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Leaf Type Recognition System Using Image Processing Method Using Convolutional Neural Network Algorithm

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Abstract

A digital image-based leaf recognition system is one of the modern solutions in the fields of botany and agriculture to identify plants automatically. This study developed a leaf recognition system using image processing methods and Convolutional Neural Network (CNN) algorithms. CNN was chosen because of its ability to independently extract features through convolution layers, thus capturing important visual patterns such as shape, edges, textures, and leaf veins without requiring manual feature engineering processes. The research dataset consists of a collection of leaf images from several types of plants obtained through direct photo-taking and public dataset sources. Each image goes through a pre-processing stage, including cropping, resizing, image quality enhancement, and pixel normalization to ensure data consistency before entering the training stage. The CNN model is designed with several convolutional layers, pooling, activation functions, and fully connected layers to produce optimal classification performance. Model training is carried out by dividing training and testing data, as well as augmentation techniques to increase image variation. System performance is evaluated using accuracy, precision, recall, and confusion matrix. The test results show that the CNN model is able to recognize leaf types with a high level of accuracy and is stable under various test conditions, including variations in lighting and shooting angles. Overall, this study proves that CNN is an effective and reliable approach in building an automatic leaf recognition system. This system has the potential to be applied in the fields of precision agriculture, mobile application-based plant identification, and botanical research that require speed and accuracy in plant classification.

Introduction

Indonesia boasts extraordinary biodiversity, known as "megadiversity," and boasts the highest biodiversity of any country. One of the most prominent features of Indonesia's biodiversity is its diverse plant species, with over 30,000 plant species found in Indonesian forests (Ayu et al., 2022). With technological advancements, digital image processing (image processing) is widely used to aid the identification of biological objects. With image processing, leaf images can be preprocessed through stages such as grayscale conversion, segmentation, and noise reduction. Next, features such as shape, texture, and color are extracted, which are key components of the classification process (Ngii et al., 2023; Chandra et al., 2024; Sihombing et al., 2022; Kelishadrokhi et al., 2023; Li et al., 2022).

In plant morphology studies, leaves can generally be divided into two types: simple leaves and compound leaves (Min et al., 2022; Nakayama et al., 2023; Soheili et al., 2023). Simple

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leaves have only one leaflet on a stalk, while compound leaves have several smaller leaves (leaflets) attached to a single main stalk (Guo et al., 2025; Liu et al., 2023; Efroni et al., 2010). These structural differences also affect the shape, size, and leaf shape index. Research by Wu et al. (2019) showed that compound leaves have a slimmer and more elongated shape, providing an adaptive advantage to high light by reducing overlap between leaf blades.

With technological advancements, leaf type recognition can now be performed using digital image processing approaches combined with artificial intelligence (Zhan, 2022; Bhargava et al., 2024; Tripathy et al., 2022; Yuan et al., 2022). One of the most widely used algorithms in this field is the Convolutional Neural Network (CNN). CNN is a deep learning algorithm specifically designed to process image data through a series of convolutional, pooling, and fully connected layers to automatically recognize visual patterns without the need for manual feature extraction (Kumar & Singh, 2022; Kshatri & Singh, 2023; Alsajri & Hacimahmud, 2023).

The main advantage of CNN lies in its ability to extract local and global features from images hierarchically, resulting in more accurate recognition results compared to traditional methods such as Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) (Rahmawati & Siregar, 2023; Jalaja & Prerita, 2024; Kaul & Raina, 2022; Shdefat et al., 2024). Based on research by Ghosh et al. (2022), the combination of CNN and KNN architectures produced an average accuracy of 92.3%, higher than the combination of CNN and SVM, which only achieved 91.0%. These results indicate that CNN has superior performance in recognizing complex visual patterns such as leaf structure.

Another study by Lee et al. (2021), entitled "Comparing Performances of CNN, BP, and SVM Algorithms for Differentiating Sweet Pepper Parts for Harvest Automation," also demonstrated the superiority of CNN. The study showed that CNN achieved up to 99.5% accuracy in recognizing plant parts (fruit, leaves, stems, and shoots), far surpassing SVM, which only achieved 63.75%. These findings confirm that CNN is able to identify plant characteristics significantly better than other machine learning algorithms.

Based on this background, this research focuses on developing a leaf type recognition system using image processing methods with a CNN algorithm. This system is expected to be able to automatically recognize leaf types from digital images, thereby facilitating the fast, efficient, and accurate plant identification process. Furthermore, the application of this method could be a first step toward automated plant identification, potentially applicable in agriculture, conservation, and education.

This research aims not only to implement CNN on leaf images but also to evaluate the algorithm's performance and effectiveness in recognizing visual leaf patterns across various plant species. Therefore, the research findings are expected to contribute to the development of machine learning-based technology in botany, particularly in digital image-based leaf recognition systems.

Methods

Research Type

This research falls into the research and development (R&D) category. It focuses not only on data collection or theoretical analysis but also on the creation and implementation of an intelligent system that can recognize and classify leaf images fed into the system. Therefore, a research and development approach was chosen. In other words, this research focuses on the creation of an artificial intelligence-based IT product. The designed system will undergo a design, testing, and evaluation process to ensure it is sufficiently accurate and effective in recognizing visual leaf patterns.

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Research Location and Object

This research was conducted in the area around the campus because it is considered to have a natural environment, making it highly conducive to data collection in the form of leaf images from various plant species. This location was also selected based on the consideration that the surrounding campus area is home to a diverse range of vegetation, including ornamental plants, fruit trees, and wild plants that grow naturally, providing a variety of leaf shapes and types representative enough for the research needs. The objects of this research are leaf images from various types of compound and single fruit-bearing plants.

Data and Data Sources

The data used in this research are primary and secondary. This data is obtained directly through photographing leaves in the field, and can also be taken from datasets found online. The data source is direct observation and documentation in the field.

Image Processing Method

Image Acquisition

Image acquisition is the initial stage in the image processing process, capturing images of leaves as input data for the system. Leaf images are obtained through direct photography using a digital camera or from publicly available online datasets. Image acquisition is carried out with attention to adequate lighting, an appropriate shooting distance, and a relatively simple background to minimize visual noise. Image quality at this stage significantly impacts the success of the processing and classification processes in subsequent stages.

Image Preprocessing

Image preprocessing aims to improve image quality and standardize the data format before being processed by the CNN model. The preprocessing stages implemented in this study include:

Resizing, which resizes the image to specific dimensions to suit the input requirements of the CNN model. Standardizing image size helps improve computational efficiency and improve the stability of the training process.

Grayscale or color normalization, which is performed by adjusting pixel intensity values to a specific range to accelerate model convergence and reduce the influence of lighting differences.

Noise reduction aims to reduce image disturbances such as spots or shadows that can obscure the main features of the leaf. This process helps improve the sharpness of the leaf.

Contrast enhancement is used to clarify the edges and vein patterns of the leaf, making visual features more easily recognizable.

Cropping is performed to focus the image on the leaf area and remove irrelevant background elements. This way, the processed information is more focused on the main object.

Image Segmentation

Image segmentation aims to separate the leaf from the background. At this stage, the image is processed so that the leaf area can be clearly identified. Segmentation techniques used can include thresholding, masking, or edge detection, depending on the image characteristics. Good segmentation will produce clearer leaf shapes and assist the model in recognizing leaf morphological structures.

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Feature Extraction

Feature extraction is the process of extracting important information from leaf images, such as shape, texture, and vein patterns. Traditional methods of feature extraction are performed manually using specific mathematical calculations. However, in this study, feature extraction was performed automatically by a CNN through convolutional layers. Each convolutional layer extracts features with varying levels of complexity, ranging from simple features to more complex ones.

Classification

The classification stage is the final stage of the image processing method. After the leaf images have undergone all processing, the probabilities for each leaf class are assigned, and the class with the highest probability is determined as the recognition result. This process allows the system to automatically and accurately recognize leaf types based on the visual patterns learned during the training process.

Results and Discussion

This research aims to develop and evaluate a leaf recognition system using image processing with a Convolutional Neural Network (CNN) algorithm. The results were obtained through training and testing a CNN model on a pre-processed leaf image dataset.

CNN Model Training and Testing Results

The CNN model training process was carried out by dividing the dataset into training data and testing data. During the training process, the model learned to recognize visual leaf patterns such as shape, texture, edges, and veins through convolution and pooling layers. The results showed that accuracy values gradually increased with increasing epochs, while loss values decreased, indicating that the model was able to learn data patterns well and stably.

During the testing phase, the CNN model demonstrated good performance in classifying leaf types based on the given images. Performance evaluation was conducted using metrics such as accuracy, precision, recall, and confusion matrix (Foody, 2023; Valero-Carreras et al., 2023; Heydarian et al., 2022; Riehl etal., 2023). The test results showed that the system was able to recognize leaf types with a high level of accuracy and relatively small classification errors for each leaf class.

Confusion Matrix Analysis

A confusion matrix is used to observe the distribution of model prediction results for each leaf class. Based on the results of the confusion matrix, most leaf images were correctly classified according to their class. Classification errors generally occur in leaf types that have similar shape and texture, such as leaves with similar size and vein patterns. This indicates that although CNNs have strong automatic feature extraction capabilities, visual similarity between leaves remains a challenge in the classification process.

System Implementation

The implementation of the leaf type recognition system is carried out by building a computer-based application capable of accepting input in the form of leaf images and producing output in the form of leaf type classification results. This system integrates image processing stages and a pre-trained convolutional neural network (CNN) model (Peng et al., 2024; Norouzi et al., 2025).

System Architecture

The system architecture generally consists of three main components: input, processing, and output. In the input stage, the user enters leaf images into the system through the application

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interface. The uploaded images can come from a digital camera or a pre-prepared dataset. The system then processes the images through several image processing and classification stages. The final result, in the form of leaf type information, is displayed in the system output section.

Image Preprocessing Implementation

In the preprocessing implementation stage, the uploaded leaf image is first adjusted to the requirements of the CNN model. This process includes resizing the image to a uniform size according to the model's input layer, normalizing pixel values to improve the stability of the training and testing processes, and cropping to focus on the leaf object and reduce background influences. This stage aims to ensure that the data entering the model is of consistent quality and format.

CNN Model Implementation

The convolutional neural network model is implemented using an architecture consisting of several convolutional layers, pooling, activation functions, and fully connected layers. The convolutional layers function to extract important features from leaf images, such as edges, shape, texture, and vein patterns. The pooling layers are used to reduce the data dimensionality while retaining key features, thereby speeding up the computational process and reducing the risk of overfitting (Musthafa et al., 2024; Salam et al., 2021; Santos & Papa, 2022). The activation function is used to add and reduce nonlinearities to the model, while the fully connected layers play a role in the final classification process based on the extracted features. The trained CNN model is then saved and reused during the system testing and implementation phase.

Classification Process Implementation

In the classification phase, preprocessed leaf images are fed into the CNN model for prediction. The model generates probabilities for each available leaf class, and the system then determines the class with the highest probability as the recognition result. This process is automatic and fast, allowing users to obtain leaf type identification results quickly.

System Interface Implementation

The interface is designed to be simple and easy to use. Users simply upload leaf images using the upload feature available in the application. Once the image is processed, the system displays the classification results in the form of the name or type of recognized leaf. This interface is designed to support general users, including students, researchers, and agricultural practitioners.

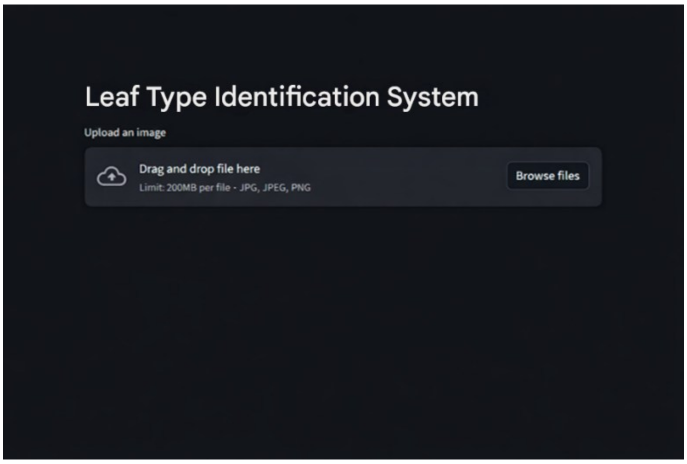

Figure 1. System Landing Page

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The Leaf Type Recognition System landing page allows users to upload leaf images for the system to recognize. The user interface is designed to be simple and intuitive, allowing users to simply drag and drop images into the provided area or use the browse files button. The system supports JPG, JPEG, and PNG image formats with a file size limit of up to 200 MB per file. Once uploaded, the system automatically processes and analyzes the image to quickly and accurately recognize the leaf type.

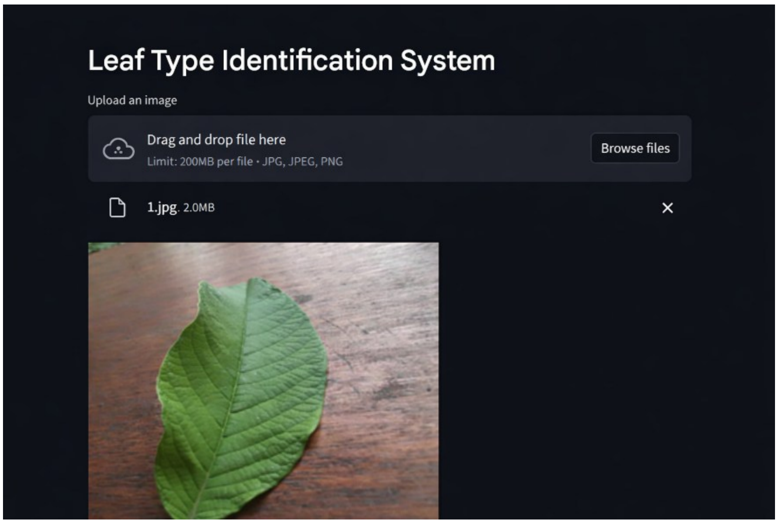

Figure 2. User uploads leaf image

This shows the system interface where users can upload leaf images for leaf type recognition. There is a drag-and-drop upload area and a Browse files button to select image files directly from the user's device. Once a file is selected, the system displays the file name and size of the uploaded file, allowing users to verify the image is suitable for further processing. This interface is designed to be simple and intuitive to provide ease and convenience for users in uploading images in the specified format and size.

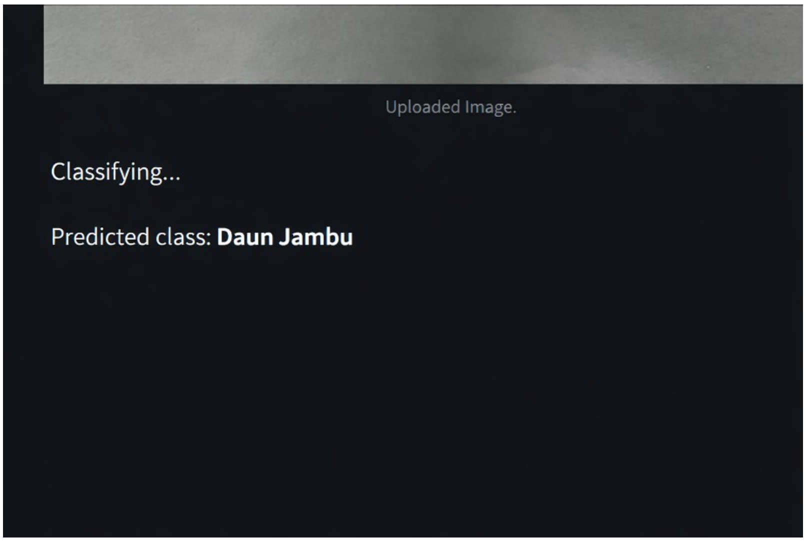

Figure 3. System displays classification results

Figure 3 shows that after the user uploaded a leaf image to the system, the system automatically performed the classification process. The classification results are displayed as Predicted class: Guava Leaf, indicating that the uploaded image was successfully recognized as a guava leaf. This process indicates that the system is able to automatically recognize the leaf type based on the image provided by the user.

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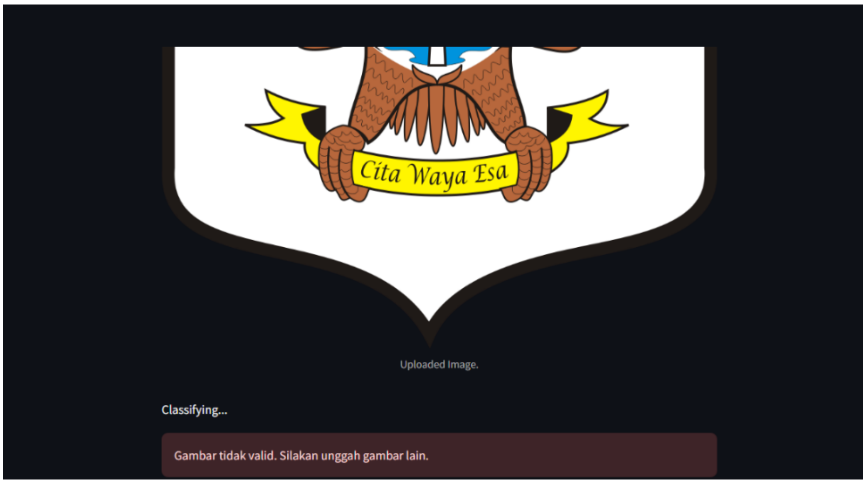

Figure 4. System Display When Uploading an Invalid Image

Figure 4 shows a situation where the system cannot recognize an image uploaded by a user. In this situation, the system displays an informative and easy-to-understand error message. The notification explains that the uploaded image is invalid or does not conform to the specified format. This information aims to help users understand the cause of the error and provide an opportunity to re-upload a suitable image. With clear notifications, users can immediately make corrections without experiencing confusion or frustration.

System Functional Testing

Functional testing was conducted to ensure that each system component functioned according to its intended purpose. The test results showed that the system was able to accept image input, perform pre-processing, run the classification process using CNN, and display leaf type recognition results effectively. The system was also able to handle a variety of leaf images with varying lighting and shooting angles.

The results of this study align with the Confolutionary Neural Network theory, which states that CNNs are highly effective in handling image data because they are capable of extracting features hierarchically, from simple features such as edges and corners to complex features such as shape and object structure. This advantage allows CNNs to identify leaf characteristics without requiring manual feature extraction as in traditional methods. The findings of this study also support previous research that stated that CNNs have superior performance compared to conventional machine learning algorithms in image-based object recognition. CNNs are able to adapt to variations in lighting, shooting angles, and differences in leaf size, so the system still produces stable classification results.

Furthermore, the application of pre-processing and data augmentation techniques has been shown to help improve model performance by enriching the variety of training data. This reduces the risk of overfitting and improves the model's generalizability to new data that has not been previously trained. Overall, the research results show that the developed CNN-based leaf type recognition system is effective and accurate. This system has the potential for further development and implementation in web-based or mobile applications as a plant identification tool in agriculture, farming, and education

Conclusion

Based on the research results and discussion, it can be concluded that the image processing-based leaf recognition system with the Convolutional Neural Network (CNN) algorithm is capable of automatically recognizing and classifying leaf types with a high degree of accuracy. The CNN model successfully extracted visual features of leaves such as shape, texture, edges, and vein patterns effectively through convolutional layers, resulting in stable

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classification performance across various lighting conditions and shooting angles. The implementation of the computer-based system also demonstrated that the application is easily usable by users through a simple and intuitive interface. As a recommendation, future research is expected to increase the number and variety of datasets from more plant types to improve the system's generalization capabilities. Furthermore, the system can be developed as a web-based or mobile application for greater accessibility by farmers, students, and researchers. The development of additional features such as leaf morphology information, plant benefits, and integration with Internet of Things (IoT) technology could also add value to the system's application in smart agriculture.

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