Classification of Wild Edible Plants Using InceptionV3 with Transfer Learning and Metadata Integration as Decision Support System

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ABSTRACT

Deep learning has advanced intelligent systems for plant identification; however, distinguishing edible wild plants remains challenging due to limited datasets and the need for contextual information beyond visual classification. This study develops a Convolutional Neural Network (CNN) framework that integrates metadata as a decision support system to enhance food safety and strengthen community-based food security. A dataset of 16,076 images across 34 classes of edible wild plants was collected and enriched with metadata containing plant descriptions, consumption status, and nutritional values. The dataset was split into 75% training, 20% validation, and 5% testing to ensure reliable evaluation. The proposed solution employs InceptionV3 with transfer learning as the primary model, chosen for its ability to capture complex visual features in limited datasets, while MobileNetV3-Large serves as a lightweight comparative architecture. Results show that InceptionV3 achieved superior performance with a test accuracy of 0.87 and F1-score of 0.88, whereas MobileNetV3-Large obtained only 0.03 accuracy, indicating poor generalization. This highlights the importance of selecting architectures with sufficient depth for domains characterized by high visual variability. Metadata integration enhanced the system's role as a decision support tool, providing contextual information such as edibility status and nutritional content. The novelty of this research lies in combining CNN-based classification with metadata integration, transforming the system into a practical framework for safe consumption decisions. Limitations include the dataset containing only edible plants. Future work should incorporate non-edible classes, evaluate performance under real-world conditions, and explore advanced architectures and explainable AI techniques to improve robustness, transparency, and accessibility.

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1. INTRODUCTION

Food security and agricultural sustainability depend on the ability to accurately identify plant species that are safe for consumption. In many rural areas and developing countries, communities still rely on traditional knowledge to distinguish edible plants from harmful ones. However, manual identification is often time-consuming, error-prone, and requires specialized expertise. Reports from the FAO emphasize that global food security challenges remain significant, making technological innovation crucial to ensure access to healthy diets [2]. Indonesia itself possesses extraordinary biodiversity, with approximately 30,000 medicinal plant species out of a global total of 40,000 found within its territory [3]. This condition highlights the relevance of image-based plant classification technology both globally and locally.

The main problem addressed in this study is the absence of a classification system for wild edible plants that combines CNN-based image analysis with metadata integration as a decision support framework. Previous studies have largely focused on cultivated plants or agricultural commodities, leaving the aspect of food safety in wild plants underexplored. This gap has two consequences: (1) health risks for rural communities that rely on alternative food sources, since manual identification is prone to error; and (2) limited utilization of artificial intelligence technologies to strengthen community-based food security. Therefore, a system is needed that can provide fast and accurate identification while also presenting contextual information such as consumption status and nutritional content, enabling safer consumption decisions.

This research carries dual significance: academically, it expands the application of transfer learning and metadata integration in wild plant classification; practically, it offers a tangible solution for food diversification, improved consumption safety, and strengthened food security in regions with limited access to cultivated crops.

Advances in digital image processing and artificial intelligence open opportunities to automate plant identification. Convolutional Neural Networks (CNNs) have proven effective in various image classification tasks, including plant recognition, disease detection, and crop monitoring [4]–[6]. Popular models such as VGGNet, ResNet, Inception, and MobileNet have been widely applied with promising results [7]–[9]. However, most studies focus on cultivated plants, while research on wild edible plant classification remains scarce. Recent studies show that hybrid CNN–Transformer architectures can achieve up to 99% accuracy in leaf disease classification [11], while EfficientNetB3 excels in detecting citrus diseases with 99.58% accuracy [14]. And other study also demonstrated that metadata integration in plant recommendation systems can enhance agricultural decision-making [23].

Additionally, a related study identified 37 species of wild edible plants utilized by the community of Pakis Baru Village as alternative food sources, dominated by vegetables (24 species), tubers (6 species), and fruits (6 species) [24]. However, this study relied on manual identification through interviews and observation, underscoring the need for AI-based approaches to support safer and more accurate consumption of wild plants.

Transfer learning was chosen because it has been proven to improve efficiency and accuracy in limited datasets. The pretrained InceptionV3 model, trained on ImageNet, has been widely applied across domains and demonstrated high effectiveness. For example, in the classification of traditional Ulos fabric motifs using VGG, Inception, and MobileNet, InceptionV3 achieved the highest accuracy [21]. Research on medicinal plant classification in Indonesia also confirmed that InceptionV3 can reach up to 97% accuracy with stable precision, recall, and F1-score [3]. These findings reinforce the relevance of transfer learning in diverse domains and highlight the need for further exploration in wild edible plant classification.

Thus, the research gap addressed here is the lack of metadata integration with deep learning models specifically designed for wild edible plants. The novelty of this study lies in combining InceptionV3 with transfer learning and metadata integration to build a decision support system. InceptionV3 was selected for its deep and modular architecture, capable of capturing complex visual patterns with high accuracy, while MobileNetV3-Large was used as a lightweight comparative model suitable for devices with limited computational resources.

This study aims to fill the gap by developing a CNN-based classification system to detect wild edible plant species. The primary model used is InceptionV3 with transfer learning, trained on a preprocessed and augmented dataset. As a comparison, MobileNetV3-Large was trained with identical augmentation settings, allowing performance differences to be directly attributed to architectural differences. Furthermore, the system integrates metadata such as plant descriptions, consumption status, and nutritional values to strengthen its role as a decision support framework. The expected contribution is to advance academic research in artificial intelligence while providing practical applications in agriculture, food security, and community-based plant identification.

2. RESEARCH METHOD

The flowchart in Figure 1 illustrates the research workflow, starting from the initial stages (dataset and metadata), preprocessing, model selection (InceptionV3 and MobileNetV3-Large), training process, evaluation, and finally deployment and decision support. This workflow emphasizes that the system functions not only as an image classifier but also as a decision support framework through metadata integration.

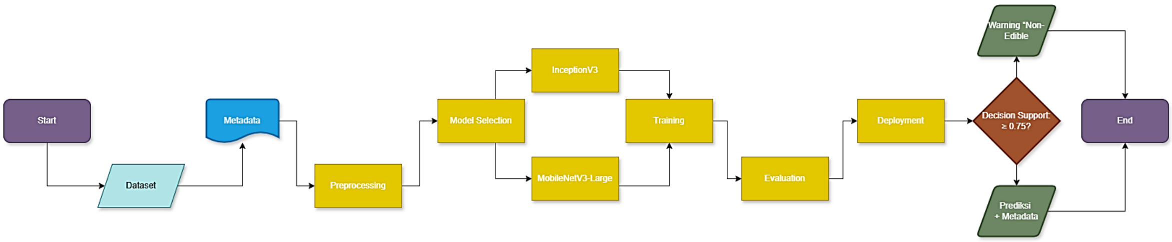

Figure 1. Flowchart Research

2.1 Dataset

The dataset for this study was obtained from the open-source platform Kaggle under the title Edible Wild Plants, which provides a collection of wild edible plant images with verified species labels. This dataset was selected due to the validity of its labels and its direct relevance to the research objectives. The labels were also community-verified, ensuring higher quality ground truth.

The dataset consists of 16,076 images distributed across 34 classes. The number of images per class ranges from 300 to 390, with ground_ivy being the largest class (390 images) and cow_parsley the smallest (300 images). The dataset was split into 75% for training, 20% for validation, and 5% for testing. This partitioning was chosen to ensure reliability: the validation set was used to monitor model generalization during training, while the test set was reserved for final evaluation.

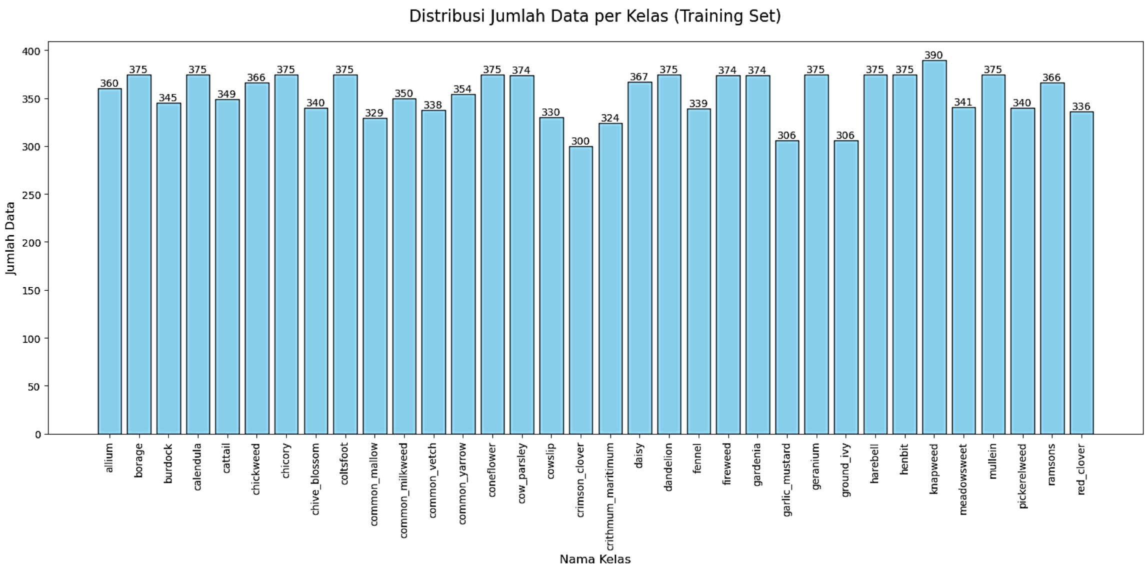

Figure 2. Data Distribution

Figure 2 presents the distribution of data per class in the training set. This visualization is important for assessing dataset balance, as imbalance can affect model performance, particularly on recall and F1-score metrics. Metadata head and tail can be seen in Table 1.

Table 1. Metadata Head and Tail

Name	Description	Status	Nutrition
Allium	Tanaman dalam` genus bawang, termasuk bawang putih dan bawang merah, kaya akan rasa dan sering digunakan sebagai bumbu masakan.	Edible	Mengandung senyawa sulfur, vitamin C, vitamin B6, mangan, dan antioksidan.
Borage	Daun borage memiliki rasa gurih seperti mentimun dan sering digunakan dalam salad atau teh herbal.	Edible	Kaya akan asam lemak gamma-linolenik (GLA), vitamin C, dan serat.
Burdock	Akar burdock sering digunakan dalam masakan Asia dan memiliki rasa manis serta berserat.	Edible	Sumber serat prebiotik, kalium, magnesium, dan antioksidan.
Calendula	Kelopak bunga yang dapat dimakan, sering digunakan sebagai pewarna alami dan bahan teh herbal.	Edible	Mengandung flavonoid, karotenoid, dan vitamin C.
Cattail	Bagian akar dan pucuk muda cattail dapat dimakan, dengan rasa seperti asparagus atau mentimun.	Edible	Mengandung karbohidrat, protein, dan serat.

Name	Description	Status	Nutrition
....	....	....	....
Meadowsweet	Bunga harum sering digunakan dalam teh herbal atau makanan penutup.	Edible	Mengandung senyawa salisilat, antiinflamasi, dan antioksidan.
Mullein	Daun dan bunga digunakan dalam teh herbal untuk kesehatan pernapasan.	Edible	Mengandung senyawa antiinflamasi dan vitamin C.
Pickerelweed	Biji pickerelweed dapat dimakan, sering dimasak sebagai gandum.	Edible	Sumber karbohidrat dan protein.
Ramsons	Daun dan bunga dengan rasa bawang putih, sering digunakan dalam salad atau masakan.	Edible	Mengandung vitamin C, vitamin A, dan senyawa sulfur.
Red Clover	Bunga merah sering digunakan dalam teh herbal atau salad.	Edible	Kaya akan isoflavon, vitamin C, dan zat besi.

In addition to images, the dataset is complemented by a manually constructed metadata file (*edible_plants.csv*) to strengthen the system as a decision support framework. The metadata includes plant descriptions, consumption status (edible/non-edible), and nutritional content. This information is linked to the images through species names, ensuring that each classification result can be directly enriched with relevant contextual information.

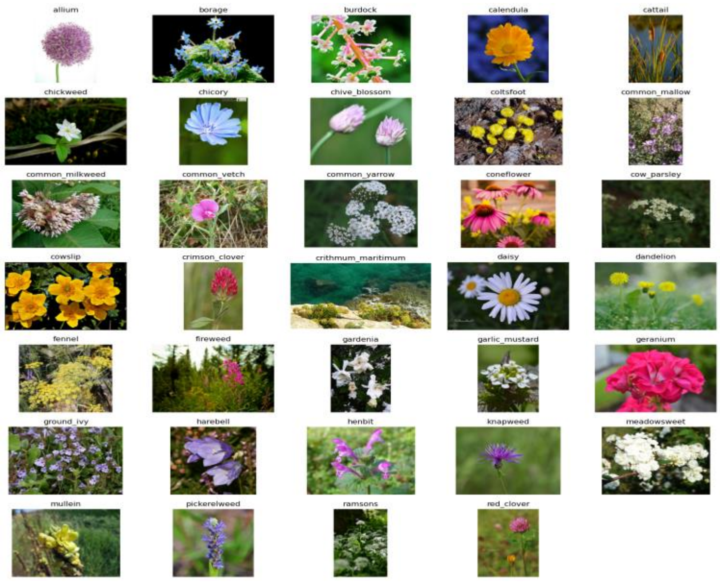

Figure 3. Image Dataset

Figure 3 displays visual examples from each class of wild plants in the dataset. Each image is labeled with the species name to facilitate the identification process and model validation. The main limitation of the dataset is that it only includes edible plants, meaning the model cannot directly distinguish non-edible species. This limitation points to future research directions, where expanding the classification system to include non-edible plants would make it more robust and applicable in real-world contexts.

2.2 Preprocessing

To enhance model generalization and reduce the risk of overfitting, preprocessing was performed through image augmentation. The augmentation techniques applied include:

1. Horizontal and vertical flips to simulate variations in leaf orientation.
2. Width shift (±0.2) and height shift (±0.2) to mimic object displacement within the frame.
3. Rotation (±30°) to introduce viewpoint variations.
4. Shear (0.2) to simulate perspective distortion.
5. Zoom (0.2) to represent differences in image capture distance.
6. Brightness adjustment (±20%) to account for varying lighting conditions in the field.

All images were normalized to a scale of 1/255 to match the CNN input format and accelerate convergence. In addition, cropping was applied to highlight the main leaf area, ensuring that relevant visual features were more dominant than the background. This augmentation strategy not only increased visual diversity but also helped mitigate the impact of dataset imbalance, as classes with fewer samples gained more diverse representations.

Figure 4 displays the augmentation results applied to several classes of wild plants. These visual variations simulate real-world conditions such as changes in viewpoint, lighting, and plant orientation, thereby making the model more robust against noise and minor class imbalances. This approach is consistent with best practices that have been proven to enhance CNN accuracy in plant and leaf disease classification [5][18].

Figure 4. Image Dataset After Augmentation

2.3 Main Model

The primary model used in this study is InceptionV3, initialized with pretrained weights from ImageNet through a transfer learning approach. In the initial stage, all base layers were frozen to preserve the general features learned from the large-scale dataset. Subsequently, the last 15 layers were fine-tuned to adapt to the characteristics of the wild edible plant dataset. The early layers retain general features such as edges and textures, while the later layers adjust to the new domain, specifically leaf and flower morphology. This strategy enables the model to leverage general visual representations while adapting effectively to a relatively limited dataset. Model main architecture can be seen in Table 2.

Table 2. Model Main Architecture

Layers	Function
GlobalAveragePooling2D	Reducing feature dimensionality
BatchNormalization	Stabilizing data distribution
Dropout (0.5)	Reducing overfitting
Dense layer (softmax)(34)	Neurons according to the number of classes.

The selection of InceptionV3 was based on its modular architecture with factorized convolutions, enabling efficient capture of complex visual patterns. Previous studies have demonstrated that InceptionV3 excels in medicinal plant classification in Indonesia, achieving accuracy rates of up to 97% [3]. Compared to other architectures such as ResNet or VGG, InceptionV3 offers a balanced trade-off between network depth and computational efficiency, making it well-suited for domains with high visual variability such as wild plants. Furthermore, applying transfer learning with InceptionV3 has been shown to improve accuracy on limited datasets, as the model already possesses general visual representations learned from millions of images in ImageNet.

2.4 Comparison Model

As a comparative model, MobileNetV3-Large was employed with pretrained weights from ImageNet using a transfer learning approach. Similar to InceptionV3, the initial layers were frozen to retain general features, while the last 15 layers were fine-tuned to adapt to the characteristics of the wild edible plant dataset. The additional architecture applied was identical to that of InceptionV3. Model comparison architecture can be seen in Table 3.

MobileNetV3-Large was chosen for its lightweight and efficient design, making it suitable for applications on resource-constrained devices such as smartphones or IoT systems. Additionally, this model was used to evaluate whether a lightweight architecture could effectively handle a complex domain. Thus, this study compares the performance of a lightweight architecture (MobileNetV3-Large) with a more complex one (InceptionV3) in the classification of wild edible plants.

Table 3. Model Comparison Architecture

Layers	Function
GlobalAveragePooling2D	Reducing feature dimensionality
BatchNormalization	Stabilizing data distribution
Dropout (0.5)	Reducing overfitting
Dense layer (softmax)(34)	Neurons according to the number of classes.

2.5 Training

The models were compiled using the Adam optimizer with a learning rate of 1e-4. This value was chosen to stabilize the transfer learning process and maintain a balance between convergence speed and accuracy. The loss function applied was categorical crossentropy, which is appropriate for multi-class classification tasks. Training was conducted for 35 epochs with a batch size of 64, selected to balance computational efficiency and gradient stability. To prevent overfitting, an EarlyStopping mechanism with a patience of 10 was implemented, along with the option to restore best weights, ensuring that the optimal parameters were preserved and reused during evaluation.

Experiments were executed on an NVIDIA RTX 3050 GPU with 16 GB RAM, using TensorFlow-GPU 2.10.0 and Python 3.10.13. These details were included to ensure reproducibility and transparency of the experimental process. The hyperparameter configuration was selected based on best practices in plant image classification. The use of Adam with a low learning rate has been proven to stabilize convergence without sacrificing accuracy [4][7][8]. Similarly, the EarlyStopping mechanism aligns with standard deep learning practices to prevent overfitting in limited datasets [9][11].

2.6 Evaluation

Evaluation was conducted on the training set, validation set, and test set to ensure that model performance could be comprehensively assessed. The metrics used include:

1. Accuracy: measures the percentage of correct predictions across the entire dataset.
2. Precision: evaluates the proportion of correctly predicted positive samples relative to all positive predictions made by the model.
3. Recall: assesses the model's ability to identify all true positive samples.
4. F1-score: represents the harmonic mean of precision and recall, providing a balanced view of model performance.

In addition, a confusion matrix was employed to examine the distribution of misclassifications across classes. This analysis helps identify which classes are most frequently misclassified, serving as the basis for further discussion in the *Results and Discussion* section. The model was also tested with new images not included in the dataset to measure its generalization capability. This test is crucial to determine whether the model merely memorizes training data or can genuinely recognize visual patterns of wild edible plants under real-world conditions. This evaluation approach is consistent with prior studies on plant and leaf disease classification, which employed similar metrics to assess deep learning performance [7][9][14]. Consequently, the results obtained can be directly compared with established benchmarks in plant image classification research.

2.7 Deployment and Decision Support

The trained models were saved in .keras and .h5 formats to ensure compatibility across various implementation platforms. During prediction, a confidence threshold of 0.75 was applied to determine system output:

1. If confidence < 0.75, the system displays a warning: *"Non-Edible, Better Not Eat The Plants Because Confidence is Low."*
2. If confidence ≥ 0.75, the system presents the plant name along with its description, consumption status, and nutritional content retrieved from the metadata file (*edible_plants.csv*).

Metadata integration represents the novelty of this research, as most previous studies focused solely on visual image classification without additional contextual information. By incorporating metadata, the system functions not only as an image classifier but also as a decision support framework, providing direct recommendations on consumption and nutritional insights. This approach aligns with prior research on medicinal plant classification using InceptionV3, which emphasized high accuracy [3], as well as citrus disease detection using EfficientNetB3, which highlighted practical field applications [14]. Therefore, metadata integration transforms the system from a mere image classifier into a robust decision support framework, offering practical utility for safe consumption of wild plants.

3. RESULTS AND DISCUSSION

This section presents the experimental results and performance analysis of the models. Evaluation was conducted by comparing InceptionV3 as the primary model and MobileNetV3-Large as the comparative model. The analysis includes accuracy and loss curves during training, a results comparison table, confusion matrices, classification reports, and prediction outputs enriched with metadata. The purpose of this analysis is to assess the models' ability to classify wild edible plants while also examining the contribution of the system as a decision support framework.

3.1 Accuracy/loss graph

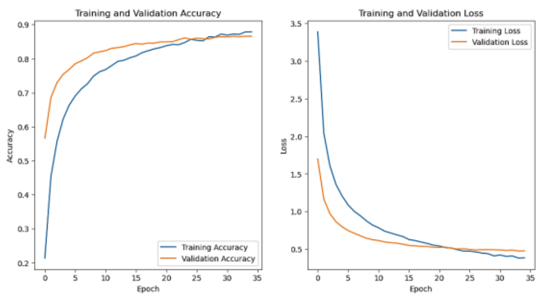

Figure 5. Training and Validation Accuracy and Loss of InceptionV3

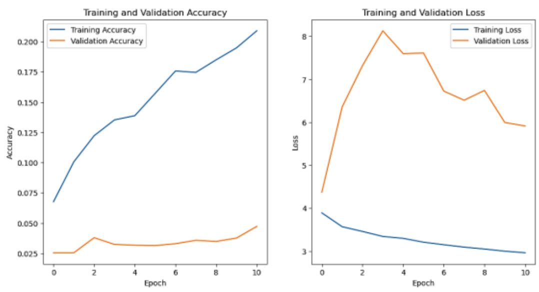

Figure 6. Training and Validation Accuracy and Loss of MobileNetV3-Large

Figure 5 illustrates the accuracy and loss trends for InceptionV3. Training accuracy increased steadily, reaching 0.93, while validation accuracy remained consistent at approximately 0.86. Loss decreased gradually and stabilized toward the final epochs, indicating that the model was able to learn effectively and generalize well to the validation data. This outcome was reinforced by the EarlyStopping mechanism, which successfully prevented overfitting. In contrast, Figure 6 shows the performance of MobileNetV3-Large. Validation accuracy stagnated at around 0.02, far below the training accuracy, while validation loss fluctuated significantly. This pattern indicates severe overfitting, as the lightweight architecture was insufficient to capture the complex visual features of wild plants. The difference highlights that complex architectures such as InceptionV3 are more suitable for plant classification tasks with high visual variability, whereas lightweight models like MobileNetV3-Large fail to generalize effectively in domains requiring detailed visual representation. These findings are consistent with prior research that employed InceptionV3 for grape leaf disease classification [4] and studies comparing lightweight and complex architectures in rice disease detection [8].

3.2 Comparison Table of Results

Table 4. Comparison of Model Performance

Model	Train Acc	Val Acc	Test Acc	F1-Score	Notes
InceptionV3	0.93	0.86	0.87	0.88	Stable, high accuracy
MobileNetV3-Large	0.02	0.02	0.02	0.03	Lighter, lower accuracy

The Table 4 demonstrates that InceptionV3 consistently outperforms MobileNetV3-Large, which fails to generalize effectively. This significant difference underscores that architectural capacity has a direct impact on classification performance. The findings are consistent with prior research on medicinal plant classification using InceptionV3, which also achieved high accuracy [3], thereby reaffirming the relevance of modern architectures in botanical domains. Consequently, the choice of InceptionV3 as the primary model is validated, while MobileNetV3-Large is more suitable for lightweight deployment scenarios but not for domains with high visual complexity.

3.3 Confusion Matrix

Figure 7 presents the confusion matrix for InceptionV3, with dominant diagonal values ranging from 0.90 to 1.00, indicating relatively accurate classification across classes. Nevertheless, some misclassifications occurred in visually similar classes, such as *chicory* versus *fennel*, or *clover* versus *red clover*. These findings suggest that despite high accuracy, the model remains sensitive to morphological similarities in leaves and flowers.

Conversely, Figure 8 shows the confusion matrix for MobileNetV3-Large. The pattern reveals frequent misclassifications, with the model tending to bias predictions toward a single dominant class (e.g., *common_yarrow*). This indicates the inability of MobileNetV3-Large to capture inter-class variation, rendering its performance unsuitable for complex wild plant classification tasks. This analysis reinforces that InceptionV3 possesses the architectural capacity better suited for botanical domains with high visual variability, whereas MobileNetV3-Large is only appropriate for lightweight scenarios and ineffective for detailed wild plant classification.

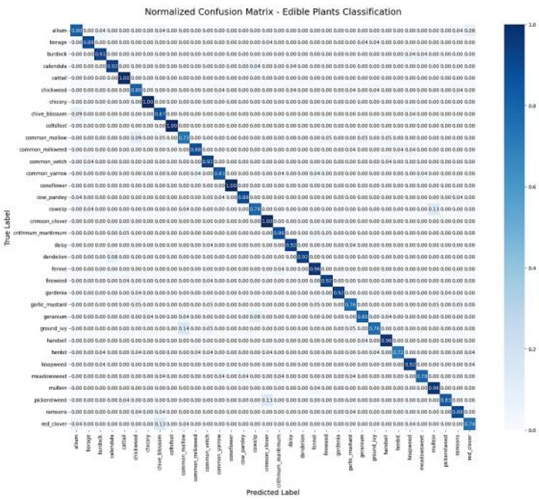

Figure 7. Confusion Matrix InceptionV3

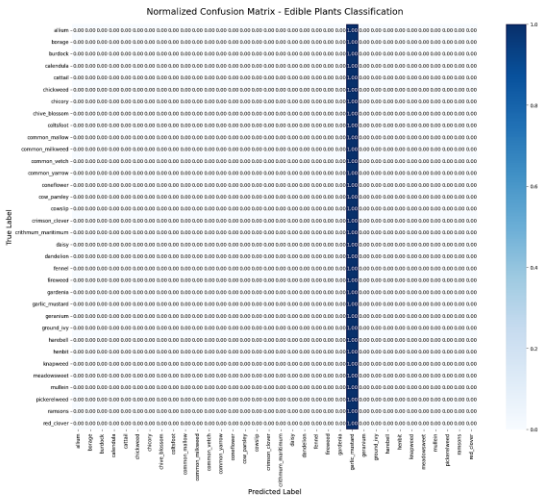

Figure 8. Confusion Matrix MobileNetV3-Large

3.4 Classification Report

Table 5. Classification Report Results

Model	Accuracy	Macro Avg F1	Weighted Avg F1	Class Example
InceptionV3	0.88	0.88	0.88	coltsfoot (1.00), chicory (0.98), fennel (0.90)
MobileNetV3-Large	0.03	0.00	0.00	garlic mustard (0.05), and other class(0.00)

In Table 5, the classification report results show that InceptionV3 achieved consistent performance with an overall accuracy of 0.88 and a high F1-score. Several classes even reached perfect scores, such as *coltsfoot* (1.00), and nearly perfect scores for *chicory* (0.98). However, classes with fewer samples tended to have lower recall, indicating that dataset imbalance influenced model performance. In contrast, MobileNetV3-Large performed almost entirely unsuccessfully, with an accuracy of only 0.03 and an F1-score close to zero. The model recognized only a very small subset of classes (e.g., *garlic mustard* with a score of 0.05), while most classes were not detected at all. This analysis confirms that InceptionV3 provides balanced and accurate classification, whereas MobileNetV3-Large is unsuitable for complex botanical domains due to its inability to generalize across diverse plant classes.

3.5 Prediction output with metadata

Table 6. Prediction Output with Metadata

Image	Real Name	Prediction	Confidence	Status	Description	Nutrition
	Ramsons	Ramsons	0.89	Edible	Daun dan bunga dengan rasa bawang putih, sering digunakan dalam salad atau masakan	Vitamin C, Vitamin A, senyawa sulfur

Image	Real Name	Prediction	Confidence	Status	Description	Nutrition
	Solanum	Chicory	0.67	Non-Edible, Better Not Eat The Plants Because Confidence is Low	-	-

Table 6 demonstrates that the system not only provides prediction labels but also additional information such as consumption status, brief descriptions, and nutritional content. This mechanism strengthens the role of the system as a decision support framework, making classification results more applicable in real-world contexts. In the first example, the model successfully detected *Ramsons* as edible with a relatively high confidence score of 0.89. Conversely, in the second example, the poisonous plant *Solanum* was misclassified as *Chicory* (an edible plant), but with a low confidence score of 0.67. Since this value is below the threshold of 0.75, the system assigned the status Non-Edible and withheld both description and nutritional information.

3.6 Discussion

The results of this study show that InceptionV3 achieved a test accuracy of 0.87 and an F1-score of 0.88, whereas MobileNetV3-Large obtained only 0.03 accuracy. This significant difference confirms that architectural capacity directly influences the performance of wild edible plant classification. These findings are consistent with research on taro leaf disease classification, where InceptionV3 demonstrated more stable performance compared to ResNet-50 and Vision Transformer in visually complex domains [9]. Another study on grapevine leaf variety classification also reported that InceptionV3 achieved high accuracy and strong generalization, further reinforcing the relevance of this model for botanical applications [26].

Conversely, the poor performance of MobileNetV3-Large in this study aligns with findings in citrus leaf disease classification, where MobileNetV3-Large struggled to capture complex visual details compared to EfficientNet-B0 [25]. While lightweight architectures such as MobileNetV3 offer computational efficiency and are relevant for deployment on mobile devices, the results highlight their limitations in domains with high visual variability, such as wild edible plants.

Moreover, the integration of metadata in this system provides significant added value. Similar approaches have been applied in machine learning–based plant recommendation systems, where metadata improved agricultural decision-making and supported decision support frameworks [23]. By incorporating metadata (consumption status, nutritional content, and plant descriptions), the system functions not only as an image classifier but also as a practical decision support tool for safe plant consumption.

4. CONCLUSION

This study successfully achieved its objective of developing a reliable and practical classification system for wild edible plants through metadata integration. InceptionV3 with transfer learning attained strong performance (Test Accuracy: 0.87, F1-score: 0.88), consistent with the goal of robust classification in visually complex domains. The novelty of this work lies in combining CNN-based classification with contextual metadata, enabling the system to function not only as a classifier but also as a decision support framework that enhances food safety and supports community-based food security.

From an academic perspective, this research extends the application of transfer learning in plant classification. From a practical standpoint, it provides a framework for safer consumption decisions in rural communities. Limitations remain, as the dataset only covered edible plants and relied on a rule-based confidence threshold. Future work should incorporate non-edible classes, evaluate performance under real-world conditions, and explore multimodal approaches (image + text).

Testing architectures such as EfficientNet or ResNet, applying explainable AI techniques (e.g., Grad-CAM), and validating lightweight models for mobile deployment would further strengthen robustness, transparency, and accessibility. The integration of metadata with CNN-based classification represents the key novelty of this study, transforming plant identification into a decision support system that bridges artificial intelligence with real-world food security needs. This ensures that the system is not only academically relevant but also practically impactful in supporting food security for rural communities.

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