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Flora Folium: Plant Leaf Identification Using Convolutional Neural Networks (CNN)

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Abstract

Image processing is a technique to translate an image into digital form and execute some operations on it to obtain an improved image or extract some useful information from it. FloraFolium aimed to address the challenges in plant identification, especially in the Philippines, where many plant species are not well-studied or properly recorded. Many people struggle to tell which plants are edible, medicinal, or toxic because of limited access to official guides and reliable information. To solve this problem, the FloraFolium project created a mobile application that uses Convolutional Neural Networks (CNNs) to identify plant leaves and classify them into three categories: edible, medicinal, or toxic. The system was tested and evaluated based on ISO 25010 software quality standards. The results showed high ratings for functionality, usability, and efficiency, making the app reliable for everyday use. While the app performed well, some areas, like security and reliability in unusual conditions, need improvement. The study also found that the image quality greatly affects the system's accuracy. A balanced dataset of 15,000 images was divided into 80% for training and 20% for testing/validation. The model achieved a test accuracy of 99% and an overall validation accuracy of 98.8%, with the best weights saved at epoch 20 during the 30-epoch training period. The FloraFolium app is a helpful tool for outdoor enthusiasts, gardeners, farmers, and anyone interested in learning more about plants. It can also help preserve traditional knowledge about medicinal plants.

Keywords: Convolutional Neural Network, Deep learning, Image processing, Leaf identification, plants.

I. Introduction

Image processing is a technique to translate an image into digital form and execute some operations on it to obtain an improved image or extract some useful information from it. It is a type of signal dispensation wherein the input is an image, and the output may either be an image or some characteristics associated with it. Several studies have demonstrated the effectiveness of CNNs in plant leaf identification. For instance, a system using ResNet-50 architecture achieved over 98% accuracy in identifying five types of Malaysian leaves, highlighting the robustness of CNNs in handling different image backgrounds and noise levels [1]. The domain of digital image processing has experienced amazing advancements, particularly through the evolution of deep learning-based algorithms, which have enhanced capabilities in many real-life applications, such as image object detection [2], recognition [3], segmentation [4], edge detection [5], and restoration [6]. Deep learning models process high-dimensional data with great ease and efficiency. The absence of a comprehensive official list of plants from local authorities like the Agriculture Department, DENR, and Biliran Campus further worsens the problem, and most people have difficulty identifying plants, especially those of today's generation, forcing individuals to rely on incomplete or external sources. Given the difficulties in identifying the species and their applications, there is an urgent need for more readily available, accurate, and comprehensive plant identification. The Philippines has 13,500 plant species, accounting for 5% of the world's flora [7].

However, only a few are used as food by humans. This means that many of the plant species in our world have not been utilized and studied effectively [8]. There are more than 1500 medicinal plants used by traditional healers that have already been documented, and 120 plants have been validated scientifically for safety and efficacy use [9].

To address the identified problems, the researcher proposed a digital solution to make a significant contribution to the region. Implementing such a system has the potential to transform the traditional method of identifying plants. This study will use plant leaves to identify the species and provide health benefits, procedures, percentages, and hazards to provide an accurate result. This study attempts to close this gap by integrating a toxicity, medicinal, and edibility classification system with plant leaf identification [10]. We plan to integrate a convolutional neural network (CNN) algorithm into a single system that is user-friendly and accessible to Filipino citizens. Our research involved gathering a comprehensive dataset of plant leaf images categorized as edible (safe for consumption), medicinal (with therapeutic properties), and toxic (posing health risks). We then developed a Convolutional Neural Network (CNN) model for accurate plant leaf identification. The predictive model's performance was assessed based on accuracy rate (evaluating classification precision) and human evaluation (verifying results against expert assessments) [11]. We designed and implemented a mobile application capable of classifying plant leaves based on their category and providing recommendations on health benefits and potential hazards. Finally, we evaluated the developed application using ISO 25010 software quality standards [12].

II. Methods

A. Data Collection

In the first phase, the researchers conducted internet research to establish the gap in the study. They found that plants play an important role in human life as they provide food, medicine, and all needs. They also found that research on plant identification primarily focused on medicinal plants only and not on other important uses. Additionally, the researchers conducted interviews at Canaan Hills, Verol Eco Farm, Agriculture, DENR, ERDB- DENR Eastern Visayas, and with (3) traditional healers in different Barangays [13]. They also surveyed 100 random people including gardeners to gather information and their knowledge about plants. During the interviews, the researchers found that some personnel at the two farms were unable to identify unfamiliar plants, regardless of whether they were edible, medicinal, or toxic. In a discussion with DENR, they suggested researching toxic plants on the internet and reaching out to the ERDB-DENR to obtain a plant list. The ERDB- DENR provided a list of medicinal plants promoted by DOH [14]. Some respondents could correctly identify various plant species but were uncertain about their potential uses. Other respondents were knowledgeable about specific plants and their properties, but lacked information about their uses, health benefits, and potential hazards.

B. Design System and Processes

Our approach involved a comprehensive workflow comprising requirement analysis and documentation, followed by detailed software design and system product and process evaluation. We created structured development and testing plans, produced a descriptive prototype, established a clear implementation roadmap, and thoroughly documented the implementation results.

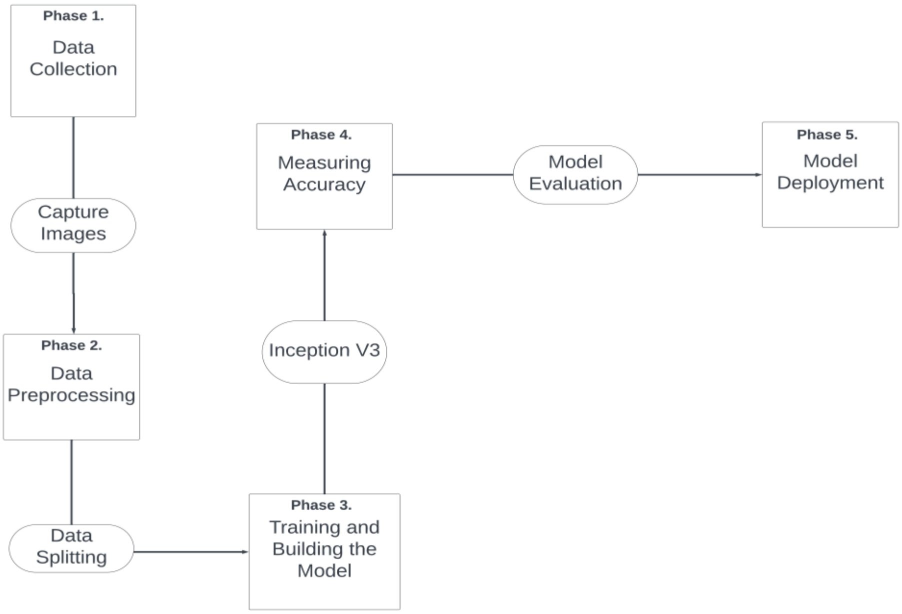

Figure 1. Schematic Diagram Model

The schematic diagram model is shown in Figure 1. The first step in the process is data collection, which involves taking pictures to compile a dataset. Data pre-processing comes next, we clean and get these pictures ready for analysis. To train the model it splits up your data into a training and testing set so that it may train on one dataset and then test its behavior on another. We teach the model from our prepared data using the Inception V3 architecture during training and model construction, assisting it in identifying patterns and formulating predictions. Once the model is trained, phase 4 focuses on measuring accuracy, we test the model's performance on the testing set to see how well it learned and to ensure it's reliable. This involves also the model evaluation which assesses the model's performance on a holdout dataset to determine its accuracy [15]. In the last part, the model is deployed where it is put into use in a real-world application.

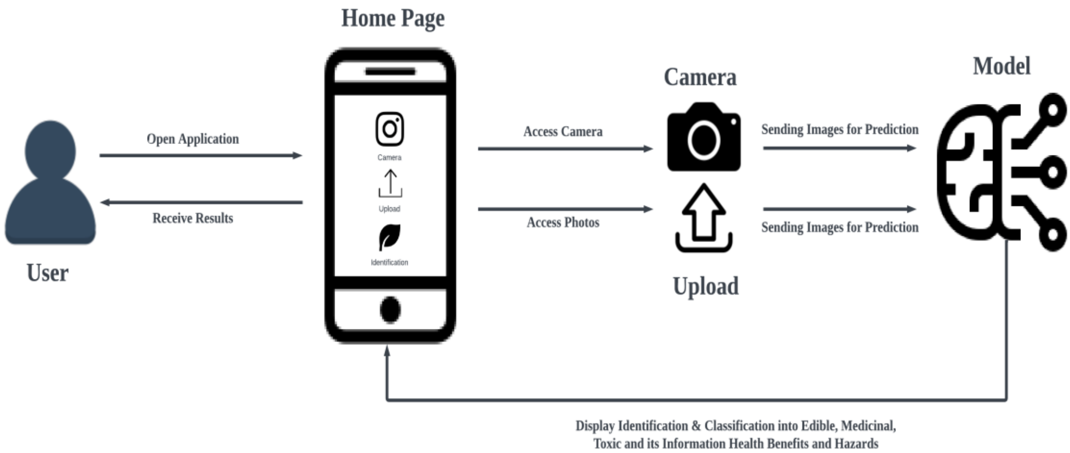

Figure 2. System Architecture

The system architecture for this project, which aims to identify plant leaves and categorize them as toxic, edible, and medicinal, is depicted in Figure 2. The user opens the app and navigates to the home page, where they can view identification results, upload photos, and use the camera. After that, the app forwards the photos to a model that has already been trained for processing. Following the procedure, the app shows the outcomes, which include the identification and classification of the plant as well as its recommendation of health benefits and hazards.

C. Software Development Plan

The project will employ a mobile-based system to provide contrast to conventional approaches which will be accessible on diverse digital platforms. To help the readers fully understand the terms or concepts used in this study, the following are defined conceptually and operationally. Flutter framework will be as a foundation or its user interface frontend framework. As the backend, the proponents will use Python with its components Anaconda and Pylab to train datasets of plant leaf identification using image processing.

III. Results and Discussions

A. Data Collection Process

The process involves creating a diverse dataset of Convolutional Neural Network (CNN) images of plant leaf identification, including Alugbati, Balbas Pusa, Buntot Pusa, Damong Maria, Giant Dumb Cane, Kampanilya, Kumintang, Monstera, Peace Lily, Snake Plant, Tobacco, Arrowhead, Balimbing, Caimito, Devils Backbone, Kadok, Kandi-Kandilaan, Lagundi, Niog-Niogan, Sagilala, Soro-soro, Welcome Plant, Atis, Bangkuro, Caladium, Devils Ivy, Kakawate, Kataka-taka, Lansi-lansian, Oregano, Sambong, Taingang Daga, Yahong-yahong, Bago, Bignai, Chili, Ganas, Kalachuchi, Kulitis, Libas, Pansit-pansitan, Serpintina, Talinum, Yerba Buena and San Francisco from various sources, including research and agricultural organizations, to ensure efficient leaf identification and classification.

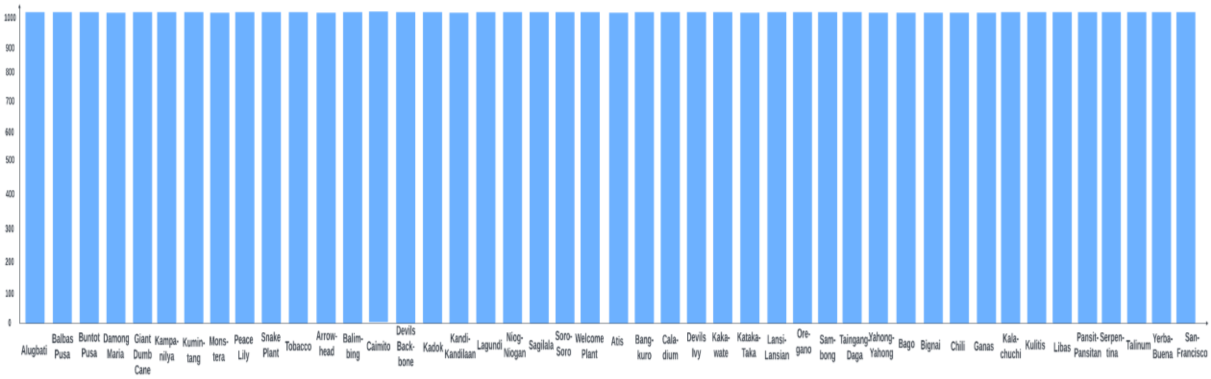

Figure 3. Datasets Distribution

Figure 3 shows the statistical representation of the complete dataset of FloraFolium plant leaf identification. The value for each dataset is equivalent to 1,000, for a total of 45,000 images collected. The list of the plants for the datasets was obtained from some experts, and the researcher personally captured the leaf images.

Below are samples of edible, medicinal, and toxic plant species:




Figure 4. Sample Edible Leaf

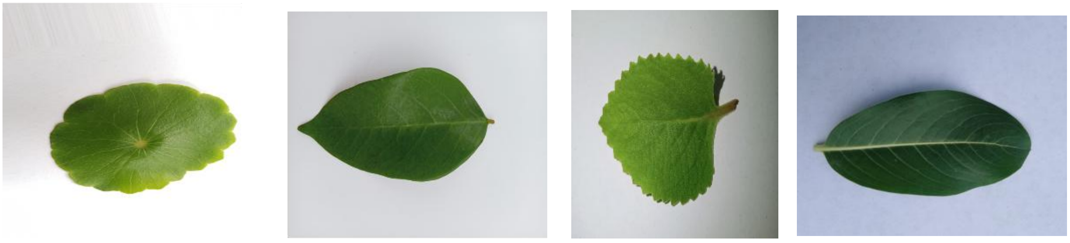

Figure 5. Sample Medicinal Leaf

Figure 6. Sample Toxic Leaf

Figures 4, 5 and 6 show the example plant leaf for classification. All pictures were taken one by one, so that every angle was captured and there was a balanced amount.

B. Develop a CNN model for plant leaf identification

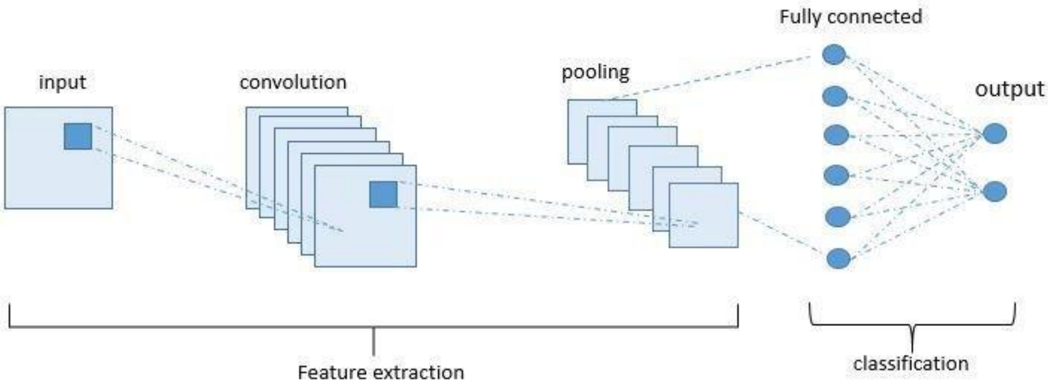

Figure 7. Basic Architecture of CNN

The input would be a picture of a leaf from a plant. The image may contain various patterns, textures, and shapes unique to that species of plant. This image is composed of pixels, which are tiny squares with varying colors and shades. CNN will examine these pixels to understand the leaf's details. The convolutional layers use kernels or filters to scan the input image (leaf). These filters have selected the important features that the leaf possesses, such as its veins, edges, textures, or some special outline. Pooling preserves the most crucial information while shrinking the feature maps' size. This aids the network in ignoring unimportant details and concentrating on the leaf's key characteristics. The model's focus on identifying plant leaves is maintained through pooling.

C. Evaluate the predictive model in terms of Model Accuracy

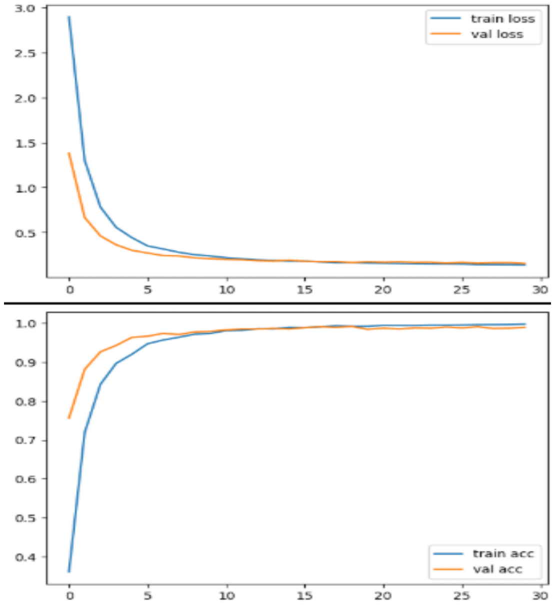

Figure 8. Model Accuracy

As illustrated in Figure 8, the graph shows the training loss and accuracy that is calculated on training and validation. The graph appears well-trained and has no overfitting. After about 20 epochs, the loss and accuracy stop improving, meaning the model has learned so much. Thus, the model shows a good performance with its low loss value and a high accuracy value

D. Developed a user-friendly Mobile Application

Figure 9. Capture plant leaf images

Figure 10. Display Results and Prediction

Figure 9 captures plant leaf images for analysis and Figure 10 displays the results and predictions of the leaf that has been detected. It shows the related description and other information, including plant type and scientific name.

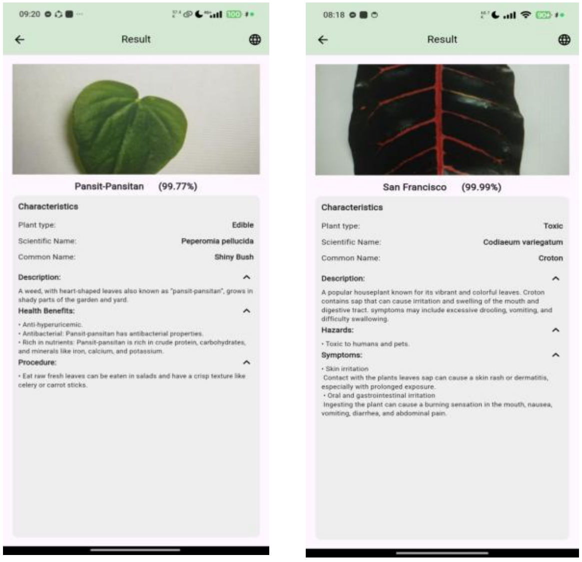

Figure 11. Recommend health benefits and hazards

Figure 11 presents a recommendation panel from a plant identification application, which provides hazards, symptoms health benefits, and other information based on the identified plant.

E. Evaluate the developed application using ISO 25010 software quality standards

The researchers conducted a system evaluation with 30 users who evaluated the system.

Table 1. Summary of Evaluation

Indicators	Mean	Description
Functional Suitability	4.5	High Extent
Performance Efficiency	4.3	High Extent
Compatibility	3.9	Moderately Extent
Usability	4.3	High Extent
Reliability	3.9	Moderately Extent
Security	3.2	Moderately Extent
Maintainability	3.9	Moderately Extent
Portability	4.3	High Extent
Average Weighted Mean (AWM)	**4.0**	**High Extent**

The summary of evaluation of the application by the users in the region through the ISO 25010 software quality standards resulted in a high extent (4.0) overall performance, with a high extent performance of the efficient functionality (4.5) and performance efficiency (4.3) and portability (4.3) of the application. Moreover, the application performed moderately in compatibility (3.9), reliability (3.9), security (3.2), and Maintainability (3.9).

IV. Conclusions

The study indicates that FloraFolium app successfully addresses challenges in plant identification, providing a practical and accessible solution for categorizing plants as edible, medicinal, and toxic. The integration of CNN technology allows for accurate classification, while the app's design ensures ease of use. The integration of multiple languages, and the ability to offer recommendations of health benefits and hazards further enhance the app's usability, making it a promising tool for agricultural and botanical management. However, limitations such as dataset size, language accessibility, and security require attention to enhance the app's overall performance and reliability.

References

[1] Taslim, A. S. (2021). Plant leaf identification system using convolutional neural network. *Bulletin of Electrical Engineering and Informatics,*, 10, 3341-3352. doi:https://doi.org/10.11591/EEI.V10I6.2332.

[2] Alassafi, M.O.; Ibrahim, M.S.; Naseem, I.; AlGhamdi, R.; Alotaibi, R.; Kateb, F.A.; Oqaibi, H.M.; Alshdadi, A.A.; Yusuf, S.A. A novel deep learning architecture with image diffusion for robust face presentation attack detection. *IEEE Access* **2023**, *11*, 59204–59216.

[3] Tan, Z.; Liu, A.; Wan, J.; Liu, H.; Lei, Z.; Guo, G.; Li, S.Z. Cross-batch hard example mining with pseudo large batch for id vs. spot face recognition. *IEEE Trans. Image Process.* **2022**, *31*, 3224–3235.

[4] Sheikhjafari, A.; Krishnaswamy, D.; Noga, M.; Ray, N.; Punithakumar, K. Deep learning-based parameterization of diffeomorphic image registration for cardiac image segmentation. *IEEE Trans. NanoBiosci.* **2023**, *22*, 800–807.

[5] Felt, V.; Kacker, S.; Kusters, J.; Pendergrast, J.; Cahoy, K. Fast Ocean front detection using deep learning edge detection models. *IEEE Trans. Geosci. Remote Sens.* **2023**, *61*, 4204812.

[6] Zhang, Q.; Dong, Y.; Yuan, Q.; Song, M.; Yu, H. Combined deep priors with low-rank tensor factorization for hyperspectral image restoration. *IEEE Geosci. Remote Sens. Lett.* **2023**, *20*, 5500205.

[7] Luna, R. G., Rosales, M. A., & Dadios, E. P. (2019). Classification of philippine herbal plants via leaf using different machine learning algorithms. *Journal of Computational Innovations and Engineering Applications*, 29-34.

[8] Rosales, Eunice & Amistad, Vanessa & Picardal, Jay. (2019). Floristic Inventory and Ethnobotany of Wild Edible Plants in Cebu Island, Philippines. Asian Journal of Biodiversity. 9. 90-114. 10.7828/ajob.v9i1.1236.

[9] Dapar, M.L.G., Alejandro, G.J.D., Meve, U. *et al.* Quantitative ethnopharmacological documentation and molecular confirmation of medicinal plants used by the *Manobo* tribe of Agusan del Sur, Philippines. *J Ethnobiology Ethnomedicine* 16, 14 (2020). https://doi.org/10.1186/s13002-020-00363-7

[10] Berihu, M., Fang, J., & Lu, S. (2022). Automatic Classification of Medicinal Plants of Leaf Images Based on Convolutional Neural Network. *SpringerLink*, 108-116.

[11] Taslim, A., Saon, S., Muladi, M., & Hidayat, W. N. (2021). Plant leaf identification system using convolutional neural network. *Bulletin of Electrical Engineering and Informatics*, *10*(6), 3341-3352.

[12] Salka, T. D., Hanafi, M. B., Rahman, S. M. S. A. A., Zulperi, D. B. M., & Omar, Z. (2025). Plant leaf disease detection and classification using convolution neural networks model: a review. *Artificial Intelligence Review*, *58*(10), 322.

[13] Thanjaivadivel, M., Gobinath, C., Vellingiri, J., Kaliraj, S., & Femilda Josephin, J. S. (2025). EnConv: enhanced CNN for leaf disease classification. *Journal of Plant Diseases and Protection*, *132*(1), 32.

[14] Ali, H., Shifa, N., Benlamri, R., Farooque, A. A., & Yaqub, R. (2025). A fine-tuned EfficientNet-B0 convolutional neural network for accurate and efficient classification of apple leaf diseases. *Scientific Reports*, *15*(1), 25732.

[15] Paul, H., Udayangani, H., Umesha, K., Lankasena, N., Liyanage, C., & Thambugala, K. (2025). Maize leaf disease detection using convolutional neural network: a mobile application based on pre-trained VGG16 architecture. *New Zealand Journal of Crop and Horticultural Science*, *53*(2), 367-383.