Jurnal Teknik Informatika (JUTIF) Vol. 7, No. 3, June 2026, Page. 2646-2659
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2026.7.3.5645

Banana Leaf Disease Classification Using CNN Feature Extraction and Naive Bayes Algorithm

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Received : Jan 28, 2026; Revised : Feb 12, 2026; Accepted : Feb 12, 2026; Published : Jun 15, 2026

Abstract

Banana leaf diseases such as Black Sigatoka, Cordana, and Pestalotiopsis significantly reduce productivity and require early, accurate detection to prevent severe yield losses. While Convolutional Neural Networks (CNN) have demonstrated high performance in plant disease classification, most existing approaches rely on computationally intensive end-to-end deep learning models, limiting their deployment on resource-constrained devices. This study proposes a lightweight hybrid classification framework that integrates MobileNetV2-based CNN feature extraction with a Gaussian Naive Bayes classifier. The novelty of this research lies in the systematic transformation of deep 1,280-dimensional feature representations into a probabilistic classification space, enabling competitive accuracy with substantially lower computational complexity. A balanced dataset consisting of 3,200 training images and 1,311 testing images collected from Pamekasan Regency was preprocessed through resizing, normalization, and augmentation. Experimental results show that the end-to-end CNN achieved 98.70% accuracy, while the proposed hybrid CNN–Naive Bayes model attained 95.73% accuracy with F1-scores above 0.90 across all classes. Despite not relying on backpropagation during classification, the hybrid approach maintains strong predictive performance while reducing training time and memory requirements. These findings demonstrate that integrating deep feature extraction with probabilistic learning provides an efficient and deployable solution for edge-based precision agriculture systems.

Keywords : *Banana Leaf Disease, CNN, Image Classification, MobileNetV2, Naive Bayes, Precision Agriculture.*

1. INTRODUCTION

Banana is a major agricultural commodity, contributing approximately 16% of global fruit production. However, its productivity is frequently threatened by foliar diseases such as Black Sigatoka, Fusarium wilt (Panama disease), and Cordana, which can cause yield losses of up to 100%.[1][2][3][4] Diseases like Black Sigatoka and Cordana progressively damage leaf tissue, disrupt photosynthesis, and ultimately reduce both the quality and quantity of banana fruit. Therefore, early and accurate detection of banana leaf diseases is critical to prevent widespread damage. Delays in diagnosis may lead to drastic yield reductions and increased costs of disease management.[5]

Traditional methods such as field-based visual inspection remain widely used for identifying banana leaf diseases. Although practical, these approaches have significant limitations as they rely heavily on the expertise of observers, are time-consuming, and prone to subjective errors. Variations in field conditions, including lighting, disease severity, and physical leaf damage, further increase the risk of misdiagnosis.[6] Consequently, farmers may apply inappropriate control measures, such as excessive pesticide use, which raises production costs and poses environmental risks.[7] These challenges highlight the need for automated systems based on digital image processing to detect and classify banana leaf diseases more rapidly, efficiently, and accurately.[8]

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In recent years, research on plant disease classification has advanced considerably with the adoption of Convolutional Neural Networks (CNN).[9] CNNs are capable of automatically extracting visual features without requiring complex manual feature engineering.[10] Numerous studies have reported that CNN architectures achieve very high accuracy in plant disease datasets, with performance ranging between 98.49% and 99.85%.[11] In the context of banana leaf diseases, CNNs have also shown promising results. For instance, MobileNet achieved 90.62% accuracy, GoogleNet reached 92.00%, while DenseNet-201 obtained 98.12%, outperforming models such as BananaSqueezeNet with 96.25%. These findings confirm that CNNs deliver superior performance compared to classical methods like Support Vector Machines (SVM) or K-Nearest Neighbor (KNN), particularly when handling complex image datasets.[12]

Nevertheless, most CNN approaches remain end-to-end and computationally intensive.[13] Deep networks require substantial memory, long training times, and costly hardware. This challenge opens opportunities to develop more efficient yet accurate methods. To address this need, the present study proposes a hybrid approach that combines CNN as a feature extractor with the Naive Bayes algorithm as a classifier. The novelty of this approach lies in leveraging rich CNN-derived features for classification using a lightweight probabilistic method that is fast and efficient. This hybrid strategy is expected to deliver high accuracy while reducing computational complexity, enabling deployment on low-resource devices.[14]

Furthermore, this study emphasizes optimization in image preprocessing, including resizing, normalization, and augmentation, to improve input quality.[15] By integrating CNN and Naive Bayes, the research contributes to the development of a banana leaf disease classification system that is more efficient, lightweight, and accurate, with strong potential for implementation in large-scale digital agriculture and early disease detection systems.[16]

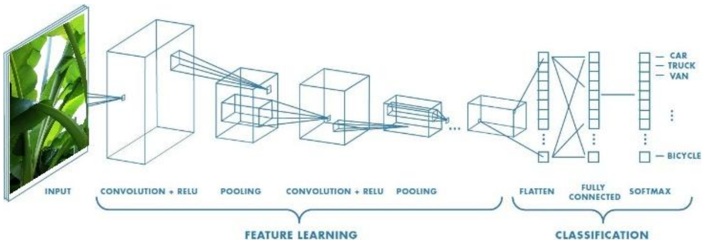

Figure 1. CNN architecture

Figure 1 illustrates the CNN architecture employed in this study. Due to the complexity of leaf textures and pest patterns, the architecture is divided into two main components:

a. Feature Learning (Feature Extraction Layer) In this stage, the network receives raw image inputs and processes them into multidimensional arrays. The feature learning process consists of convolutional and pooling layers, each producing feature maps represented as numerical values that capture visual characteristics of the image. These feature maps are then forwarded to the classification stage.[17]
b. Classification Layer This stage is composed of fully connected layers, where neurons are densely linked to one another. The input from the feature learning stage is flattened and passed through several hidden layers. The final output provides classification results in the form of accuracy scores or class probabilities.

Convolutional Neural Networks (CNNs) are a deep learning architecture specifically designed for grid-like data such as images.[18] CNNs have proven highly effective in various computer vision tasks, including classification, object detection, and segmentation. In agricultural applications, CNNs can automatically detect pests or diseases in crops by leveraging visual features such as color, texture, and shape of infected leaves. CNNs operate hierarchically, with each layer extracting increasingly complex features from the input image.[3]

Convolutional Layer This layer extracts local features using convolution operations. A kernel (filter) slides across the image to generate feature maps, capturing patterns such as edges, textures, and shapes.

$$(f*g)(x,y) = \sum_{j=1}^{\infty}(f(i,j) \cdot g(x-i, y-j) \quad (1)$$

where ff is the input matrix (image), gg is the kernel/filter, and (x,y)(x,y) denotes the pixel position.

Activation Layer Activation functions such as ReLU (Rectified Linear Unit) introduce non-linearity, enabling the CNN to learn complex relationships:

$$ReLU\ (z) = \max\ (0, z) \quad (2)$$

Pooling Layer Pooling operations (commonly Max Pooling or Average Pooling) reduce the spatial dimensions of feature maps, lowering computational cost while preserving essential features.

$$Pi,j = \frac{Max}{m,n\ Ri,j}bh \quad (3)$$

Fully Connected Layer (FC Layer) This layer connects all neurons from the previous stage to perform the final classification, similar to traditional neural networks.

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (4)$$

CNN performance is highly dependent on the quality of input image data. Therefore, image preprocessing becomes a critical step.[19] Preprocessing procedures such as resizing, color normalization, noise removal, and data augmentation can significantly improve the quality of the training dataset. Leaf segmentation from the background further assists the model in focusing on the diseased regions.[20] Previous studies have concluded that the combination of efficient preprocessing techniques with deep learning architectures creates a highly accurate disease detection pipeline. Through such an integrated pipeline, CNNs are capable of recognizing complex disease patterns on plant leaves under varying lighting conditions and environmental backgrounds. Consequently, optimizing preprocessing techniques is expected to enhance CNN performance in classifying banana leaf diseases.[21]

Naive Bayes, within the category of machine learning algorithms, relies on probabilistic and statistical calculations. It is considered an efficient and fast classification method because it assumes that the features used are mutually independent.[22] The algorithm determines the highest probability to classify testing data into the most appropriate category.[23] One of its advantages is that it requires relatively small amounts of training data to estimate the parameters needed for classification. Naive Bayes can also provide class membership probabilities, showing similarities with decision tree and neural network approaches. The conditional probability can be expressed as:

$$P(c\backslash x) \quad = \frac{P(x\backslash c).P(c)}{P(x)} \quad (5)$$

where P(c|x)P(c|x) represents the posterior probability of a class given the predictor, P(c)P(c) is the prior probability of the class, P(x|c)P(x|c) is the likelihood of the predictor given the class, and P(x)P(x) is the prior probability of the predictor itself. Testing and evaluation are essential stages to

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assess system performance, aiming to measure accuracy and reliability in producing correct results.[7] In this study, 20% of the dataset was allocated for testing, separated from the training data. During evaluation, the results were analyzed and interpreted to gain deeper insights into system performance.[8] Repeated testing and evaluation are necessary to improve reliability, and performance was measured using accuracy, precision, recall, and F1-score.[24] This research aims to develop a banana leaf disease classification method by leveraging CNN and optimized image preprocessing to improve detection accuracy. With this approach, the study seeks to provide a faster and more accurate automatic diagnostic system, supporting farmers in making timely disease control decisions and promoting sustainable banana production.[25]

2. METHOD

The stages of this study include data input, image resizing, preprocessing, CNN construction and classification, model testing, and evaluation.

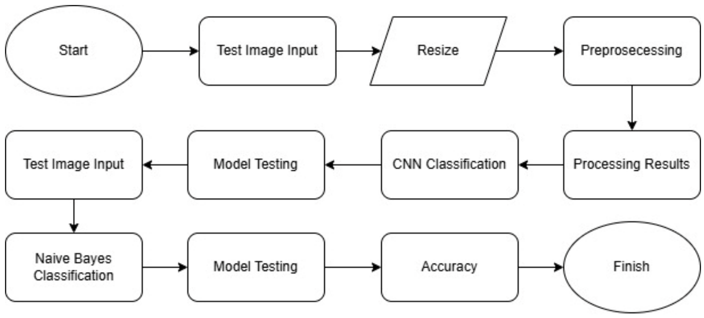

Figure 2. Research Workflow

As illustrated in Figure 2, The research process begins with data collection, where banana leaf images representing four classes (Cordana, Healthy, Pestalotiopsis, and Sigatoka) were gathered from Pamekasan Regency. The collected images were then divided into training and testing datasets to ensure proper model validation. In the preprocessing stage, all images were resized to 224 × 224 pixels to match the input requirements of the MobileNetV2 architecture. Additional preprocessing steps included pixel normalization to scale values into a standardized range and data augmentation techniques to enhance generalization and reduce overfitting.[26] After preprocessing, the images were fed into the Convolutional Neural Network (CNN) for feature extraction and classification. In the first pathway, the CNN performed end-to-end classification through fully connected layers, and the model was evaluated using the testing dataset to measure its performance. In the second pathway, features extracted from the CNN (after the Global Average Pooling layer) were used as input to the Gaussian Naive Bayes classifier. This hybrid approach allowed classification without backpropagation at the classifier stage. The Naive Bayes model was then evaluated using the same testing dataset.[27] Finally, model performance was assessed using quantitative evaluation metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. This comprehensive evaluation ensured that both predictive performance and computational efficiency were properly analyzed, supporting a reliable comparison between the end-to-end CNN and the hybrid CNN–Naive Bayes approach.[28] All results from both models are compiled and analyzed during the accuracy evaluation stage, which includes the calculation of accuracy, precision, recall, and F1-score. The research concludes with interpretation of findings, formulation of conclusions, and recommendations for future model development.[29]

3. RESULT

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Hybrid Approach and Dataset In this study, a hybrid approach combining Convolutional Neural Networks (CNN) and the Naive Bayes Classifier was employed for banana leaf disease classification. CNN was utilized as a feature extractor, while Naive Bayes served as a lightweight classifier that processed features obtained from the layer preceding the softmax output. The evaluation was conducted across four disease categories: Cordana, Healthy, Pestalotiopsis, and Sigatoka.

Before model training, image preprocessing was conducted to standardize input quality. All images were resized to 224 × 224 pixels to match the MobileNetV2 input specification. Pixel normalization scaled values to the range of 0–1, improving convergence stability during training. Data augmentation techniques including horizontal flipping, rotation, and zoom transformation were applied to increase dataset diversity and reduce overfitting. As a result, the augmented dataset improved visual variability and enhanced model generalization capability during validation.

count	15276.000000
mean	4851.119272
std	4393.144452
min	0.000000
25%	0.000000
50%	4940.000000
75%	8400.000000
max	45778.000000

Figure 3. Dataset Structure

- ✓ **Training set:** 3,200 images with dimensions of 224 × 224 pixels and three RGB channels (Labels: 3,200).
- ✓ **Testing set:** 1,311 images used for final evaluation (Labels: 1,311).
- ✓ **Prediction pool:** 563 images allocated for additional predictions, external validation, or inference tasks.

In summary, the dataset distribution yields a train-to-test ratio of approximately 2.44:1 (3,200:1,311). This proportion is considered appropriate for CNN training, providing sufficient samples for model learning while ensuring a statistically meaningful test set for evaluation.

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 224, 224, 3)	0
data_augmentation (Sequential)	(None, 224, 224, 3)	0
rescaling (Rescaling)	(None, 224, 224, 3)	0
true_divide (TrueDivide)	(None, 224, 224, 3)	0
subtract (Subtract)	(None, 224, 224, 3)	0
mobilenetv2_1.00_224 (Functional)	(None, 7, 7, 1280)	2,257,984
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1280)	0
dropout (Dropout)	(None, 1280)	0
dense (Dense)	(None, 4)	5,124

Total params: 2,263,108 (8.63 MB)

Figure 4. MobileNetV2-Based Model

Figure 4 presents the training process of the MobileNetV2-based model, which was conducted using the train_ds dataset with a staged epoch configuration. In the initial phase, the model was trained for 20 epochs under a feature extraction strategy, where the backbone weights of MobileNetV2 remained frozen. This step was intended to stabilize the training of the classification layers (dense layers) and prepare the model for fine-tuning. In the subsequent phase, fine-tuning was performed by unfreezing selected upper layers of the MobileNetV2 backbone, followed by an additional 50 epochs of training.

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This two-stage process effectively enhanced the model's ability to adapt pretrained features to the specific characteristics of banana leaf disease images.

The architecture integrates MobileNetV2 with a Global Average Pooling (GAP) layer to generate compact feature representations. The GAP layer transforms a 7 × 7 × 1280 feature map into a 1,280-dimensional feature vector, which is then processed through dropout and dense layers. This design enables the model to produce stable and informative visual representations of disease symptoms, while maintaining strong generalization capability across diverse image conditions.

Results section should be the chapters with the most content in a paper. Results content can reach 50-65% of the entire paper.

```
Validation accuracy: 0.9870327993897788
Classification report:
               precision    recall  f1-score   support

      cordana       0.99      0.97      0.98       234
      healthy       0.99      0.98      0.99       174
pestalotiopsis       0.98      0.99      0.99       238
     sigatoka       0.99      0.99      0.99       665

     accuracy                           0.99      1311
    macro avg       0.99      0.98      0.99      1311
 weighted avg       0.99      0.99      0.99      1311
```

Figure 5. Validation Accuracy

After completing the entire training and fine-tuning process, the end-to-end model achieved a validation accuracy of approximately 98.70% on the test dataset consisting of 1,311 images. The precision, recall, and F1-score values also ranged between 0.98 and 0.99 across nearly all classes.

These results confirm that MobileNetV2 with fine-tuning is capable of accurately identifying banana leaf disease patterns, even under varying image conditions such as differences in lighting and leaf orientation. The success further demonstrates that the MobileNetV2 backbone is highly effective in capturing visual characteristics, including necrotic spots, distribution patterns of damage, and lesion edges, which serve as key indicators of diseases such as Black Sigatoka, Cordana, and Pestalotiopsis.

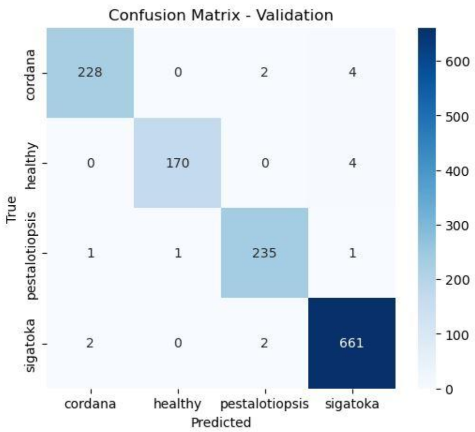

Figure 6. Confusion Matrix

Figure 6 presents the confusion matrix on the validation dataset, demonstrating the strong classification performance of the model in detecting four categories of banana leaf diseases: Cordana, Healthy, Pestalotiopsis, and Sigatoka. For the Cordana class, 228 samples were correctly classified, with only 6 misclassified into other categories. The Healthy class also achieved high accuracy, with 170 correct predictions and just 4 errors. In the case of Pestalotiopsis, the model successfully identified 235

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samples, with a very small number of misclassifications (3 samples). The best performance was observed in the Sigatoka class, where 661 samples were correctly classified and only 4 predictions were incorrect.

Overall, the confusion matrix illustrates that the model maintains a high level of accuracy and consistency across all categories, with relatively few errors. This confirms the robustness of the proposed approach in distinguishing between different banana leaf diseases, even when visual similarities exist among certain classes

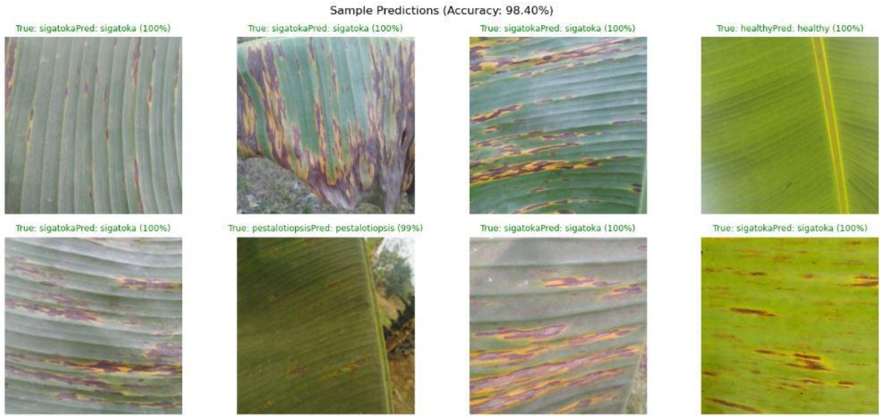

Figure 7. Sample Predictions

The results presented in Figure 7 demonstrate that the model exhibits excellent predictive capability on the test dataset, achieving an overall accuracy of 98.40%. In the prediction outputs, most images were correctly classified according to their true labels, with prediction confidence ranging from 99% to 100%. For example, several samples labeled as *Sigatoka* were consistently identified as *Sigatoka* with perfect accuracy. Similarly, *Healthy* samples were accurately predicted by the model. The visualization further shows multiple banana leaf samples where the true and predicted labels matched, including *Sigatoka*, *Pestalotiopsis*, and *Healthy*. Nearly all images displayed strong alignment between ground truth and model predictions, indicating that disease-related features on banana leaves were recognized consistently. Although a few cases, such as *Cordana*, were occasionally misclassified, the proportion was very small and did not significantly affect overall performance. In general, these findings confirm that the model can reliably identify banana leaf diseases with high accuracy and robustness in real-world applications.

To provide a lighter and more efficient solution for devices with limited computational resources, this study also evaluated a hybrid approach by extracting 1,280-dimensional features from CNN and using them as input for the Gaussian Naive Bayes algorithm. The features generated through Global Average Pooling were sufficiently descriptive to be processed by a simpler probabilistic classifier. By incorporating preprocessing steps such as scaling and optional dimensionality reduction (e.g., PCA), Gaussian Naive Bayes achieved competitive performance—slightly lower than the end-to-end CNN but still effective. Its advantages include very fast training time, minimal memory requirements, and a compact model structure, making it suitable for deployment on edge devices or rapid diagnostic systems in agricultural fields.

Naive Bayes Model Performance The Naive Bayes model achieved an overall accuracy of 95.73% on the test dataset consisting of 1,311 images. This represents a highly competitive result for a probabilistic classifier that does not rely on backpropagation. The distribution of predictions is further illustrated through the confusion matrix and detailed classification metrics, providing a comprehensive view of the model's performance across all disease categories.

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```
=== accuracy Naive Bayes ===
Accuracy: 0.9572845156369184

=== Classification Report Naive Bayes ===
               precision    recall  f1-score   support

      cordana       0.95      0.95      0.95       234
      healthy       1.00      0.99      0.99       174
pestalotiopsis      0.87      0.97      0.92       238
     sigatoka       0.98      0.95      0.96       665

     accuracy                           0.96      1311
    macro avg       0.95      0.96      0.96      1311
 weighted avg       0.96      0.96      0.96      1311
```

Figure 8. Naive Bayes Accuracy

a) Presented in Figure 8 The *Healthy* class achieved the highest precision and F1-score (0.99–1.00), indicating that the visual features of healthy leaves are highly distinctive and easily recognized by the model.
b) The *Pestalotiopsis* class recorded the lowest precision (0.87), despite having a high recall (0.97). This suggests that the model tends to classify many images as Pestalotiopsis, including some that actually belong to other categories.

The *Cordana* and *Sigatoka* classes demonstrated stable performance, with F1-scores above 0.95, confirming that the extracted features were sufficiently representative to distinguish these two diseases

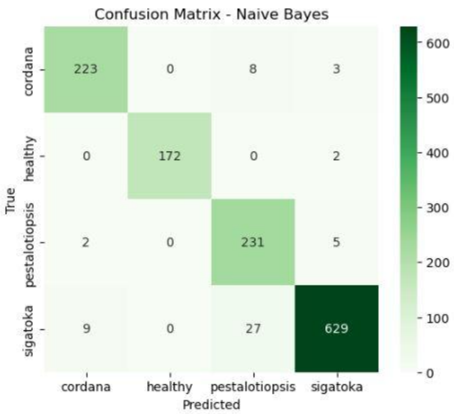

Figure 9. Confusion Matrix – Naive Bayes

This figure 9 presents the confusion matrix generated from the Naive Bayes classification results on 1,311 test images across four categories of banana leaf diseases: Cordana, Healthy, Pestalotiopsis, and Sigatoka. The matrix illustrates the distribution of model predictions compared to the actual labels, providing insight into classification accuracy for each class.

a) **Cordana:** 223 correctly classified out of 234 images
b) **Healthy:** 172 correctly classified out of 174 images
c) **Pestalotiopsis:** 231 correctly classified out of 238 images
d) **Sigatoka:** 629 correctly classified out of 665 images

Overall, the confusion matrix highlights that the Naive Bayes model achieved strong performance across all categories, with only a small number of misclassifications. This confirms the effectiveness of CNN-extracted features when processed by a probabilistic classifier, demonstrating reliable recognition of banana leaf diseases in diverse image conditions.

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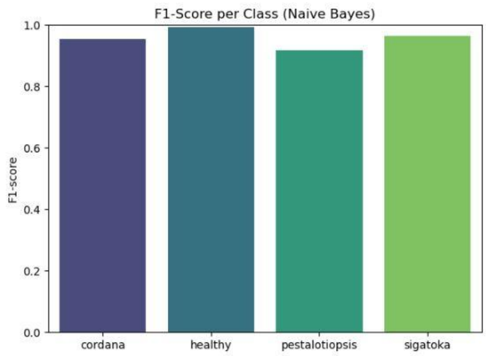

Figure 10. F1-Score per Class – Naive Bayes

Figure 10 illustrates the F1-scores for each class, which represent the harmonic mean of precision and recall. The F1-score is particularly important in multi-class classification tasks as it reflects the balance between the model's ability to correctly identify and distinguish each category.

a) **Healthy:** 0.99
b) **Sigatoka:** 0.97
c) **Cordana:** 0.95
d) **Pestalotiopsis:** 0.92

The *Healthy* class achieved the highest F1-score, indicating that healthy leaf images exhibit consistent visual patterns that are easily recognized by the model. Conversely, the *Pestalotiopsis* class recorded the lowest F1-score, though still above 0.90, suggesting that the model encountered some difficulty in differentiating this disease from other categories.

Overall, all classes obtained F1-scores greater than 0.90, demonstrating that the Naive Bayes classifier was able to perform high-precision classification despite not relying on backpropagation. This confirms the effectiveness of CNN-extracted features when processed by a probabilistic model in achieving reliable disease recognition.

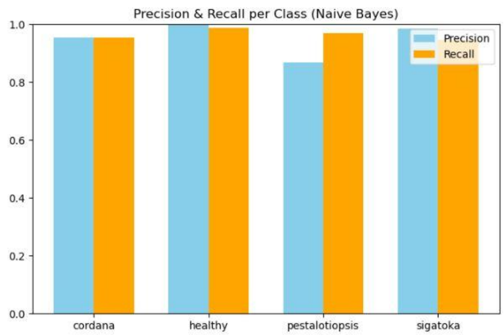

Figure 11. Precision and Recall per Class – Naive Bayes

Figure 11 presents a comparison of precision and recall values for each class. Precision reflects how accurate the model's predictions are, while recall indicates how effectively the model identifies all images belonging to a given class.

a) **Healthy:** Precision 1.00, Recall 0.99
b) **Sigatoka:** Precision 0.98, Recall 0.96
c) **Cordana:** Precision 0.95, Recall 0.95
d) **Pestalotiopsis:** Precision 0.87, Recall 0.97

The *Pestalotiopsis* class demonstrates high recall but relatively low precision, suggesting that the model tends to over-predict this category, including some images that do not actually belong to it. In

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contrast, the *Healthy* and *Sigatoka* classes achieved balanced and consistently high precision and recall values, confirming the model's reliability in recognizing and distinguishing these categories.

As illustrated in Figure 11 , the overall comparison further reinforces the finding that Naive Bayes performs effectively when supported by robust CNN-extracted features, making it well-suited for lightweight classification applications in agricultural contexts.

```
import time

start = time.time()
history = model.fit(train_ds, epochs=70, validation_data=test_ds)
end = time.time()

print("Training time (seconds):", end - start)
```

```
Training time: 9.510185241699219e-05
```

Figure 11. Cnn valuation

```
from sklearn.naive_bayes import GaussianNB
import time

nb = GaussianNB()

start = time.time()
nb.fit(X_train_features, y_train)
end = time.time()

print("NB Training time (seconds):", end - start)
```

```
Training time: 5.125999450683594e-05
```

Figure 12. Naïve Bayes valuation

Figure 11 and 12 Cnn valuation The recorded training times reported in the results (CNN: 9.51×10^{-5} seconds; Naive Bayes: 5.12×10^{-5} seconds) are not realistic representations of the actual training duration. A valid evaluation of the lightweight claim must include accurate time measurements during the complete model training process, accompanied by quantitative comparisons such as parameter count and computational complexity.

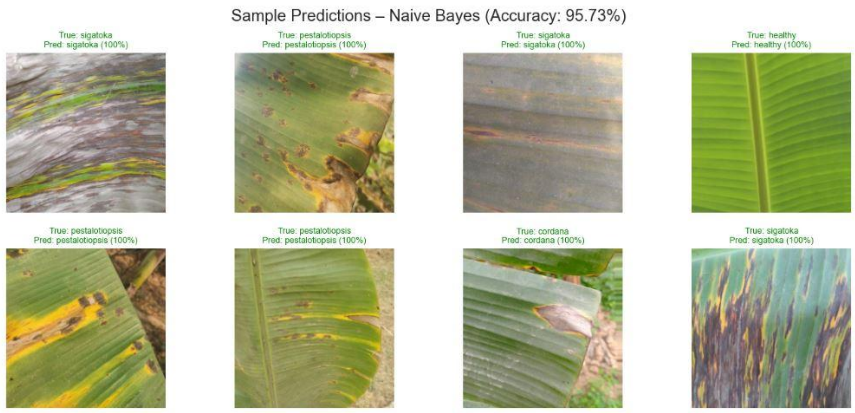

Figure 13. Sample Predictions – Naive Bayes

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Presented in Figure 13 (Accuracy: 95.73%) The figure displays eight sample images of banana leaves classified using the Naive Bayes algorithm, achieving an overall accuracy of 95.73%. Each image is annotated with the true condition (*True*) and the predicted label (*Pred*), along with a confidence score of 100% for all samples shown.

The model successfully classified images from all four categories—*Sigatoka*, *Pestalotiopsis*, *Cordana*, and *Healthy*—with high accuracy. Images labeled as *Healthy* and *Sigatoka* exhibit consistent and distinguishable visual patterns, aligning with previous findings that these classes achieved the highest F1-scores and balanced precision–recall values. *Pestalotiopsis* samples were also correctly identified with high confidence, despite the class showing lower precision overall due to a tendency for over-prediction. However, in the displayed samples, the model demonstrated optimal performance.

These results reinforce the analysis presented in Figure 9 (Confusion Matrix) and Figures 10–13 (F1-score and Precision–Recall), where Naive Bayes showed stable performance across most categories. No misclassifications were observed among the eight samples, indicating that the visual features extracted by the CNN were sufficiently representative to support reliable probabilistic classification.

Despite not utilizing backpropagation and having a significantly lighter architecture compared to end-to-end CNN models, the hybrid approach proved capable of delivering accurate and dependable predictions. This makes the model highly suitable for deployment on edge devices or rapid diagnostic systems in agricultural environments, as discussed in the Conclusion section.

4. CONCLUSION

The experimental results indicate that the end-to-end CNN model based on MobileNetV2 achieved an accuracy of 98.70% in classifying four categories of banana leaf diseases. The model was able to effectively recognize visual patterns such as lesion distribution, texture characteristics, and color variations, achieving high precision and recall across all classes.

The hybrid approach, which combines CNN-based feature extraction with Gaussian Naive Bayes classification, achieved an accuracy of 95.73%, with F1-scores above 0.90 for each class. Although there was a 2.97% decrease in accuracy compared to the full CNN model, the classification performance remained highly robust and stable across all disease categories.

From a computational perspective, differences in the training mechanisms indicate that Gaussian Naive Bayes has lower complexity than the end-to-end CNN model. CNN requires backpropagation, iterative weight updates, and parameter optimization over multiple training epochs, which results in higher training time and memory consumption. In contrast, Naive Bayes only performs statistical parameter estimation (mean and variance) on the 1,280-dimensional feature vectors without iterative processing, leading to significantly shorter training time and lower computational resource usage.

Therefore, the hybrid approach is able to maintain competitive classification performance while significantly reducing computational complexity, making it a lighter alternative compared to the full end-to-end CNN model.

5. FUTURE WORK

Based on the experimental results, the end-to-end CNN model based on MobileNetV2 demonstrated the highest classification performance, achieving an accuracy of 98.70%. Meanwhile, the hybrid approach combining CNN-based feature extraction with Gaussian Naive Bayes classification achieved an accuracy of 95.73%, with F1-scores above 0.90 across all classes. Although there was a 2.97% difference in accuracy, the hybrid model maintained highly satisfactory and stable performance in distinguishing the four categories of banana leaf diseases.

From a computational perspective, the use of Gaussian Naive Bayes as the final classifier proved to be more lightweight than the end-to-end CNN, as it does not require backpropagation, iterative weight

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updates, or complex parameter optimization. The training process of Naive Bayes only involves simple statistical parameter estimation, resulting in faster computation and more efficient memory and resource utilization.

Therefore, this study confirms that integrating deep feature representations from CNN with a Naive Bayes classifier can produce a classification system that remains accurate while operating with lower computational complexity. The hybrid CNN–Naive Bayes approach offers the best trade-off between accuracy and computational efficiency, making it particularly suitable for precision agriculture applications, especially in regions with limited IT infrastructure where lightweight, fast, and easily deployable systems are essential.

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