resulting subsets consisted of 395 training images (71.95%), 44 validation images (8.01%), and 110 testing images (20.04%), corresponding approximately to a 72:8:20 ratio. The partitioning was performed in two sequential stages. First, the dataset was divided into development and testing sets at an approximate ratio of 80:20. Subsequently, the development set was further divided into training and validation subsets at an approximate ratio of 90:10. Stratified sampling was used to maintain class proportions across the subsets.

2.4. Label Encoding

Class labels in text form (folder names) were converted into numerical representations. This process is necessary because machine learning algorithms such as SVM require numerical input rather than categorical input.

2.5. EfficientNet-B0 and ResNet-50

EfficientNet-B0 and ResNet-50 are widely used CNN architectures for image classification because of their ability to generate highly discriminative feature representations. EfficientNet-B0 employs a compound scaling mechanism that balances network depth, width, and input resolution, whereas ResNet-50 relies on residual learning to mitigate the vanishing gradient and degradation problems commonly encountered in very deep networks [14],[15]. In this study, both architectures served as backbone networks to extract feature representations from the preprocessed cacao leaf images.

Transfer Learning

During the transfer learning stage, the models were initialized with pre-trained ImageNet weights and loaded without their top classification layers (include_top=False). The model architecture consisted of a convolutional base, a Global Average Pooling layer, a Dropout layer with a rate of 20%, and a Dense layer with a softmax activation function. All layers in the convolutional base were frozen so that their weights remained unchanged during the initial training stage. Consequently, only the classification layers were trained to adapt the models to the characteristics of the cacao leaf dataset. The training process was performed for 10 epochs using Early Stopping and Reduce Learning Rate strategies to prevent overfitting and improve training stability.

Fine-Tuning

After the transfer learning stage, a fine-tuning process was conducted to improve the models' ability to recognize the characteristics of cacao leaf images. During this stage, all layers were frozen again, and the last 50 layers were subsequently unfrozen for retraining. The Batch Normalization layers remained non-trainable to preserve the stability of the feature distributions during training. Fine-tuning was performed using a smaller learning rate than that used in the previous stage to ensure more stable parameter updates. This stage aimed to optimize the feature representations generated by the CNN models.

Feature Extraction

After the training process was completed, the classification layers were removed, and the output from the Global Average Pooling layer was used as the feature vector. During training, several data augmentation techniques, including horizontal flipping, rotation, zooming, and contrast adjustment, were applied to increase data variability. Feature extraction was performed using a batch size of 32. Features were extracted from the training, validation, and testing datasets, allowing each image to be represented as a one-dimensional feature vector for the subsequent classification process.

Principal Component Analysis (PCA)

Before the classification stage, the feature vectors obtained from the feature extraction process were first normalized using StandardScaler. This normalization step ensured that all features were transformed to the same scale, allowing each feature to contribute equally during the analysis. Normalization is particularly important because PCA is sensitive to differences in feature scales. Without normalization, features with larger numerical values may dominate the generation of principal components. After normalization, the features were processed using Principal Component Analysis (PCA) for dimensionality reduction. In this study, PCA was applied while preserving 95% of the total data variance to ensure that most of the important information was retained while reducing the number of features. This dimensionality reduction process aimed to eliminate feature redundancy, reduce computational complexity, and improve model efficiency. The PCA model was fitted using the training features and subsequently applied to transform the validation and testing features. Finally, the reduced feature vectors were used as input for the Support Vector Machine (SVM) classifier.

2.6. SVM

After the feature extraction and dimensionality reduction processes were completed, the reduced feature vectors obtained from PCA were used as input for the SVM classifier. In this study, SVM employed the Radial Basis Function (RBF) kernel because of its ability to model nonlinear relationships within the data. To obtain the optimal model configuration, a hyperparameter optimization process was performed using Grid Search. The optimized parameters included the regularization parameter C with values of 5 and 10 and the gamma parameter with values of scale, 0.00001, 0.0001, 0.001, 0.01, and 0.1. Each parameter combination was systematically evaluated to determine the configuration that produced the best classification performance. During the hyperparameter optimization process, 5-Fold Stratified Cross Validation was employed. Under this scheme, the training data was partitioned into five equally sized subsets, with the class proportions preserved consistently across each partition. In every iteration, four of these subsets were designated for training the model, while the one remaining subset was reserved for validation purposes. This cycle was carried out five separate times, allowing each subset to serve as the validation data on one occasion. Subsequently, the best-performing model was identified based on the mean accuracy computed across all five iterations.

2.7. Validation and Final Testing

After the hyperparameter optimization process was completed, the best model obtained from Grid Search was evaluated using the validation dataset. This stage aimed to assess the model's ability to recognize unseen data that had not been used during the training and optimization processes. Subsequently, final testing was conducted using the testing dataset, which represented 20% of the total dataset. The testing data were not involved in the training, cross-validation, or validation stages, thereby providing a more objective assessment of the model's generalization capability. During this stage, the trained model was used to predict the class label of each image based on the feature vectors generated by the CNN models and reduced using PCA.

2.8. Evaluation

The Model performance was assessed by comparing predicted labels against the ground-truth labels of the test data, using four metrics accuracy, precision, recall, and F1-score, as formulated in Equations 1–4 [16].

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$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \quad (1)$$

$$Precision = \frac{True\ Positive}{True\ Positive\ + False\ Positive} \quad (2)$$

$$Recall = \frac{True\ Positive}{True\ Positive\ + False\ Negative} \quad (3)$$

$$F1 - Score = 2 \times \frac{Precision\ \times Recall}{Precision + Recal} \quad (4)$$

Accuracy denotes the ratio between correctly classified samples and the overall number of predictions produced by the model, as formulated in Equation (1). Meanwhile, precision reflects how reliably the model identifies a given class, computed by dividing the number of true positives by the total predictions assigned to that class, encompassing both correctly and incorrectly classified instances (false positives), as expressed in Equation (2). Recall, on the other hand, captures the model's ability to detect all actual instances belonging to a particular class; it is obtained by dividing the true positives by the total number of genuine samples in that class, including those the model failed to identify (false negatives), as shown in Equation (3). Lastly, the F1-score, presented in Equation (4), represents the harmonic mean of precision and recall. This metric offers a single, balanced indicator of the model's capacity to simultaneously reduce misclassification errors and undetected instances, thereby making it particularly valuable for assessing model performance on datasets with skewed class distributions.

3. RESULT AND DISCUSSION

3.1. Model Training and Testing

Model EfficientNet-B0

Based on the experimental results, the model was trained in two stages: transfer learning and fine-tuning. During the transfer learning stage, all layers of the convolutional base were frozen, allowing only the classification layers to be trained. The training process was conducted for 10 epochs using a learning rate of 0.001. In the fine-tuning stage, selected layers of the convolutional base were unfrozen and retrained to improve the model's performance. The fine-tuning process was performed for 30 epochs using learning rates of 0.00001 and 0.000005.

Table 1. Transfer Learning Training Results

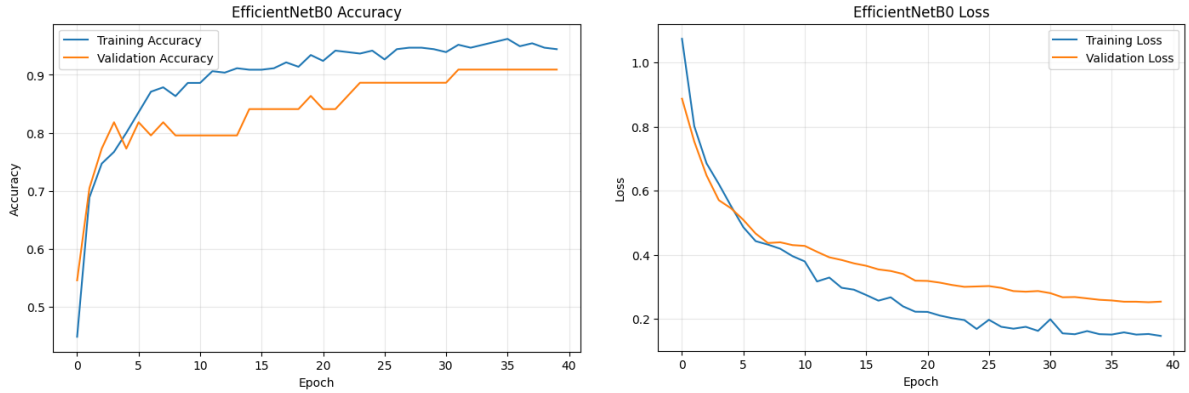
Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss	Learning Rate
1	44,81%	1,0742	54,55%	0,8875	0,0010
2	68,86%	0,8015	70,45%	0,7537	0,0010
3	74,68%	0,6856	77,27%	0,6479	0,0010
4	76,71%	0,6211	81,82%	0,5707	0,0010
5	80,00%	0,5520	77,27%	0,5453	0,0010
6	83,54%	0,4863	81,82%	0,5092	0,0010
7	87,09%	0,4430	79,55%	0,4666	0,0010
8	87,85%	0,4321	81,82%	0,4371	0,0010
9	86,33%	0,4193	79,55%	0,4394	0,0010
10	88,61%	0,3962	79,55%	0,4306	0,0010

Based on the training results presented in Table 1, the transfer learning stage demonstrated a significant improvement in model performance over 10 epochs. The training accuracy increased from 44.81% in the first epoch to 88.61% in the tenth epoch. This improvement indicates that the model was able to learn the patterns in the training data effectively. At the same time, the training loss gradually decreased from 1.0742 to 0.3962, indicating that the model's prediction errors became smaller throughout the training process. The validation results also showed a positive trend. The validation accuracy increased from 54.55% to 79.55%, with the highest value of 81.82% achieved in the 4th, 6th, and 8th epochs. Meanwhile, the validation loss decreased from 0.8875 to 0.4306, suggesting that the model was able to generalize reasonably well to the validation data.

Table 2. EfficientNet-B0 Fine-Tuning Training Results

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss	Learning Rate
1	88,61%	0,3797	79,55%	0,4281	0,000010
2	90,63%	0,3171	79,55%	0,4097	0,000010
3	90,38%	0,3293	79,55%	0,3925	0,000010
4	91,14%	0,2975	79,55%	0,3842	0,000010
…	…	…	…	…	…
26	96,20%	0,1515	90,91%	0,2579	0,000005
27	94,94%	0,1584	90,91%	0,2540	0,000005
28	95,44%	0,1515	90,91%	0,2540	0,000005
29	94,68%	0,1533	90,91%	0,2524	0,000005
30	94,43%	0,1473	90,91%	0,2542	0,000005

Based on the training results presented in Table 2, the fine-tuning process successfully improved the model's performance compared to the transfer learning stage. The training accuracy increased from 88.61% in the first epoch to a peak of 96.20% in the 26th epoch, and ended at 94.43% in the final (30th) epoch. In addition, the validation accuracy improved from 79.55% in the first epoch to 90.91% in the final epoch, while the validation loss decreased from 0.4281 to 0.2542. The reduction in the loss value indicates that the model became more capable of generalizing to the validation data. At the 16th epoch, the ReduceLROnPlateau mechanism automatically reduced the learning rate from 0.00001 to 0.000005 because the improvement in model performance had begun to plateau. This adjustment helped the model achieve better optimization during the remaining training epochs.



Validation Accuracy Validation Loss

Figure 3. EfficientNet-B0 Training Curves

Figure 3 illustrates the training results of the EfficientNet-B0 model. The results show that the training accuracy increased gradually from 44.81% in the first epoch to 88.61% in the tenth epoch. A similar trend was observed for the validation accuracy, which increased from 54.55% to 79.55%. In

addition to the improvement in accuracy, both the training loss and validation loss decreased throughout the training process. The training loss decreased from 1.0742 to 0.3962, while the validation loss decreased from 0.8875 to 0.4306. These results indicate that the model was able to learn the underlying patterns in the training data and generate more informative feature representations during each epoch. After completing the transfer learning stage, the model underwent a fine-tuning process by unfreezing the last 50 layers of the EfficientNet-B0 architecture. During this stage, the learning rate was reduced to 0.00001 to maintain the stability of the training process. The results showed that the training accuracy increased to 94.68%, while the validation accuracy reached 90.91%. In addition, the implementation of ReduceLROnPlateau at the 16th epoch automatically reduced the learning rate to 5×10^{-6} because the model's performance improvement had started to plateau. This learning rate adjustment allowed the model to optimize its parameters more effectively, as reflected by the decrease in validation loss from 0.4281 in the first epoch to 0.2524 in the 29th epoch.

Model ResNet-50

Table 3. Transfer Learning Training Results

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss	Learning Rate
1	50,63%	1,0413	77,27%	0,5947	0,0010
2	70,13%	0,6855	72,73%	0,5083	0,0010
3	76,96%	0,5300	75,00%	0,4899	0,0010
4	77,97%	0,5064	79,55%	0,4290	0,0010
5	83,04%	0,4070	84,09%	0,4025	0,0010
6	87,85%	0,3477	77,27%	0,4200	0,0010
7	88,35%	0,3372	79,55%	0,3899	0,0010
8	88,61%	0,3014	81,82%	0,3768	0,0010
9	90,13%	0,2879	81,82%	0,3674	0,0010
10	89,87%	0,2950	84,09%	0,3524	0,0010

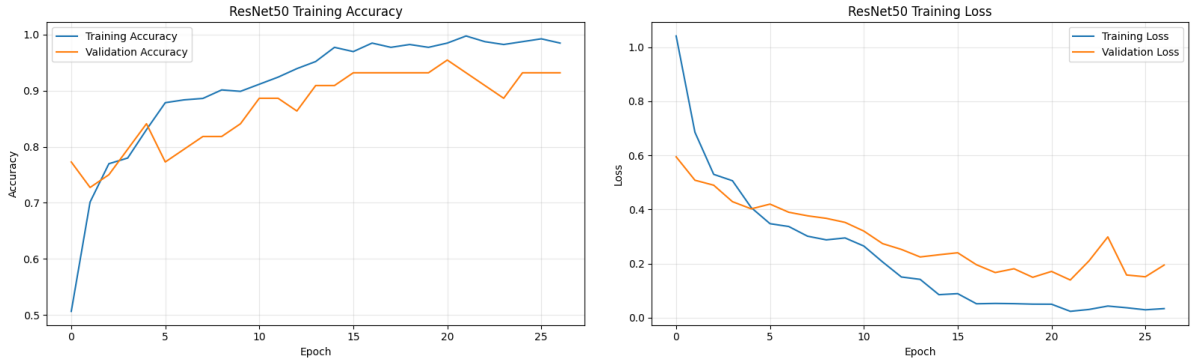
Based on the training results presented in Table 3, the ResNet-50 model demonstrated a considerable improvement in performance over the 10 training epochs. The training accuracy increased from 50.63% in the first epoch to 89.87% in the tenth epoch. This improvement indicates that the model was able to effectively learn the patterns contained in the training dataset. In addition, the training loss decreased significantly from 1.0413 to 0.2950. The reduction in the loss value suggests that the model's prediction errors gradually decreased during the training process. For the validation data, the validation accuracy increased from 77.27% to 84.09%, while the validation loss decreased from 0.5947 to 0.3524. Although the validation accuracy fluctuated slightly during several epochs, the overall trend remained positive, indicating that the model was able to maintain stable performance on the validation dataset.

Table 4. Fine Tuning Training Result ResNet-50

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss	Learning Rate
1	91,14%	0,2650	88,64%	0,3203	0,000010
2	92,41%	0,2062	88,64%	0,2740	0,000010
3	93,92%	0,1507	86,36%	0,2526	0,000010
4	95,19%	0,1419	90,91%	0,2247	0,000010
…	…	…	…	…	…
14	98,23%	0,0433	88,64%	0,2987	0,000005
15	98,73%	0,0370	93,18%	0,1581	0,0000025

16	99,24%	0,0294	93,18%	0,1515	0,0000025
17	98,48%	0,0339	93,18%	0,1948	0,00000125

Based on the training results presented in Table 4, the training process was terminated at the 17th epoch through the Early Stopping mechanism to prevent overfitting. The ResNet-50 model demonstrated a substantial improvement in performance compared to the transfer learning stage. The training accuracy increased from 91.14% in the first epoch to 98.48% in the 17th epoch and reached its highest value of 99.75% in the 12th epoch. In addition, the training loss decreased considerably from 0.2650 to 0.0339, indicating that the model became more effective at learning the patterns in the training data. On the validation dataset, the validation accuracy improved from 88.64% to 93.18%, with the highest value of 95.45% achieved in the 11th epoch, while the validation loss reached its lowest value of 0.1395 in the 12th epoch. During the training process, the ReduceLROnPlateau mechanism automatically reduced the learning rate three times, from 0.00001 to 0.000005, then to 0.0000025, and finally to 0.00000125. These adjustments helped the model achieve a more optimal convergence process and contributed to the improvement in overall performance.



Validation Accuracy Validation Loss

Figure 4. ResNet-50 Training Curves

Based on the ResNet-50 training curves shown in Figure 4, the validation accuracy exhibited an overall upward trend throughout the training process. At the beginning of training, the validation accuracy was approximately 77%, and it gradually increased to 95.45% at the 11th epoch. Although slight fluctuations occurred at the 13th and 14th epochs, the validation accuracy remained relatively stable at around 93%, indicating that the model was able to maintain its performance on the validation dataset. Similarly, the validation loss decreased significantly from 0.5947 to 0.1395, suggesting that the model's prediction errors became progressively smaller during training. The lowest validation loss was achieved at the 12th epoch, indicating that the model reached its optimal performance at this stage. After the 12th epoch, the validation loss began to fluctuate and temporarily increased to nearly 0.30, suggesting a tendency toward overfitting, in which the model continued to improve on the training data without a corresponding improvement in validation performance. However, the relatively small difference between the training accuracy and validation accuracy curves during most of the training process indicates that the model achieved good generalization and did not experience underfitting.

3.2. Validation Result

EfficientNet-B0

Before the evaluation process, the SVM model was optimized using the Grid Search method to determine the most appropriate combination of hyperparameters. The optimization results showed that the combination of C = 10 and gamma = 0.0001 achieved the highest average 5-fold cross-validation accuracy of 96.71%, indicating that the selected parameters were able to provide optimal classification performance. In addition, Principal Component Analysis (PCA) was applied to reduce the dimensionality of the extracted features. The number of features was successfully reduced from 1,280 to 226, while maintaining an explained variance of 95.01%. This result demonstrates that PCA was able

to preserve most of the important information contained in the original features despite the substantial reduction in feature dimensionality.

Table 5. Validation Result EfficientNet-B0

Class	Metrics		
	precision	**recall**	**F1-score**
Leaf Blight	93%	93%	93%
Healthy	100%	100%	100%
Vascular Streak Dieback	93%	93%	93%

Table 5 presents the validation results obtained during the testing process. The model achieved an average accuracy of 95.45%, while the precision, recall, and F1-score reached 95.40%, indicating that the model was highly effective in identifying and distinguishing the three cacao leaf classes: Leaf Blight, Healthy, and Vascular Streak Dieback. At the class level, the Healthy category demonstrated the best performance, with precision, recall, and F1-score values of 100%, indicating that all healthy leaf images in the validation dataset were classified correctly without any prediction errors. The Leaf Blight class achieved 93% for all evaluation metrics, suggesting that the model was able to identify most infected leaf images with a high level of accuracy, although a small number of images were still misclassified. Meanwhile, the Vascular Streak Dieback class achieved 93% for precision, recall, and F1-score, demonstrating that the model was highly effective in recognizing the symptoms of this disease while maintaining a very low classification error rate.

Table 6. Final Test EfficientNet-B0

Class	Metrics		
	precision	**recall**	**F1-score**
Leaf Blight	91%	89%	90%
Healthy	90%	100%	95%
Vascular Streak Dieback	94%	86%	90%

Table 6 shows that the model achieved an accuracy of 91.82%, with an average precision of 91.93%, recall of 91.79%, and F1-score of 91.72%. These results indicate that the model was able to maintain good performance when evaluated on previously unseen data. At the class level, the Healthy class demonstrated the best performance, achieving a recall of 100% and an F1-score of 95%, indicating that all healthy leaf images were correctly identified by the model. The Leaf Blight class achieved a precision of 91%, recall of 89%, and F1-score of 90%, while the Vascular Streak Dieback class obtained a precision of 94%, recall of 86%, and F1-score of 90%. Overall, these findings demonstrate that the model was capable of accurately classifying the three cacao leaf classes while maintaining relatively balanced performance across all evaluation metrics.

Table 7. Confusion Matrix EfficientNet-B0

	Class	Predicted Class		
		Leaf Blight	***Healthy***	***Vascular Streak Dieback***
Actual class	*Leaf Blight*	32	2	2
	Healthy	0	37	0
	Vascular Streak Dieback	3	2	32

Based on the confusion matrix presented in Table 7, the EfficientNet-B0 model was able to classify most cacao leaf images correctly. Of the 36 Leaf Blight images, 32 were correctly classified,

while 2 images were misclassified as Healthy and another 2 were misclassified as Vascular Streak Dieback. The Healthy class showed the best performance, with all 37 healthy leaf images correctly identified without any classification errors. This result is consistent with the 100% recall achieved during the final testing stage. Meanwhile, among the 37 Vascular Streak Dieback images, 32 were correctly classified, whereas 3 images were incorrectly classified as Leaf Blight and 2 as Healthy. The misclassification observed between the Leaf Blight and Vascular Streak Dieback classes suggests that these two diseases share relatively similar visual characteristics. The similarity of disease symptoms on the leaf surface made it more difficult for the model to distinguish between these classes. Nevertheless, the model successfully classified 101 out of 110 images correctly, resulting in a final test accuracy of 91.82%.

ResNet-50

Before the evaluation process, the SVM model was first optimized using the Grid Search method to determine the most appropriate hyperparameter combination. The optimization results showed that the combination of C = 5 and gamma = scale achieved the best performance, with an average 5-fold cross-validation accuracy of 97.22%, indicating that the selected parameters improved the model's ability to classify cacao leaf images effectively. In addition, Principal Component Analysis (PCA) was applied to reduce the dimensionality of the features extracted by ResNet-50. The PCA results showed that the number of features was successfully reduced from 2,048 to 240, while maintaining an explained variance of 95.02%. These findings indicate that, despite the substantial reduction in the number of features, most of the important information contained in the original feature set was successfully preserved.

Table 8. Validation Result ResNet-50

Class	Metrics		
	precision	**recall**	**F1-score**
Leaf Blight	93%	87%	90%
Healthy	88%	100%	94%
Vascular Streak Dieback	100%	93%	96%

Based on Table 8, the ResNet-50 model achieved an accuracy of 93.18%, with a precision of 93.70%, recall of 93.17%, and F1-score of 93.23%. These results indicate that the model was able to classify cacao leaf images with a high level of accuracy on the validation dataset. At the class level, Vascular Streak Dieback demonstrated the best performance, achieving a precision of 100%, recall of 93%, and F1-score of 96%, indicating that the model was highly effective in identifying images belonging to this class. The Healthy class achieved a precision of 88%, recall of 100%, and F1-score of 94%, showing that all healthy leaf images in the validation dataset were correctly identified by the model. In contrast, the Leaf Blight class achieved a precision of 93%, recall of 87%, and F1-score of 90%. The lower recall value for this class suggests that several Leaf Blight images were still misclassified during the validation process.

Table 9. Final Test ResNet-50

Class	Metrics		
	precision	**recall**	**F1-score**
Leaf Blight	92%	92%	92%
Healthy	92%	95%	93%
Vascular Streak Dieback	94%	92%	93%

Based on the testing results, the model achieved an accuracy of 92.73%, with a precision of 92.74%, recall of 92.72%, and F1-score of 92.72%, indicating that the model was able to classify cacao leaf images effectively. At the class level, Leaf Blight achieved 91.67% for precision, recall, and F1-score. The Healthy class obtained a precision of 92.11%, recall of 94.59%, and F1-score of 93.33%,

while the Vascular Streak Dieback (VSD) class achieved a precision of 94.44%, recall of 91.89%, and F1-score of 93.15%. Overall, all classes produced precision, recall, and F1-score values above 91%, demonstrating the model's ability to distinguish among the three cacao leaf classes with a high level of accuracy. Furthermore, the relatively balanced values across all evaluation metrics indicate that the model maintained stable classification performance across all classes.

Table 10. Confusion Matrix ResNet50

Class		Predicted Class		
		Leaf Blight	***Healthy***	***Vascular Streak Dieback***
Actual class	*Leaf Blight*	33	2	1
	Healthy	1	35	1
	Vascular Streak Dieback	2	1	34

Based on the confusion matrix results, the model was able to correctly classify the majority of cacao leaf images. Among the 36 Leaf Blight images, 33 were correctly classified, while 2 images were misclassified as Healthy and 1 image was misclassified as VSD. For the Healthy class, the model correctly classified 35 out of 37 images, whereas 1 image was incorrectly classified as Leaf Blight and another was misclassified as VSD. In the VSD class, 34 out of 37 images were correctly identified, while 2 images were misclassified as Leaf Blight and 1 image was classified as Healthy. Overall, the model correctly classified 102 out of 110 cacao leaf images, demonstrating its strong ability to distinguish among the three classes despite the presence of a small number of misclassifications.

3.3. Performance Comparison of EfficientNet-B0-SVM and ResNet-50-SVM

Based on the results obtained from the cross-validation, validation, and final testing stages, both EfficientNet-B0-SVM and ResNet-50-SVM demonstrated good performance in classifying cacao leaf diseases. However, several differences were observed between the two models during each evaluation stage. During the hyperparameter optimization stage, ResNet-50-SVM achieved a higher average 5-fold cross-validation accuracy of 97.22%, compared to 96.71% obtained by EfficientNet-B0-SVM. This result indicates that the features extracted by ResNet-50 provided better performance during the training process. In addition, the optimal hyperparameter combinations differed between the two models. EfficientNet-B0-SVM achieved its best performance using C = 10 and gamma = 0.0001, while ResNet-50-SVM achieved its best performance using C = 5 and gamma = scale.

Based on the validation results, EfficientNet-B0-SVM achieved a higher accuracy of 95.45%, compared to 93.18% achieved by ResNet-50-SVM. However, during the final testing stage, ResNet-50-SVM achieved an accuracy of 92.73%, which was slightly higher than the 91.82% achieved by EfficientNet-B0-SVM. The relatively small difference in accuracy suggests that both models have comparable capabilities in classifying cacao leaf diseases. According to the confusion matrix analysis, both models performed very well in identifying the Healthy class. However, misclassification still occurred in the Leaf Blight and Vascular Streak Dieback classes. This finding suggests that the visual characteristics of these two diseases are relatively similar, making them more difficult for the models to distinguish.

Overall, the results of this study demonstrate that both EfficientNet-B0-SVM and ResNet-50-SVM provide good classification performance. Although ResNet-50-SVM achieved slightly better results during the cross-validation and final testing stages, EfficientNet-B0-SVM performed better during validation. Therefore, both models can be considered effective approaches for cacao leaf disease identification.

3.2. Comparison with Previous Research

To evaluate the effectiveness of the proposed model, the results of this study were compared with several previous studies that applied direct CNN architectures and hybrid CNN-based approaches for cacao disease classification. Earlier studies employing direct CNN architectures reported varying levels of performance, such as NASNet-Mobile, which achieved 94.88% accuracy [10], and a mobile-based CNN model that achieved a lower accuracy of approximately 88% [11], indicating that classification performance using direct CNN architectures can vary considerably depending on the specific architecture employed. In comparison, the proposed EfficientNet-B0-SVM and ResNet-50-SVM models achieved final test accuracies of 91.82% and 92.73%, respectively, positioning the proposed approach between these two direct CNN benchmarks while offering the added benefit of dimensionality reduction through PCA, which reduced the number of extracted features by more than 80% without substantially compromising classification performance.

With respect to hybrid approaches, a previous study on cocoa pod disease detection that fused deep features from multiple CNNs with classical descriptors (color, texture, and shape), followed by PCA-based dimensionality reduction, achieved an accuracy of 91.48% with an SVM classifier and 93.73% with a stacking ensemble [12]. The latter is slightly higher than the final test accuracy obtained by the proposed models in this study. However, it is important to note that the 5-fold cross-validation accuracies obtained during the hyperparameter optimization stage, 96.71% for EfficientNet-B0-SVM and 97.22% for ResNet-50-SVM, exceeded both figures reported in [12]. This suggests that the extracted features and the resulting classifier were highly capable of separating the disease classes during training, although a moderate gap remained between the cross-validation and final test accuracies. This gap may be attributed to differences in dataset size, class composition, and the number of disease categories addressed across studies. It should also be noted that the 93.73% in [12] was obtained with an ensemble model, whereas the present study relies on a single SVM classifier, so the comparison is not entirely equivalent. Furthermore, these findings reinforce earlier observations that combining CNN-based feature extraction with classifiers such as SVM can enhance plant disease detection performance, particularly under conditions of high intra-class variation and limited training data [13]. Consistent with this, the present study addressed a three-class classification problem (Leaf Blight, Healthy, and Vascular Streak Dieback) characterized by considerable visual similarity between the Leaf Blight and Vascular Streak Dieback classes, which nonetheless did not prevent the proposed hybrid framework from achieving accuracy levels comparable to those reported in [10]–[13].

Overall, although the final test accuracies obtained in this study (91.82%–92.73%) did not consistently surpass all previously reported results [10]–[13], the proposed CNN-PCA-SVM framework demonstrated competitive and stable performance across cross-validation, validation, and testing stages, while additionally offering improved computational efficiency through PCA-based dimensionality reduction, an aspect that was not addressed in the compared studies. These findings suggest that the proposed hybrid approach has strong potential to be applied as a supporting system for cacao leaf disease identification, particularly in scenarios where both classification accuracy and computational efficiency are of practical importance.

4. CONCLUSION

This study proposed a CNN-PCA-SVM hybrid approach for cacao leaf disease identification by employing two Convolutional Neural Network (CNN) architectures, namely EfficientNet-B0 and ResNet-50, as feature extractors. Furthermore, Principal Component Analysis (PCA) was applied for feature dimensionality reduction, while Support Vector Machine (SVM) was used as the classification algorithm. The results demonstrated that the Grid Search method successfully identified the optimal hyperparameter combinations for each model. For the EfficientNet-B0-SVM model, the best parameters were C = 10 and gamma = 0.0001, resulting in an average 5-fold cross-validation accuracy of 96.71%. Meanwhile, the ResNet-50-SVM model achieved the best performance with C = 5 and gamma = scale, producing an average 5-fold cross-validation accuracy of 97.22%. The implementation of PCA effectively reduced the number of extracted features while preserving most of the important information. The number of features generated by EfficientNet-B0 was reduced from 1,280 to 226 features, whereas the number of features generated by ResNet-50 was reduced from 2,048 to 240 features, while

maintaining an explained variance above 95% in both models. Based on the evaluation results, the EfficientNet-B0-SVM model achieved a validation accuracy of 95.45% and a final test accuracy of 91.82%. In comparison, the ResNet-50-SVM model achieved a validation accuracy of 93.18% and a final test accuracy of 92.73%. These findings indicate that both models were capable of accurately classifying the three cacao leaf classes, namely Leaf Blight, Healthy, and Vascular Streak Dieback. Overall, the combination of CNN, PCA, and SVM proved to be effective for cacao leaf disease identification. The findings also suggest that the proposed hybrid approach can serve as a promising alternative for developing image-based plant disease classification systems.

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