# Development of a Classification Model for Banana Leaf Disease Using Google Teachable Machine


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***Abstract*—This research developed a machine learning model using Google Teachable Machine and the MobileNetV2 architecture to classify various banana leaf diseases. Banana plants, critical to global agriculture, are highly vulnerable to diseases that can greatly reduce both yield and quality. Early and precise detection of these diseases is crucial for effective management and maintaining crop health. The study utilized 408 images of banana leaves showing conditions like Black Sigatoka, Bract Mosaic, Insect Pest, Moko Disease, Panama Disease, Yellow Sigatoka, and healthy leaves. Through image augmentation, the dataset was expanded to 3,264 images to improve the model's ability to generalize. The data was split into 85% for training and 15% for testing. After training for 50 epochs, the model achieved an accuracy of 98.17%, with precision, recall, and F1-scores all surpassing 97%. The model performed particularly well in detecting Bract Mosaic, Moko Disease, and Panama Disease, while minor misclassifications occurred between visually similar diseases such as Black and Yellow Sigatoka. When compared to other models like AlexNet and LeNet, which reported accuracies of 87.5% and 99.72%, respectively, the MobileNetV2 model strikes a balance between high accuracy and efficiency. This model shows promise for deployment as a real-time disease detection tool through mobile applications, particularly benefiting small-scale farmers. Future improvements could involve expanding the dataset and optimizing the model for a wider range of environmental conditions to enhance its agricultural use.**



***Keywords*— banana leaf disease, machine learning, disease classification, Google Teachable Machine, MobileNetV2**


## I. Introduction

Banana is a staple crop in many regions of the world, with significant economic and nutritional importance. However, the productivity of banana plantations is often threatened by various diseases and pests that affect the plant's leaves, leading to reduced yield and quality. To address this challenge, the use of advanced technologies, such as machine learning and computer vision, has emerged as a promising approach for the early detection and classification of banana leaf disease conditions. [1]

Globally, banana diseases pose a significant threat to agricultural productivity. Countries in Africa and Latin America have seen severe crop yield reductions due to similar diseases. Several studies have explored machine learning models for banana disease detection in regions like South America and Asia, which further validate the necessity of such technologies.

In the Philippines, among the most common banana leaf diseases are black Sigatoka, and yellow Sigatoka [2]. In addition to black Sigatoka and yellow Sigatoka, the researchers also included Bract Mosaic, Healthy Leaf, Insect Pest, Moko Disease, and Panama Disease in their study.

These diseases can be detected through visual inspection of the leaf, but manual identification is time-consuming and prone to error, especially for small-scale and resource-limited farmers. Accurately detecting and classifying these diseases at an early stage is crucial for effective disease management and maintaining healthy banana crops.

Machine learning, and in particular deep learning techniques, have shown great promise in automating the identification of plant diseases from visual data [1] [2]. Recent studies have explored the use of convolutional neural networks for the classification of banana leaf diseases [2] [3] [4]. These studies have demonstrated the feasibility of developing accurate models for disease detection, paving the way for the development of practical, mobile-based applications that can support farmers in the field.

This study focuses on developing a machine learning model to identify diseases in banana leaves using Google Teachable Machine, a platform designed for easy model creation and deployment. The model will be trained with a dataset of banana leaf images showing different disease states and healthy conditions. After training, the model's effectiveness will be evaluated for practical application. Google Teachable Machine provides a simple interface that enables researchers to build machine learning models without requiring advanced programming skills.

Recent studies in banana leaf disease detection have predominantly focused on the application of deep learning models such as Convolutional Neural Networks (CNNs). For instance, Amara et al.[2] developed a CNN-based model for banana leaf classification, achieving an accuracy of 97%. While CNNs have proven effective, they often require substantial computational resources and technical expertise.

In contrast, our study utilizes the Google Teachable Machine, a more accessible and user-friendly platform that enables non-experts to rapidly train models without requiring advanced programming skills. Despite the simplicity of the platform, our model delivers competitive results, demonstrating that practical solutions can be achieved with less complex tools.

## II. Methodology

The researcher employed Google Teachable Machine to build a model for classifying banana leaf diseases. The model's training will involve a dataset containing images of banana leaves affected by conditions such as black sigatoka, bract mosaic, insect pests, moko disease, Panama disease, yellow sigatoka, as well as healthy leaves.

Fig. 1 presents the training interface of Google Teachable Machine, a platform designed for ease of use. This platform enables users to create and train custom machine learning models without needing advanced technical skills. Its interface guides users through each stage of the process, from data input to model training and evaluation, providing a simple and efficient workflow tailored for beginners and professionals alike.

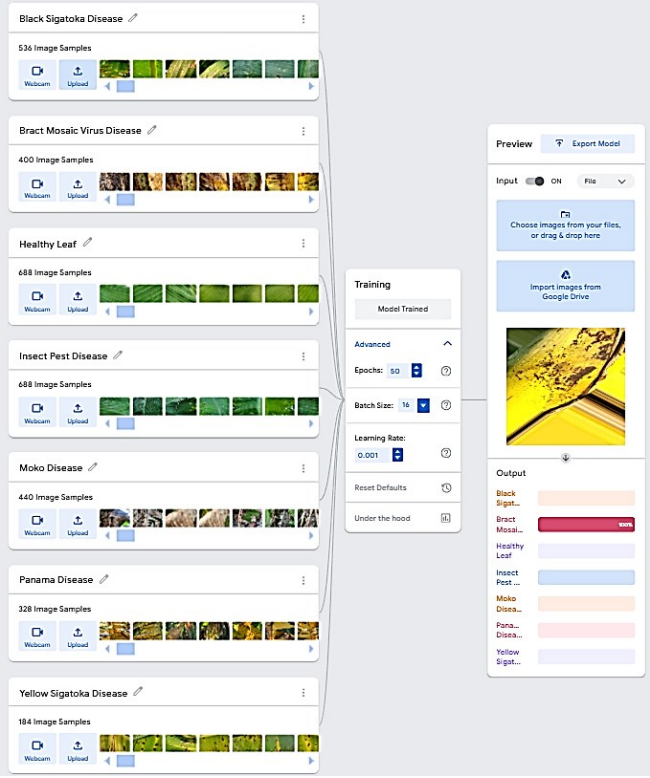


Fig. 1. Training Interface of Google Teachable Machine

### A. Dataset Collection

The dataset comprises a total of 408 banana leaf images, categorized into different conditions: 67 images of black sigatoka, 50 of bract mosaic, 86 of insect pest damage, 55 of moko disease, 41 of Panama disease, 23 of yellow sigatoka, and 86 representing healthy leaves [5]. Fig. 2 provides a visual sample of the dataset featuring Black Sigatoka.

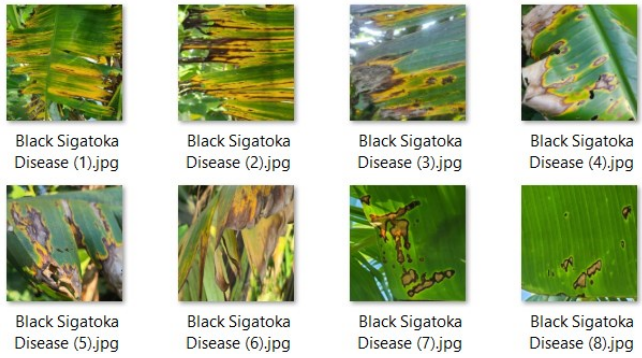


Fig. 2. Sample Dataset of Banana Leaf Diseases Images showing Black Sigatoka

### B. Dataset Preprocessing

The banana leaf image dataset was enhanced using augmentation techniques like rotation, flipping, and scaling. These augmented images were added to the dataset to increase the diversity of the training data. By applying techniques such as rotation and flipping, the dataset's variety was expanded, enabling the model to generalize more effectively. The final dataset now contains 3,264 images, distributed as follows: 536 black sigatoka, 400 bract mosaic, 688 insect pest, 440 moko disease, 328 Panama disease, 184 yellow sigatoka, and 688 healthy images.

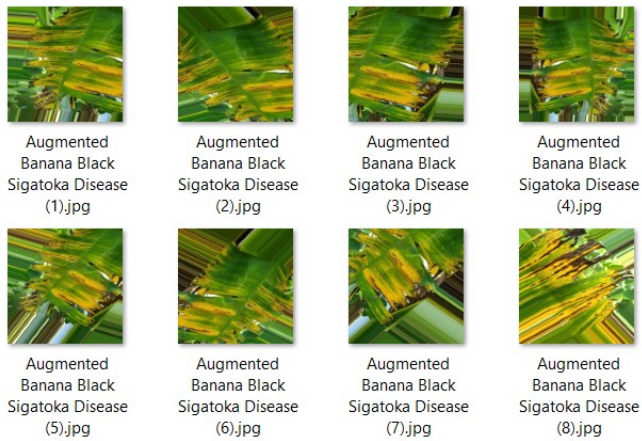


Fig. 3. Sample Augmented Dataset of Banana Leaf Disease Images showing Black Sigatoka

### C. Dataset Splitting

The dataset was strategically split into training and testing sets to assess the model's ability to generalize and accurately predict outcomes. A majority, 85%, was allocated for training purposes to help the model learn from a wide range of data. The remaining 15% was set aside exclusively for testing, ensuring a robust evaluation of the model's performance and its capacity to handle new, unseen data.

The Teachable Machine platform provides the flexibility to adjust various hyperparameters to fine-tune the model's performance. Fig. 4 presents the hyperparameter configuration utilized in this study, which includes setting the number of training epochs to 50, a learning rate of 0.001, and a batch size of 16. These values were chosen to optimize the model's learning process and overall performance.

Google Teachable Machine utilizes MobileNet, specifically MobileNetV2, as the core architecture for image classification. MobileNetV2 is selected for its lightweight nature and efficiency, making it ideal for mobile device deployment. It strikes a balance between processing speed and accuracy, making it more suitable for real-time applications compared to heavier models like ResNet, which require more computational resources. This makes MobileNetV2 an optimal choice for tasks where both performance and resource efficiency are crucial.

### *D. Setting the Hyperparameters and Training the Model*

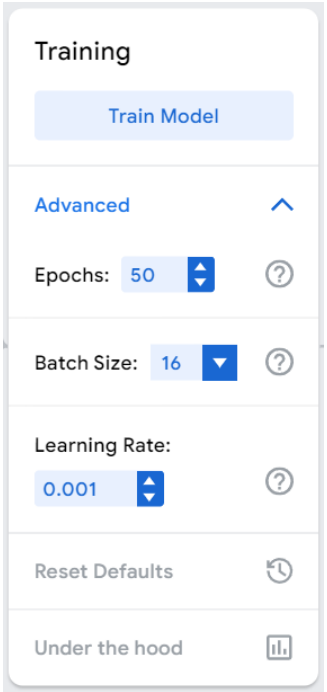


Fig. 4. Hyperparameter Settings Configured in the Teachable Machine

### *E. Evaluating the Model's Performance*

The performance of the trained model from Teachable Machine will be evaluated using several standard classification metrics. These include accuracy, which shows how often the model's predictions are correct; precision, which measures how many of the positive predictions are actually correct; recall, which assesses how well the model identifies all positive cases; and the F1-score, which balances precision and recall for a more comprehensive evaluation. These metrics offer valuable insights into the model's overall accuracy and ability to detect corn leaf diseases effectively. [6]

## III. Data and Results

In the Data and Results section, the researchers analyze the model's classification performance across the different banana leaf disease categories.

Fig. 5 presents a sample output from the Google Teachable Machine model, demonstrating the classification of a banana leaf image. The model predicts the class of the leaf based on its appearance, and the results are displayed in the output section. In this instance, the model confidently identifies the leaf as being affected by "Bract Mosaic" with a 100% certainty. The remaining classes, including Black Sigatoka, Healthy Leaf, Insect Pest, Moko Disease, Panama Disease, and Yellow Sigatoka, are assigned much lower probabilities, indicating that the model is certain the leaf is not affected by those diseases.

Fig. 6 presents the confusion matrix for the classification model developed using Google Teachable Machine. This matrix offers a comprehensive view of the model's performance across different classes, indicating how accurately it predicted each category. The rows represent the actual class labels, while the columns show the predicted labels.

For instance, the model successfully identified 77 instances of "Black Sigatoka," though it mistakenly classified 2 instances as "Yellow Sigatoka." The model demonstrated flawless classification for "Bract Mosaic" with 60 correct predictions and "Healthy Leaf" with 104 correct predictions, with no misclassifications in these categories. Other classes, such as "Insect Pest," "Moko Disease," "Panama Disease," and "Yellow Sigatoka," also showed high accuracy with minimal errors. Correct classifications are represented on the diagonal, with the color intensity reflecting the number of correct predictions, as indicated by the scale on the right.

Although the model achieved a high level of accuracy, there were some misclassifications, particularly between Black Sigatoka and Yellow Sigatoka, likely due to visual similarities in their early stages. Additional research into advanced feature extraction techniques may help minimize such errors in the future.

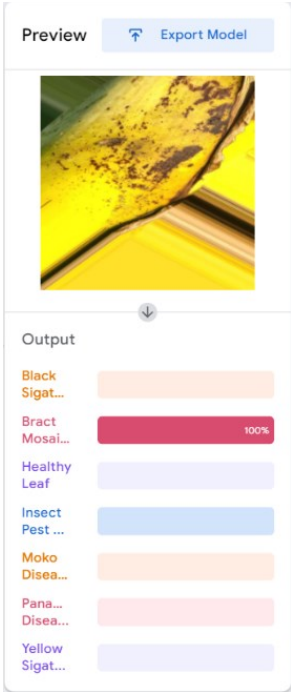


Fig. 5. Google Teachable Machine Model's Sample Output

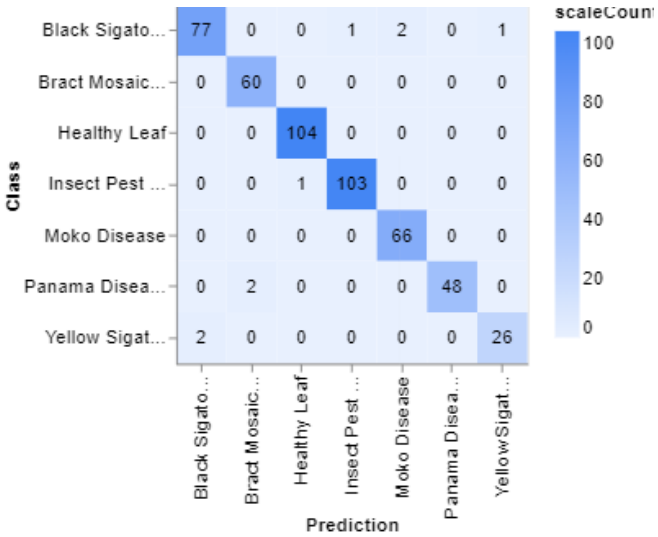


Fig. 6. Confusion Matrix

Fig. 7 depicts the model's accuracy progression over 50 epochs for both the training and test datasets. The graph shows a sharp rise in accuracy during the early epochs, indicating the model's rapid learning from the dataset. By around the 10th epoch, both the training accuracy (represented by the blue line) and the testing accuracy (represented by the orange line) reach nearly perfect values, close to 1.0. This steady performance throughout the remaining epochs suggests the model has achieved optimal accuracy early in the training process, with no apparent issues of overfitting or underfitting.

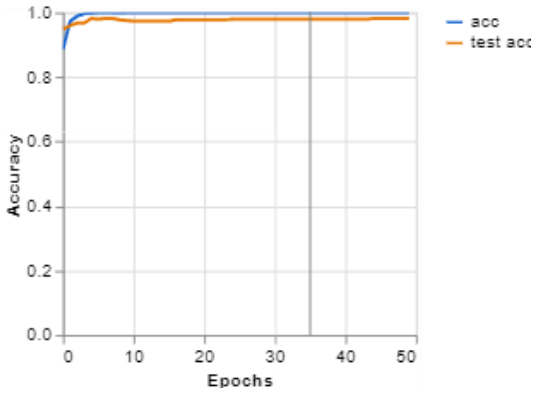


Fig. 7. Accuracy per Epoch

Fig. 8 illustrates the training and testing loss of the model over 50 epochs. Loss serves as a key indicator of the model's performance, with lower values signifying a better fit to the data. The training loss (shown by the blue line) drops steeply during the initial epochs, reaching a minimal value around the 10th epoch, indicating that the model quickly learns and optimizes its parameters. The test loss (depicted by the orange line) follows a similar downward trend, significantly decreasing within the first few epochs. After reaching a low point, the test loss stabilizes, suggesting that the model has reached a point where further improvement is minimal. While the test loss remains slightly higher than the training loss, this is typical and indicates good generalization without signs of overfitting.

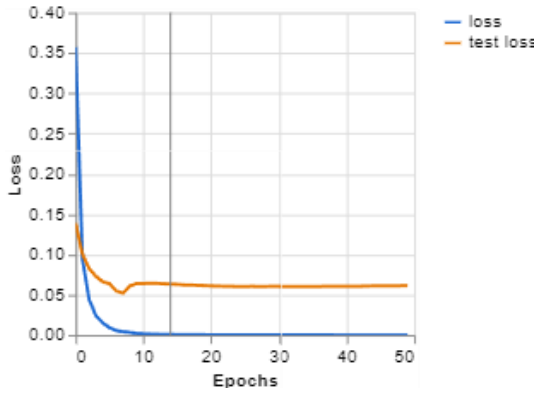


Fig. 8. Loss per Epoch

Table 1 outlines the performance metrics for each class, derived from the confusion matrix results. The metrics—Accuracy, Precision, Recall, and F1-Score—are reported for all seven categories: Black Sigatoka, Bract Mosaic, Healthy Leaf, Insect Pest, Moko Disease, Panama Disease, and Yellow Sigatoka. The model achieved consistently high classification accuracy, ranging from 0.99 to 1.00 across all classes. Similarly, Precision, Recall, and F1-Score also reflect strong performance, with most classes showing near-perfect or perfect scores.

TABLE I. METRICS PER CLASS

| *Class* | *Accuracy* | *Precision* | *Recall* | *F1-Score* | *No. of Samples* |
|---|---|---|---|---|---|
| Black Sigatoka | 0.9878 | 0.9747 | 0.9506 | 0.9625 | 80 |
| Bract Mosaic | 0.9959 | 0.9677 | 1.0000 | 0.9836 | 60 |
| Healthy Leaf | 0.9959 | 0.9811 | 1.0000 | 0.9905 | 104 |
| Insect Pest | 0.9939 | 0.9810 | 0.9904 | 0.9856 | 104 |
| Moko Disease | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 66 |
| Panama Disease | 0.9959 | 1.0000 | 0.9600 | 0.9796 | 48 |
| Yellow Sigatoka | 0.9939 | 0.9630 | 0.9286 | 0.9454 | 28 |

In particular, the Bract Mosaic, Moko Disease, and Panama Disease categories achieved flawless results (1.00) across all metrics, indicating the model made no classification errors for these classes. Black Sigatoka and Insect Pest also displayed competitive scores, with only slight deviations, demonstrating the model's strong capability to classify these conditions. This high level of performance highlights the model's effectiveness as a reliable tool for detecting and differentiating various banana leaf diseases, making it valuable for agricultural disease diagnosis.

Table 2 presents the performance metrics and dataset details of various machine learning models for banana leaf disease classification. The model developed in this study using MobileNetV2 on Google Teachable Machine, trained on an augmented dataset of 408 images expanded to 3264 images across seven disease categories, achieved an impressive accuracy of 98.17%, with precision, recall, and F1-scores all exceeding 97%. The model performed exceptionally well in

detecting diseases such as Bract Mosaic, Moko Disease, and Panama Disease, though it showed slight misclassifications between the visually similar Black and Yellow Sigatoka diseases.

In comparison, Criollo et al.'s [4] AlexNet-based CNN, trained on a smaller dataset of 623 images (comprising three classes: Black Sigatoka, Bacterial Wilt, and Healthy leaves), achieved an accuracy of 87.5%, with balanced precision, recall, and F1-scores. The smaller dataset likely limited the model's performance, but it still demonstrated reliable results given the data constraints.

Amara et al.'s [2] LeNet model, trained on a larger dataset of 3700 images (covering Healthy, Black Sigatoka, and Black Speckle categories), reported the highest accuracy at 99.72%, excelling particularly in color image classification. However, its performance declined when tested on grayscale images, especially when the size of the training set was reduced.

Selvaraj et al [1]. explored more advanced architectures such as ResNet50, InceptionV2, and MobileNetV1, trained on a large dataset with 18 disease and pest categories collected from Africa and India. While specific precision, recall, and F1-scores were not reported, the ResNet50 and InceptionV2 models achieved over 90% accuracy, indicating their potential for deployment in mobile applications for real-time disease detection.

The results suggest that while simpler models like AlexNet perform reasonably well with smaller datasets, more complex architectures such as ResNet50 and InceptionV2 provide significantly higher accuracy, particularly when trained on larger and more diverse datasets. This highlights the importance of both dataset size and model complexity in achieving superior classification performance.

TABLE II. COMPARISON OF MACHINE LEARNING MODELS FOR BANANA LEAF DISEASE CLASSIFICATION ACROSS MULTIPLE STUDIES

| ***Study*** | ***Model Architecture*** | ***Accuracy*** | ***Precision*** | ***Recall*** | ***F1-Score*** | ***Dataset Details*** | ***Highlights*** |
|---|---|---|---|---|---|---|---|
| This Study | MobileNetV2 (Teachable Machine) | 98.17% | 98.11% | 97.57% | 97.82% | 408 images, augmented to 3264 images (7 disease categories: Black Sigatoka, Bract Mosaic, etc.) | High precision and recall across classes. Achieved perfect scores for Bract Mosaic, Moko Disease, and Panama Disease. Slight misclassifications between Black and Yellow Sigatoka. |
| Criollo et al. [4] | CNN (AlexNet-based) | 87.5% | 87.04% | 87.5% | 87.39% | 3 classes: Black Sigatoka (43 images), Bacterial Wilt (220), Healthy (360) | No regularization model performed best with 87.5% accuracy. Balanced dataset used for cross-validation and test sets. |
| Amara et al. [2] | CNN (LeNet) | 99.72% | 99.70% | 99.72% | 99.71% | 3 classes: Healthy (1643 images), Black Sigatoka (240), Black Speckle (1817) | High performance on color images. Model was less accurate on grayscale images, especially when training data was reduced (accuracy dropped to 85.28%). |
| Selvaraj et al. [1] | ResNet50, InceptionV2, MobileNetV1 | >90% (ResNet50 & InceptionV2) | Not Reported | Not Reported | Not Reported | Large dataset with 18 disease/pest classes collected from Africa and India | Best performing models were ResNet50 and InceptionV2. MobileNetV1 was tested for mobile compatibility, but had lower accuracy. Results across models were benchmarked for future mobile use. |

## IV. CONCLUSION AND RECOMMENDATION

This study successfully developed a banana leaf disease classification model using MobileNetV2 through Google Teachable Machine, achieving an accuracy of 98.17%, with precision, recall, and F1-scores above 97%. The model excelled particularly in classifying diseases like Bract Mosaic, Moko Disease, and Panama Disease, with only minor misclassifications between visually similar diseases such as Black and Yellow Sigatoka. In comparison, other models such as AlexNet-based CNNs [4] achieved 87.5% accuracy, while a LeNet model [2] reported a higher accuracy of 99.72%, although it performed less well on grayscale images. Meanwhile, ResNet50 and InceptionV2 models [1] exceeded 90% accuracy, showing potential for mobile deployment in real-time disease detection. This analysis confirms that different machine learning models can provide robust solutions for banana leaf disease classification, with specific models excelling depending on the dataset and context.

To further enhance the model's robustness and generalization, expanding the dataset by incorporating more images from diverse sources and regions is recommended. This would improve the model's ability to perform under varying environmental conditions. Additionally, deploying the model as a mobile application would allow real-time disease detection, offering valuable support to small-scale farmers with limited access to expert consultation.

Future work should explore advanced techniques such as deeper convolutional neural networks and transfer learning, which could enhance the model's classification accuracy and reduce training time by leveraging pre-trained models. Expanding the model's functionality in this way would make it even more reliable and adaptable for real-world agricultural applications.

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## DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the author(s) used Jenni AI for citation finding and ChatGPT as a writing assistant. After using these tools, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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