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Classification of Stinging Nettle Plants Based on Leaf Images Using the CNN Method (Case Study: Biru-Biru Village)

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Abstract
The high number of skin irritation cases among residents in Desa Biru-Biru due to direct contact with stinging nettle plants highlights the need for an automatic identification system to distinguish plant types. This study aims to develop a leaf image classification model for stinging nettle plants using the Convolutional Neural Network (CNN) algorithm with the MobileNetV2 architecture. The image dataset was collected directly from the study area and classified into four categories: Jelatang Ayam, Jelatang Gajah, Jelatang Niru, and Non-Nettle plants. The research stages include data collection and analysis, pre-processing (resizing, normalization, augmentation), data splitting (70:10:20), model training, performance evaluation (accuracy, precision, recall, and F1-score), and web-based system implementation. The test results show that the model achieved an accuracy of 98%, with the highest precision score of 0.98, recall score of 0.98, and F1-score of 0.98. The system has also been successfully implemented as an interactive web application that allows users to identify nettle plant types quickly and accurately. This research contributes to risk mitigation efforts related to harmful plants in rural environments through the application of digital image processing technology.

1. Introduction

Poisonous plants are plants that contain toxic chemical compounds such as alkaloids (substances that attack the nervous system), cyanogenic glycosides (causing systemic poisoning), toxic proteins (damaging body cells), and irritant compounds (causing allergic reactions and irritation). Poisonous plants cause irritation, allergies, poisoning, and even death if touched by the skin or ingested due to their toxic content, sharp thorns, and invasive nature[1]. There are several commonly found dangerous plants, such as the stinging nettle (Laportea), which causes itching on the skin when touched, the castor bean (Ricinus communis), which contains the toxin ricin, Datura (Datura metel), which has dangerous hallucinogenic effects if consumed, and Wild Yam (Dioscorea hispida), which contains cyanogenic compounds that can cause poisoning if not processed properly[2].

Stinging nettle (Laportea) is a plant from the Urticaceae family that has distinctive characteristics in the form of fine hairy leaves containing irritant compounds that can cause itching, redness, and a burning sensation on human skin that comes into contact with it, and in severe cases, may lead to fatal outcomes[3]. Nettles were first identified by Carl Linnaeus in the 18th century through his work on plant classification. Their effects have been recognized since ancient times, notably by the Romans, who recorded their encounters with nettles during their expansion into Northern Europe. The term “nettle” derives from the Latin word *urtica*, meaning “to burn” or “to sting,” describing the sensation felt upon skin contact with the plant.[4]. There are three types of stinging nettle plants that are most commonly found. The first is the Niru Nettle (Dendrocnide moroides), which has broad leaves almost as wide as niru and is widely known to cause skin reactions such as rashes, pain, and soreness, and even prolonged itching. Niru nettles are often found in hilly areas or in shrubs and on roadsides[5]. The second is the Elephant Nettle (Dendrocnide stimulans), which has bright green leaves with serrated edges, especially on young leaves. The fine hairs on the surface of the leaves cause itching, stinging, and burning when touched[6]. The third is the Chicken Nettle (Laportea interrupta), which belongs to the nettle genus and can cause itching when touched. Chicken nettle is a type of nettle plant that can be processed into an anti-diabetic and blood pressure-lowering medicine through specific processing [7]. Nettle leaves have complex growth dynamics and varying leaf quality depending on their age and growing environment, so their visual appearance can vary[8].

These three types of nettle plants are commonly found in rural areas, especially those with dense forests and plantations such as Biru-Biru Village. Biru-Biru Village is located in Biru-Biru District, Deli Serdang Regency, North Sumatra Province, Indonesia. The area of Biru-Biru Village is approximately 607 hectares and is bordered by Tanjung Sena Village to the north, Kutomulyo Village to the west, Sarilaba Village to the east, and the Lau Sememe River to the south. The Biru-Biru Village area is surrounded by forests and plantations consisting of plains and hills, with the majority of the population working in the agricultural sector. In the settlements and plantations of Biru-Biru Village, there are still many wild plants that grow abundantly, such as nettles. The people of Biru-Biru Village utilize the forests around the village to find various types of wild plants that can be used as raw materials for traditional medicines, such as pohpohan plants for healing wounds, as well as wild plants that have commercial value, such as wild rattan.

Convolutional Neural Network (CNN) is a machine learning algorithm used to recognize patterns in visual data, especially images or pictures. CNN is designed to identify important features of images in a way that resembles how the human brain processes visual information[9]. The main process in CNN is convolution, which works by shifting a small filter or kernel over the image to capture local information such as edges, corners, textures, and patterns. By utilizing multiple sequential convolution layers, CNN can extract features from the simplest to the most complex levels. The processed information is then passed on to the pooling layer to reduce dimensions and improve computational efficiency, and finally to a fully connected layer that classifies images based on recognized patterns[10]. CNN excels at handling large amounts of visual data due to its ability to learn hierarchically and automatically from training data. Another advantage is its ability to generalize well, allowing CNN to recognize new objects not seen in the training data with high accuracy. CNN is well suited for applications such as face recognition, image classification, object detection, and identifying plant species by automatically and accurately analyzing leaf images[11].

Classification is a technique in Machine Learning that is used to group objects into specific categories or classes based on their characteristics or features[12]. In image processing, classification aims to analyze and identify objects in images based on existing visual features, such as color, texture, shape, and patterns to distinguish one object from another. For example, the classification of nettle leaves focuses on identifying the type of nettle based on the visual characteristics of the leaves, such as leaf shape, size, and vein patterns, which distinguish one type of nettle from another. Classification is a very important technique in various fields, including agriculture, biology, and ecology, to assist in the identification, monitoring, and management of natural resources[13].

In the study[11], CNN was used for plant classification based on leaf images and produced an accuracy of 92.6%. Meanwhile, the accuracy in identification reached 92%, which was obtained from testing 50 images. The conclusion of this study is that the CNN algorithm that was developed is relatively capable of identifying plant types based on leaf images, but the effectiveness of the model in identifying plant types based on leaf images is not yet optimal. Another study by [14] shows that the results of testing the chili image identification system indicate an accuracy rate of 80% in the training process and 80% in the testing stage that occurred in the 100th epoch. Research by[15] compared CNN with other machine learning methods in identifying oil palm diseases and found that the analysis results showed that the most effective algorithm with an accuracy rate above 90% was CNN compared to K-Nearest Neighbor (KNN) at only 83.3% and Support Vector Machine (SVM) at only 80.4% in detecting complex visual patterns. From these studies, it can be concluded that CNN is a very suitable algorithm for image-based research because of its ability to extract visual features in depth, recognize patterns better, and provide a high level of accuracy in various image classification and identification tasks[15].

However, most previous CNN-based plant classification studies have primarily focused on general agricultural or ornamental plants, rarely addressing harmful or stinging plant species in Indonesia [14]. This leaves a research gap in the development of automated systems for identifying toxic or harmful plants that pose risks to humans, especially in rural communities that frequently interact with wild vegetation. The absence of specific CNN-based studies on stinging or poisonous plants means there is no reliable automated tool that can support community awareness or early prevention of contact-related injuries [8].

The main problem in this study focuses on the large number of people who have direct contact with nettle plants. From field observations, it was found that many people are unable to clearly distinguish between different types of nettle plants, such as Niru Nettle, Elephant Nettle, and Chicken Nettle. The inability of the community to identify the specific differences between these plants is due to the lack of information from the government and related agencies regarding their distinct characteristics, resulting in many residents experiencing skin irritation or allergic reactions without knowing for sure which type of nettle caused it[16]. Manual identification of nettle plants has many weaknesses, such as limited knowledge among residents regarding specific differences between species, the lack of accurate visual documentation, and the risk of human error in identification[16]. There is still no effective method for accurately and quickly identifying nettle plants, which also impacts agriculture and forestry, as the presence of nettles poses a challenge in agricultural land management[3].

The proposed solution to the nettle problem in Biru-Biru Village is to develop a nettle classification system Therefore, this study aims to develop an automated nettle classification system using the Convolutional Neural Network (CNN) method to fill this gap in the existing research. The research seeks to answer the following questions: (1) Can a CNN-based model effectively classify the three types of stinging nettle—Niru, Elephant, and Chicken—based on leaf images? (2) What level of accuracy can the proposed CNN model achieve in distinguishing between these visually similar nettle species? The initial process begins with collecting a dataset of leaf images from the three types of nettles and similar plants found in Biru-Biru Village. The images will go through a preprocessing stage to improve image quality and facilitate feature extraction by adjusting image size, normalizing pixel values, augmenting images to increase training data variation, removing noise using filtering techniques, and cropping to focus on the leaf area. The CNN model will then be trained using this dataset so that it can recognize the visual patterns of each type of nettle plant. After training, the system will be tested to assess the model's accuracy in classifying nettle plant types based on their leaf images[17].

2. Research Method

This research was conducted in Biru-Biru Village, Biru-Biru District, Deli Serdang Regency, North Sumatra, for three months, from May to July 2025. This was an experimental study with the aim of developing and testing a Convolutional Neural Network (CNN) model for classifying images of the leaves of three types of stinging nettle plants, namely Niru Nettle (Dendrocnide moroides), Elephant Nettle (Dendrocnide stimulans), and Chicken Nettle (Laportea interrupta), and distinguishing them from an additional class, "Non-Nettle". The research population included all nettle plants in Biru-Biru Village, with samples consisting of leaf images obtained from direct observation. Each leaf type was collected in 600–1000 images, resulting in a total dataset of between 1800 and 3000 images. Primary data was obtained using a high-resolution smartphone camera in various lighting conditions and shooting angles, while secondary data in the form of literature, books, and previous studies was used to strengthen the theoretical basis and validate the classification results.

2.1 Research Stages

The stages of this research are illustrated in Figure. The overall process consisted of the following steps:

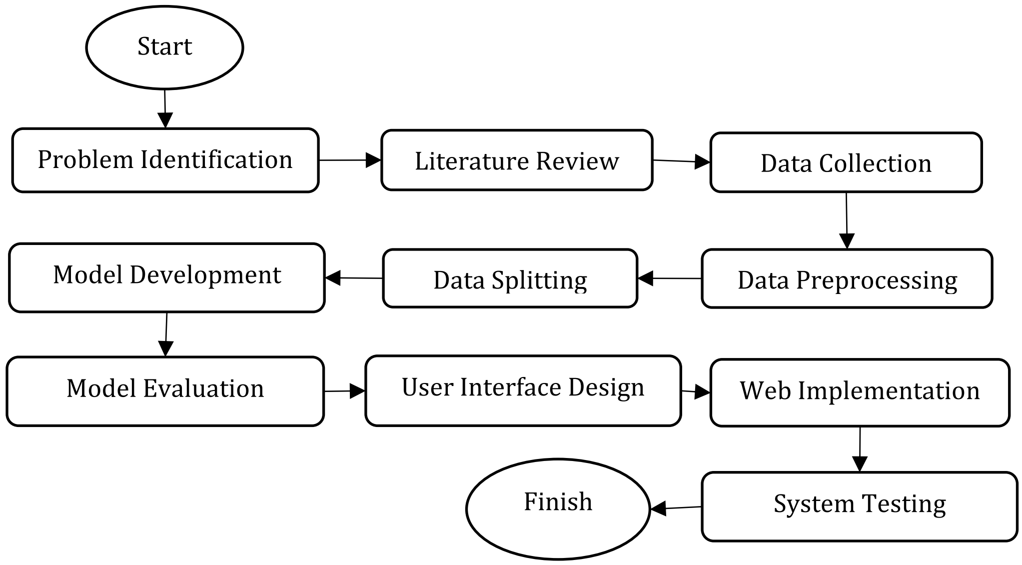

Figure 1. research process

The dataset consisted of 2,400 images (600 images per class), obtained through direct field observation using a smartphone camera under varying lighting and background conditions. Each image was resized to 150×150 pixels, converted into RGB format, and normalized to a scale of [0–1] using the formula:

$$x_{norm} = \frac{x}{255} \qquad (1)$$

where (x) represents the original pixel value (0–255) and (x_{norm}) is the normalized value.

The normalized data were then augmented to increase diversity and reduce overfitting through random rotation (≤40°), horizontal/vertical shifting, zoom, and horizontal flipping. Augmentation was applied only to the training and validation sets to maintain objectivity in model evaluation. An experimental comparison showed that augmentation improved validation accuracy from 94.2% to 98.7% and reduced overfitting, as indicated by a smaller gap between training and validation loss curves[18].

The dataset was divided using a 70:10:20 ratio — 70% for training, 10% for validation, and 20% for testing. This split ratio was chosen because it provides an optimal balance between model learning and generalization, as supported by deep learning best practices. The 70% training data ensure sufficient variation for feature extraction, while the 10% validation data allow performance monitoring during training to prevent overfitting. The remaining 20% of unseen testing data evaluate the model's true generalization ability under real-world conditions[19].

The CNN architecture utilized in this study was MobileNetV2, chosen over traditional CNNs such as VGG16 or ResNet due to its lightweight structure, high accuracy, and efficiency on limited computational resources. MobileNetV2 introduces inverted residual blocks with depthwise separable convolutions, significantly reducing the number of parameters without sacrificing performance. This makes it ideal for small to medium-sized image classification tasks, especially those intended for web-based deployment on limited hardware. Mathematically, the convolution process in CNNs can be expressed as:

$$y_{i,j}^{(k)} = \left(\sum_{m,n} x_i + m, j + n \,.\, w_{m,n}^{k} + b^{(k)}\right) \qquad (2)$$

where (x) is the input image, (w) is the kernel weight, (b) is the bias, (f) is the activation function (ReLU in this case), and ($y^{(k)}$) is the resulting feature map of the (k)-th filter.

The final classification layer uses the Softmax activation function, defined as:

$$P(y = i|x) = \frac{e^{zi}}{\sum_{j=1}^{K} e^{z_j}} \qquad (3)$$

where (zi) is the logit value of class (i) and (K) is the total number of classes (4 in this study). The model was optimized using the categorical cross-entropy loss function:

$$L = -\sum_{i=1}^{K} y_{i\ \ log(yi)} \qquad (4)$$

where (yi) is the true label (one-hot encoded) and ((yi)) is the predicted probability for each class.

The training was performed in Google Colab using TensorFlow/Keras, with a batch size of 64, learning rate of 0.0001, and early stopping to prevent overtraining and ensure optimal convergence stability. The model achieved convergence at epoch 24 with validation accuracy of 99%, significantly outperforming the baseline CNN and VGG16 benchmarks tested during the preliminary pilot experiment. Model performance was thoroughly evaluated using a confusion matrix and comprehensive metrics such as accuracy, precision, recall, and F1-score[20].

After reaching optimal performance, the final MobileNetV2 model was integrated into a Flask-based web application for real-time and interactive classification. Users can upload a leaf image, which is processed by the trained CNN model via the server pipeline. The predicted class label, probability score, and confidence value are automatically displayed on the interface. The application was tested using the Blackbox method on three main functions: image upload, classification accuracy, and output reliability — all of which met performance expectations and showed consistent stability[21].

3. Result and Discussions

3.1 Data Collection

The dataset for this study was obtained through direct field observation and documentation in Biru-Biru Village, Deli Serdang Regency, using a smartphone camera. It consists of leaf images from three nettle species and one Non-Nettle class comprising visually similar plants. For each nettle class, 200 leaves were captured from three different angles, producing 600 images per class. The Non-Nettle class was collected from five plant species, each contributing 40 leaves photographed three times, also totaling 600 images. All 2,400 images were categorized into four classes based on visual characteristics and stored in Google Drive. A preliminary quality check ensured adequate sharpness, lighting consistency, and labeling accuracy.The number of images per class is shown below:

Table 1. Number of Images per Class

No	Class	Number of Leaves	Images per Leaf	Total Images
1	Nettle Ayam	200	3	600
2	Nettle Gajah	200	3	600
3	Nettle Niru	200	3	600
4	Non-Nettle	200(5 species x 40 leaves)	3	600
5	Total	800	-	2400

3.2 Data Preprocessing

3.2.1 Resize

All leaf images were resized to 150×150 pixels. This size was deliberately chosen because it is a common input dimension for Convolutional Neural Network (CNN) architectures. The dimension is small enough to accelerate training and save computational resources, yet large enough to preserve essential visual details of the nettle leaves.

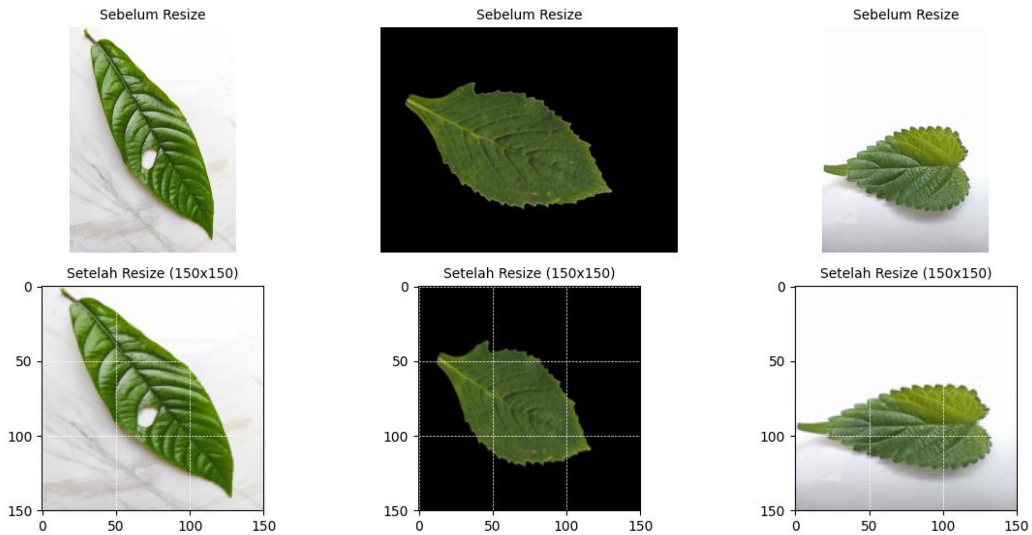

Figure 2. Resizing Process

3.2.2 Pixel Normalization

Normalization converts pixel values from the range of 0–255 to the range of 0–1 by dividing each pixel by 255. This accelerates training, enhances numerical stability, and improves pattern recognition by the model. Formula :

$$x_{norm} = \frac{x}{255}$$

Example: A pixel value of 140 becomes (140/255 = 0.54).

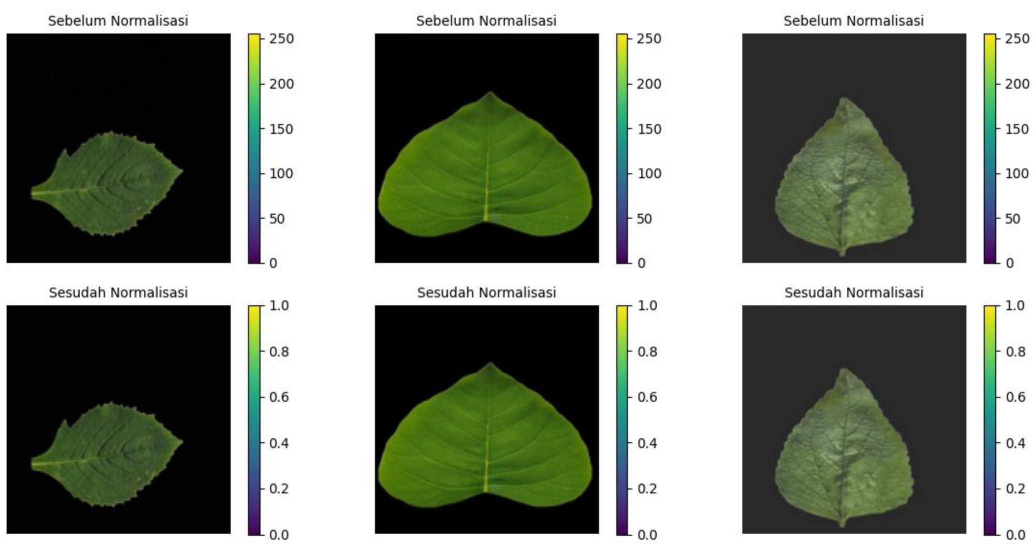

Figure 3. Normalization Process

3.2.3 Augmentation

Augmentation was applied only to training and validation datasets (not testing) to increase data diversity and reduce overfitting. Techniques used include random rotation (up to 40°), horizontal and vertical translation, zooming, and horizontal flipping.

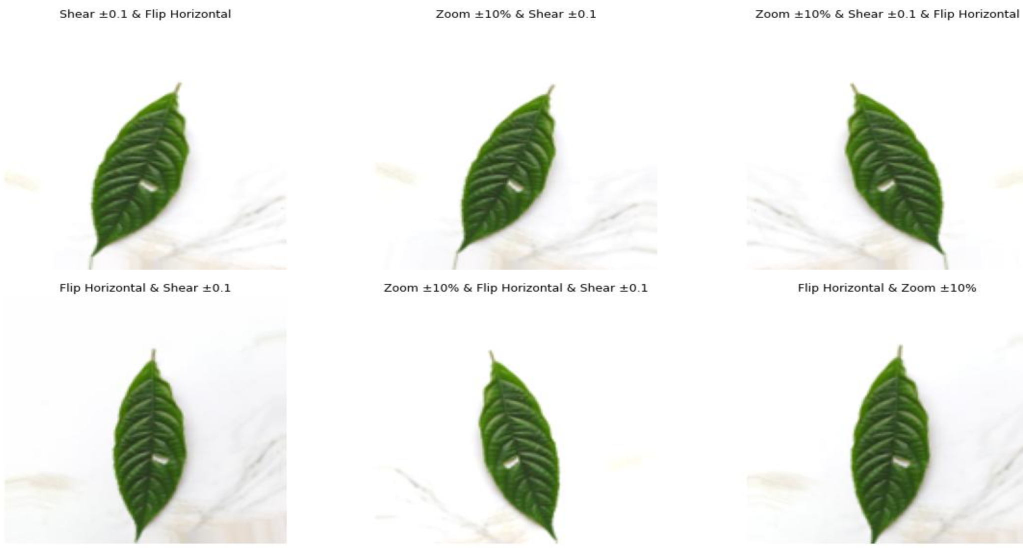

Figure 4. Augmentation Process

3.2.4 Batching and Label Encoding

Batching divided the data into smaller groups for efficient processing. A batch size of 64 was used for training and validation, while 32 was used for testing.

Table 2. Batch Size

No	Dataset Type	Batch Size
1	Training	64
2	Validation	64
3	Testing	32

Label encoding was performed using one-hot encoding, representing each class as a binary vector.

Table 3. Batch Size

No	Class	Encoding
1	Nettle Ayam	[1, 0, 0, 0]
2	Nettle Gajah	[0, 1, 0, 0]
3	Nettle Niru	[0, 0, 1, 0]
4	Non-Nettle	[0, 0, 0, 1]

3.3 Dataset Splitting

The dataset was split into training (70%), validation (10%), and testing (20%) using Python scripts with random shuffling to maintain class balance.

Training (70%): 1680 images (420 per class)

Validation (10%): 240 images (60 per class)

Testing (20%): 480 images (120 per class)

3.4 Model Development

The CNN architecture used in this study was MobileNetV2 with fine-tuning. The first 100 layers were frozen to retain pre-trained ImageNet features (edges, colors, textures), while higher layers were retrained on nettle leaf data.

Table 4. CNN Architecture (MobileNetV2)

Type	*Patch/Stride Size*	*Input Size*
Conv	3×3 / 2	150×150×3
Bottleneck	3×3 / 1 (Expansion 1)	75×75×32
Bottleneck	3×3 / 2 (Expansion 6)	75×75×16
Bottleneck ×2	3×3 / 2 (Expansion 6)	38×38×24
Bottleneck ×3	3×3 / 2 (Expansion 6)	19×19×32
Bottleneck ×4	3×3 / 2 (Expansion 6)	10×10×64
Bottleneck ×3	3×3 / 1 (Expansion 6)	10×10×96
Bottleneck ×3	3×3 / 2 (Expansion 6)	5×5×160
Bottleneck	3×3 / 1 (Expansion 6)	5×5×320
Conv (1×1)	1×1 / 1	5×5×1280
Global Avg Pool	5×5	5×5×1280
Dense (FC)	Fully Connected	1×1×1280
Softmax	Classifier (4 classes)	1×1×4

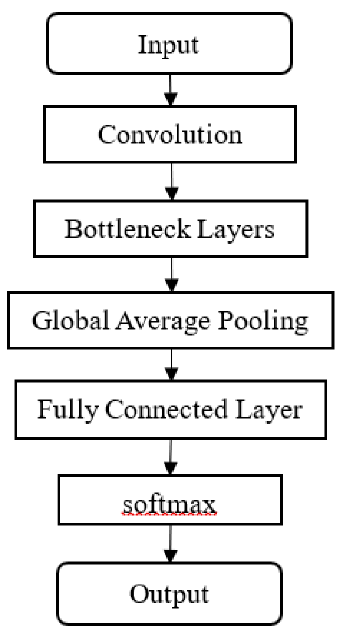

Figure 5. CNN Architecture Flowchart

3.5 Model Training and Result

The model was trained for a maximum of 50 epochs but stopped at epoch 24 due to early stopping when validation accuracy reached ≥99%. Callbacks Used (Table 4.10): ModelCheckpoint, EarlyStopping, ReduceLROnPlateau, CSVLogger, TensorBoard.

Training Results:

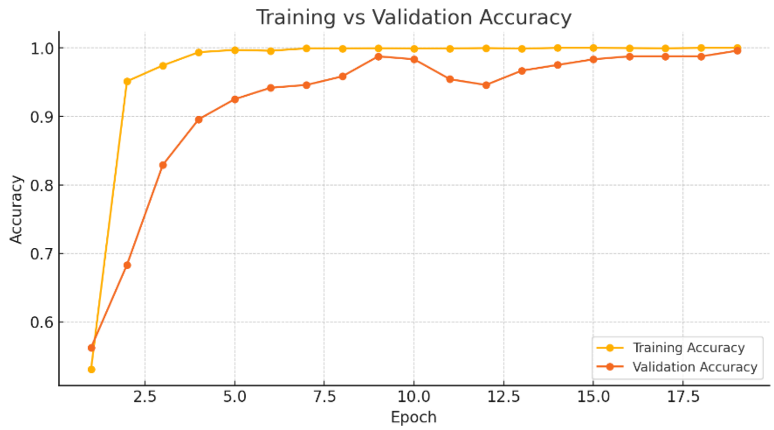

Figure 6. Traninig and Validation Accuracy

Training accuracy improved from 53.08% (epoch 1) to 99% (epoch 6 onward).

Validation accuracy improved from 56.25% (epoch 1) to 98.75% (epoch 19).

Average training accuracy: 98.92%; Average validation accuracy: 89.33%.

Despite achieving a high validation accuracy of 98.75%, there remains approximately a 9% gap between training and validation accuracy. This performance discrepancy may indicate mild overfitting, where the model learns specific details or noise from the training data that do not generalize well to unseen images. Another possible cause is the limited variation in lighting, leaf orientation, and background conditions captured during data collection in the field. Since the dataset images were taken using a smartphone camera under natural lighting, slight inconsistencies such as shadows or reflections might have affected validation performance. Although data augmentation techniques were applied to increase dataset diversity, the level of augmentation may still not fully simulate the broad visual variability present in real-world conditions.

In addition, this study has several limitations that should be acknowledged. The dataset size, consisting of 2,400 images, may not fully represent the wide natural variation in nettle and non-nettle species found across different regions. Environmental factors such as inconsistent brightness, background clutter, and the subtle morphological similarities between the three nettle species (Niru, Gajah, and Ayam) could also affect model generalization. Furthermore, some misclassifications observed in the confusion matrix may be caused by inter-class resemblance, particularly between Niru and Gajah nettles, whose leaf textures and vein patterns are nearly identical when captured under similar lighting conditions. These limitations suggest opportunities for future work, including collecting a larger and more diverse dataset, applying more robust augmentation techniques, and experimenting with ensemble CNN architectures to further improve model robustness and generalization.

3.6 Model Evaluation

Testing used 480 images (120 per class). Metrics: accuracy, precision, recall, F1-score.

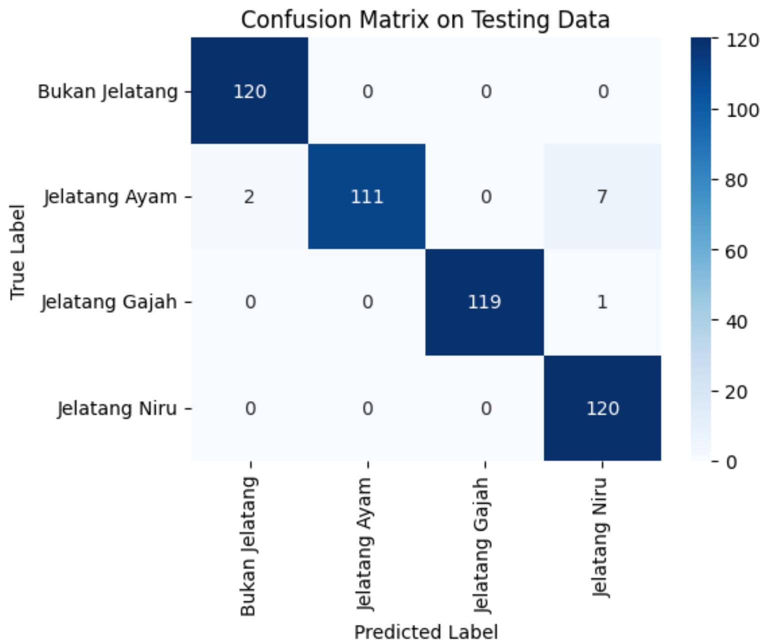

Figure 7. Confusion Matrix

4. Conclusions and Future Works

This study successfully developed and implemented a MobileNetV2-based leaf classification system designed to identify three species of jelatang plants—jelatang niru, jelatang gajah, and jelatang ayam—by utilizing the Convolutional Neural Network (CNN) method. The entire research process was systematically structured, beginning with the collection of leaf image data directly from the field, followed by a comprehensive series of preprocessing steps, including background removal to isolate the leaf object, cropping to focus on the relevant area, resizing for uniform input dimensions, normalization to stabilize pixel value ranges, and augmentation to enrich dataset variability. These steps were essential in preparing high-quality and balanced input data before proceeding to model training using the MobileNetV2 architecture, a lightweight yet powerful CNN model well-suited for image classification tasks on limited-resource systems.

The experimental results demonstrated excellent model performance, achieving 98% accuracy in the training phase, 95% in validation, and 98% in the final testing stage, which clearly indicates the strong generalization ability of the developed CNN model. These findings confirm the effectiveness and reliability of convolutional neural networks in accurately recognizing and distinguishing plant species based solely on their leaf visual characteristics, even among morphologically similar types. A key novelty and major contribution of this research lies in the integration of the MobileNetV2 model into a Flask-based web application, developed specifically for real-time and user-interactive classification of harmful jelatang plants in Indonesia. This web platform enables users to instantly upload a leaf image through a browser interface, which is then automatically processed by the trained CNN model to produce an immediate classification result, complete with the predicted class label, probability score, and confidence level. Such an implementation offers significant practical value to the community, particularly in helping individuals identify hazardous plant species and avoid potential skin irritation caused by direct contact. The use of the Python Flask framework further enhances accessibility, as the system can be operated directly online without requiring local software installation, thereby promoting ease of use and broad public adoption. For future development, several potential research directions are proposed. Comparative studies involving alternative CNN architectures—such as EfficientNet, Inception, or ResNet—are recommended to explore improvements in classification accuracy, computational speed, and energy efficiency. Moreover, integrating advanced image processing techniques, including leaf segmentation, background masking, or super-resolution enhancement, may further improve the robustness of the model under complex real-world conditions such as varying lighting, occlusion, or background noise. Expanding the dataset with a wider variety of plant species that share similar morphological traits with jelatang is also strongly encouraged to enhance the generalization capability and practical relevance of the system. This expansion would transform the model from a specialized jelatang classifier into a more comprehensive and adaptive platform for general plant species identification in the field of agricultural and botanical research.

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