Herbal Medicinal Plant Identification using Leaf Vein through Image Processing and Convolutional Neural Network

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Abstract—**The utilization of herbal medicinal plants dates to antiquity, and as human civilization has progressed and technology has advanced, a significant proportion of contemporary medicines have originated from herbal sources. The Philippines is renowned for its extensive utilization of herbal medicinal plants, exemplified by the Department of Health's recognition of ten prominent herbal medicines under the "Traditional and Alternative Medicine Act (TAMA)", or the "Republic Act No. 8423". This legislative measure not only enhances the healthcare system within the country but also underscores the nation's commitment to incorporating traditional healing methods. Many herbal medicinal plants possess valuable therapeutic properties; however, the lack of comprehensive research and clinical trials has resulted in limited knowledge regarding the specific benefits associated with each of these plants. This research endeavor culminated in developing a device capable of identifying the herbal medicinal plant name, scientific name, and medicinal purposes by capturing a leaf image. This study's initial phase entails pre-processing the captured image and extracting the leaf vein characteristics using the Histogram of Oriented Gradient (HOG) feature extraction algorithm. Subsequently, the Convolutional Neural Network (CNN) algorithm is employed to identify the leaf based on these extracted features. Following the execution of 25 trials for each of the five selected herbal medicinal plants, namely Banaba, Bayabas, Bignay, Sambong, and Serpentina, in addition to 25 tests for two untrained plants, the research findings demonstrated a commendable accuracy rate of 95%.**

***Keywords*— Herbal Medicinal Plant, Convolutional Neural Network, Histogram of Oriented Gradient, Plant Identification, Leaf Vein, Image Processing**

I. Introduction

The utilization and application of herbal medicine predate recorded human history, a fact supported by paleontological evidence, the early humans' invention of fire, and the utilization of abundant natural resources, including plants and animals, for sustenance and medicinal purposes. During this era, the distinction between poisonous and non-poisonous plants may not have been fully recognized or understood [1]. Herbal medicine encompasses diverse plant components such as seeds, roots, bark, stems, fruits, flowers, leaves, and entire plants. Historical accounts documented the employment of herbs like laurel, caraway, and thyme for medicinal purposes by the Sumerians 5,000 years ago. Furthermore, archaeological investigations reveal evidence of herbal medicine practices dating back 60,000 years in Iraq and 5,000 years in China [2]. Due to its deep-rooted historical background, Traditional Chinese Medicine (TCM) remains popular and widely practiced across various cultures worldwide. Unique best-selling products in this domain encompass Garlic (Allium sativum), Panax ginseng, and Ginkgo biloba [3]. Of the 252 essential medicines the World Health Organization (WHO) cataloged, 11% are derived exclusively from plants, while a quarter of globally prescribed drugs originated from plants. There is a growing inclination towards herbal and traditional medicine, with developing nations widely adopting this approach and developed countries embracing it due to factors such as cost-effectiveness, potential reduction in adverse effects, and the freedom to exercise choice in treatment modalities [4].

Traditional medicine has gained significant prominence in the Philippines, particularly in rural areas, where the high cost of conventional drugs is often beyond the means of the low-income population, despite legislative efforts such as the Generic Act of 1988 and the Cheaper Medicine Act of 2008 aimed at reducing medication expenses [5]. The Department of Health in 1992 officially identified ten medicinal plants, including Sambong, Akapulco, Niyog-niyogan, Bawang, Tsaang gubat, Ampalaya, Yerba Buena, Lagundi, Bayabas, and Ulasimang bato, which have undergone scientific validation. Nevertheless, Filipinos' repertoire of medicinal plants extends beyond these ten, as numerous other plants, lacking clinical trials, persist in popularity within the Philippines [6]. Implementing imaging devices capable of identifying herbal medicinal plants through image capture offers a promising avenue for conducting comprehensive and efficient studies on these botanical species.

The contemporary trend of employing advanced technology for real-time plant identification has gained substantial popularity. This technology encompasses a range of methods, including machine learning, image processing, support vector machines, and neural networks. Recent studies have primarily focused on the leaf component of plants, specifically exploring the vein characteristics. Leaf veins possess quantifiable attributes, such as the hierarchical arrangement of minor and major veins, the reticulate mesh formed by these veins, vein lineages, vein density (length of veins per unit area), vein topology, and vein tapering [7]. The discernible attributes associated with leaf characteristics render them highly distinguishable. Moreover, when considering various plant components, the leaf is prominently utilized for medicinal applications [8]. These innovations have the potential to enhance the efficiency of plant identification, particularly in the realm of research and development for new pharmaceuticals.

A Convolutional Neural Network (CNN) is a deep learning model, it mimics how the human brain works and is exceptionally known for object detection [9]. Here's a simple explanation: imagine you're crossing the street, and you see a car. Your eyes capture the vehicle's image, and your brain identifies it as a car. Similarly, CNN uses convolutions and pooling layers to develop its algorithm [10], [11]. A Convolutional Neural Network (CNN) comprises key components, namely the Convolution Layer responsible for initial input processing, the Pooling Layer that reduces input size to focus on important features, and the Fully Connected Layer which utilizes learned knowledge to accurately identify objects. [12]. Like our eyes and brain working together, CNN captures, trains, analyses, and predicts images based on familiar datasets [13]. The convolutions within the neural network allow for broader dataset training, increasing the coverage of each pixel in a photo [14]. This deep learning algorithm has proven reliable, as it effectively extracts features from input images and provides high accuracy in classification [15], [16]. However, the performance of the CNN model may depend on the distinct features it is trained on, so more data training is crucial to achieving higher accuracy rates [17]. Various studies implementing CNN on a Raspberry Pi have achieved impressive accuracy rates, such as 91.7% for abaca disease detection [18], 92% for medicinal mushroom identification [19], and up to 93% for corn leaf disease detection [20]. Raspberry Pi is a powerful microcomputer that is highly compatible with CNN models.

While CNN can extract features from identified images, it is advisable to incorporate a feature extractor when developing an image processing-based identification system for enhanced reliability and accuracy. One dependable feature extraction technique is the Histogram of Oriented Gradients (HOG), although its effectiveness depends on the specific subject being identified. In this approach, an image is represented by a collection of histograms that capture local information. Gradient orientations are accumulated within small spatial regions known as cells, and the concatenation of these 1-D histograms produces a feature vector [21]. The HOG descriptor operates by computing gradients (magnitude and angle), performing orientation binning based on the gradient angle, and then normalizing the image to obtain a feature description [22]. Integrating this feature extraction technique into the image identification system can help reduce misclassification rates.

This paper aims to achieve the following objectives: (1) Designing and developing a device that captures high-quality plant images, employs image processing techniques, HOG Feature Extraction, and Convolutional Neural Network for the identification of medicinal plants and their associated medical purposes. (2) Training a dedicated dataset for the herbal medicinal plants utilized in this study. (3) Conducting an evaluation of the developed device and system.

This paper specifically focuses on the leaf vein feature and examines five herbal medicinal plants: *Banaba (Lagerstroemia speciosa)*, known for its applications in hypertension and diabetes treatment [23]; *Bayabas (Psidium guajava)*, widely recognized for its antiseptic properties [24]; *Bignay (Antidesma bunius)*, commonly used to address urinary tract infections (UTIs) and regulate blood pressure (UTI) and controls blood pressure [25]; *Sambong (Blumea balsamifera)*, extensively utilized for UTIs, kidney stones, and hypertension management [26]; and Serpentina (Andrographis paniculata), traditionally employed for cardiovascular health, immune system enhancement, and hypertension treatment [27]. The study's findings will hold significance for researchers, particularly in the fields of botany and pharmaceutical drug development, as the introduction of such a device will streamline the manual identification process of plants and their respective purposes.

II. METHODOLOGY

In this study, the researchers utilized the iterative waterfall methodology to systematically progress through each linear sequential phase, ensuring a comprehensive completion of the research and, simultaneously, iterating the steps without the need to finish the cycle first.

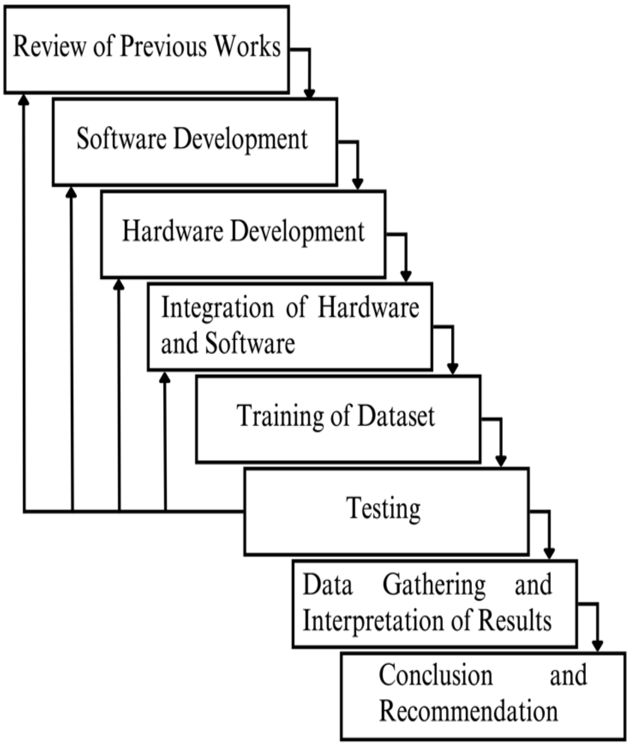


Fig. 1 Research Methodology

The research began by *reviewing previous works* which popularly used deep learning as it is one of the most common techniques, especially in object identification [28]. Previous studies have explored diverse machine learning techniques, such as Multiclass Support Vector Machines (MSVM), incorporating feature extraction methods involving morphological, vein, and texture features of leaf images. By utilizing the FLAVIA dataset, these researchers attained recognition rates ranging from 71.25% to 93.3% [29].

Similarly, in 2018, another group of researchers followed a similar approach. Utilizing Scale-Invariant Feature Transform (SIFT) along with Support Vector Machine (SVM), the researchers employed image pre-processing and feature extraction techniques, yielding an accuracy rate of 84.29% [30]. The application of SVM is beneficial, especially for producing fast results with low storage requirements and improving classification performance [31]. In the domain of object identification, it is customary to perform pre-processing on the input image to improve the ease and accuracy of identification. Subsequently, feature extraction techniques are often utilized to remove irrelevant features from the input, followed by the application of a deep learning technique for object identification. Yet, among all the methods, Convolutional Neural Network (CNN) appears to yield the highest accuracy, ranging from 88.68% to 95% [32], [33].

The researcher used the HOG Feature Extractor and CNN for plant identification based on gathered information and developed a prototype starting with the image-capturing feature to acquire pictures for the dataset. Hardware development followed, and once integrated, the system was tested and adjusted if necessary. After addressing all issues, data were gathered and interpreted using the confusion matrix. Finally, the researcher arrived at conclusions and provided recommendations for future studies.

A. Conceptual Framework

Figure 2 depicts the interconnectedness of input, process, and output, providing a cohesive understanding of the experimentation's conclusion.

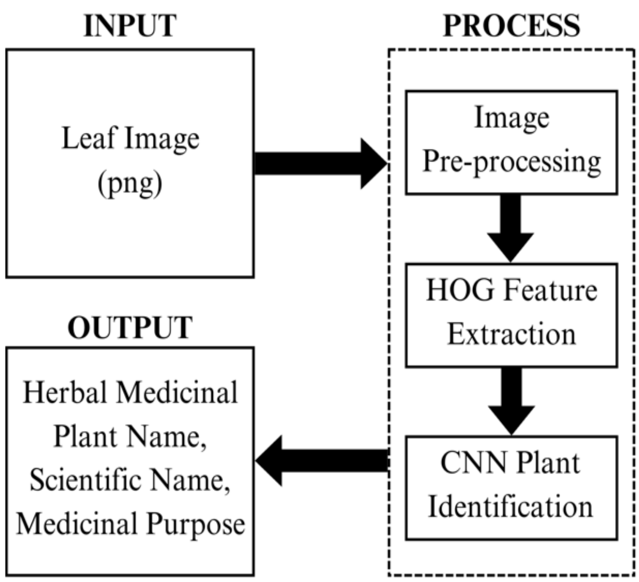


Fig. 2 Conceptual Framework Diagram

The captured leaf image serves as the input, which undergoes image pre-processing and feature extraction. This enables the CNN model to match and identify the plant leaf using trained data. The expected output includes the identified name of the herbal plant, which is displayed on the LCD screen, along with information about its medical use.

B. Hardware Block Diagram

Figure 3 portrays a block diagram that illustrates the arrangement of the hardware components.

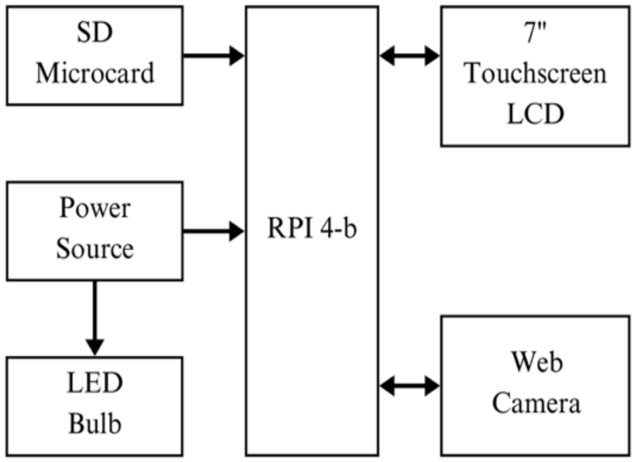


Fig. 3 Hardware Block Diagram

The brain of the system is the Raspberry Pi 4 Model B (RPI 4-B), which is powered by any power source. The LED bulb can be connected to any power source for illumination. The RPI 4-B is linked to a web camera responsible for capturing leaf images. Additionally, a 7" Touchscreen LCD is connected to and powered by the RPI 4-B, providing a user interface for capturing photos and displaying the system's output, including the herbal medicinal name, its scientific name, and the medicinal purpose of the plant.

C. Software Development

The main system flowchart, shown in Figure 4, explains the internal processes of the software system for plant identification.

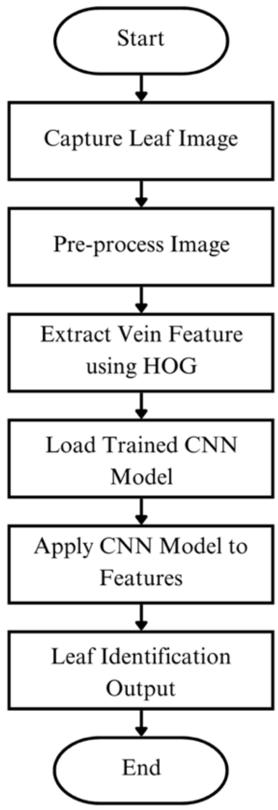


Fig. 4 Main System Flowchart

The image capture serves as the initial input for the system, undergoing pre-processing steps such as resizing, normalization, binary conversion, and image segmentation to ensure compatibility with the trained CNN model. The HOG algorithm is then employed to extract essential patterns and generate a feature vector from the pre-processed image. This vector is fed into the loaded CNN model, which applies its learned computations to produce predictions based on the trained patterns. The final output of the system includes the herbal medicinal name, scientific name, and medicinal purpose associated with the identified leaf.

D. Data Training

In accordance with the research methodology, prior to data collection, the researcher conducted training on datasets specific to the five herbal medicinal plants employed in the study, as illustrated in Figure 5.

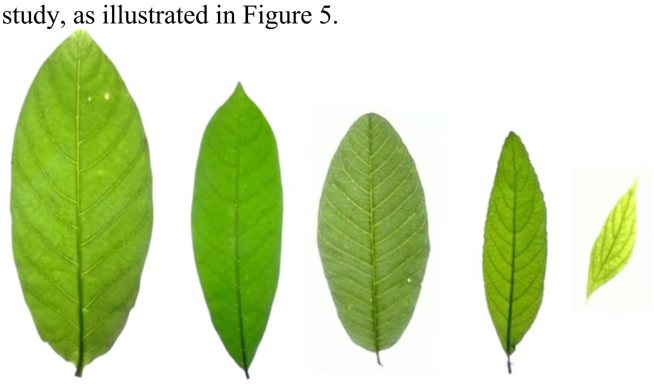


Fig. 5 Dataset of the Five Herbal Medicinal Plants (from left to right: Banaba, Bignay, Bayabas, Sambong, and Serepentina, respectively)

A minimum of 100 images were collected for each herbal medicinal plant. Subsequently, all the captured photographs were utilized for training and loaded into the CNN model.

E. Hardware Setup

Figure 6 showcases the Graphic User Interface (GUI), while Figure 7 provides a depiction of the Experimental Setup.

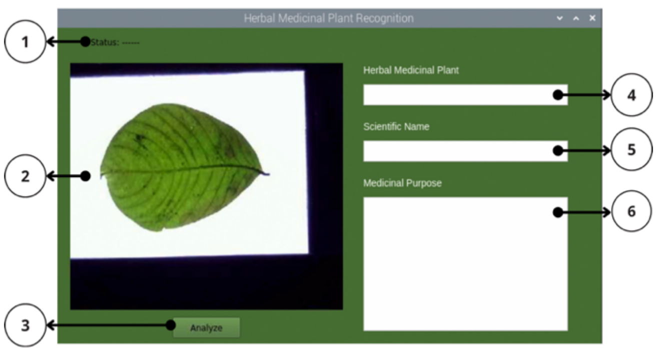


Fig. 6 Graphic User Interface

The GUI serves as the key for users to navigate the system. Here are the key components: *(1) Status Indicator.* This component provides visual feedback during different system states. When the system is idle, it displays output lines as shown in Figure 6. During the leaf analysis process, it displays "Analyzing." Once the process is completed, it shows "Done." *(2) Real-time Camera Feed and Processed Image.* This section displays the live feed from the camera and, at the end of the process, the pre-processed and analyzed image. *(3) Analyze Button.* Clicking this button initiates the image capture and analysis process. The user can also click the button to clear the display shown in section 2. Sections 4, 5, and 6 present the identified Herbal Medicinal Plant Name, Scientific Name, and Medicinal Purpose, respectively, after the completion of the identification process.

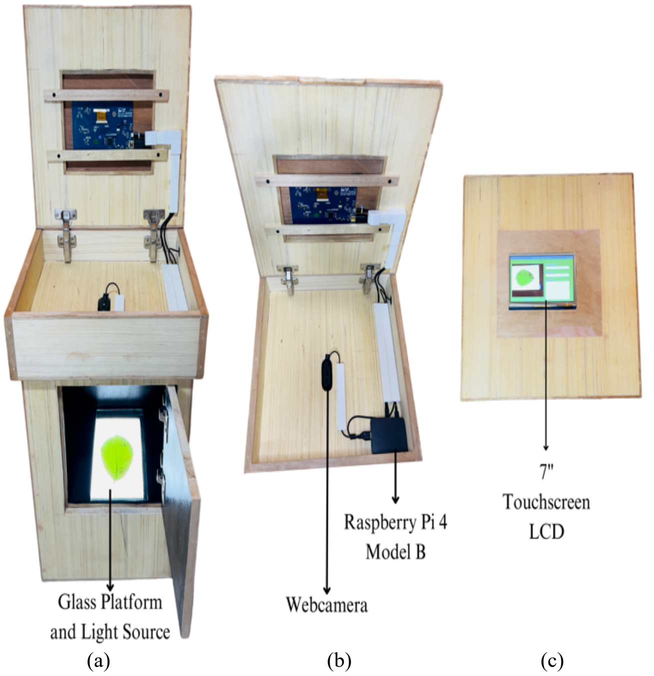
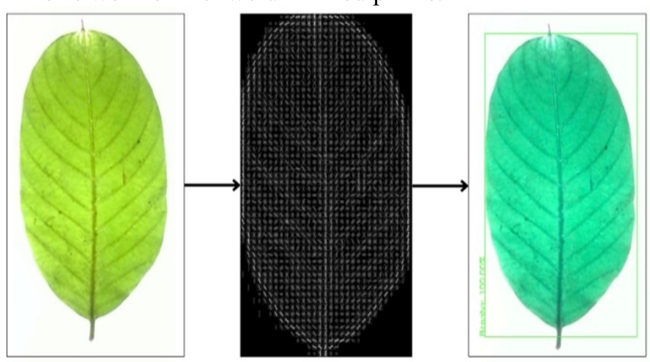


Fig. 7 Experimental Setup

The setup depicted in Figure 7-a consists of two main parts. The top part houses most of the components, including the RPI 4-b, web camera, and LCD touchscreen. When the lid of the top part is opened (Figure 7-b), the RPI 4-b becomes visible. The LCD touchscreen is readily visible for easy user navigation (Figure 7-c). The lower part of the system contains the light source positioned beneath the input platform. Additionally, there is a glass platform where the input, such as plant leaves, is placed for image capturing. Positioning the light beneath the leaf enhanced the clarity of the captured leaf vein.

III. Result and Discussion

The researcher performed a total of 175 trials, consisting of 25 trials for each of the five herbal medicinal plants and 25 trials as well for the two untrained plants.



(a) (b) (c)

Fig. 8 Captured Banaba Leaf Image

A comparison between the captured image in Figure 8-a and the resulting image in Figure 8-c reveals distinct variations in appearance, primarily in color. Figure 8-c represents the pre-processed output, with the enclosed rectangle indicating the resized area that contains the specific details extracted using HOG, as illustrated in Figure 8-b.

TABLE I
Trials Gathered Data

		Actual Result						
		Banaba	Bayabas	Bignay	Sambong	Serpentina	Plant A	Plant B
Predicted Result	Banaba	25	0	2	0	0	0	0
	Bayabas	0	25	0	0	0	0	0
	Bignay	0	0	20	0	0	0	1
	Sambong	0	0	0	25	0	0	0
	Serpentina	0	0	0	0	25	2	0
	Unidentified	0	0	3	0	0	23	24

The gathered data from the trials is presented in Table I. The findings reveal that Bignay data showed two cases of false positive results, incorrectly identified as Banaba in both trials. In addition to three false negative results occurred for Bignay as well. Surprisingly, Plants A and B, expected to output "unidentified," produced false positive results. Plant A incorrectly identified Serpentina in two trials, while Plant B identified Bignay once.

TABLE II
Summary of Results

	True Positive	True Negative
False Positive	120	5
False Negative	3	47

Table II presents a summary of the results, indicating that the True Positive (TP) value was 120, slightly below the expected value of 125, resulting in a False Positive (FP) value of 5. Furthermore, the True Negative (TN) value was 47, slightly lower than the expected value of 50, leading to a False Negative (FN) value of 3. To determine the performance and effectiveness of the system, the accuracy and misclassification rate are computed using the formula derived from the confusion matrix. The accuracy rate is obtained by applying the following calculation:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}\,x100 \quad (1)$$

The accuracy rate represents the percentage of correct predictions obtained from the conducted trials. Based on the results of the trials, the accuracy rate is determined to be 95% using Equation 1.

$$Misclassification = \frac{FP + FN}{TP + FP + TN + FN}\,x100 \quad (2)$$

The misclassification rate refers to the percentage of incorrect predictions made for the actual positive and negative outputs. By analyzing the outputs presented in Table II and applying Equation 2, the misclassification rate is determined to be 5%.

IV. Conclusion

Through the study, extensive enhancements and integration of existing approaches for plant identification using the leaf vein feature were conducted, resulting in a notable accuracy rate of 95%. The research objectives were successfully achieved, beginning with the development of a device capable of effectively identifying herbal medicinal plants. This entailed employing image pre-processing techniques, HOG feature extraction, and CNN algorithms to precisely locate the leaf. Furthermore, a comprehensive dataset was curated specifically for the five herbal medicinal plants examined in the study: Banaba, Bayabas, Bignay, Sambong, and Serpentina. These curated data significantly contributed to more accurate outcomes. Lastly, by utilizing the developed device, the researchers were able to comprehensively analyze and interpret the gathered data, attributing the higher accuracy rate to the placement of the LED bulb beneath the leaf, which enhanced image definition while minimizing noise compared to placing it above the input image.

V. Future Works

To enhance the system further, the researcher suggests incorporating a web camera with autofocus capability to reduce manual adjustments by the user. Additionally, implementing multi-threading processes could expedite recognition speed. Future researchers may also explore optimization techniques to further improve system efficiency. To achieve higher accuracy, expanding the training dataset is recommended. Considering that this study solely concentrated on leaf vein features, future investigations could explore other leaf characteristics or different plant parts. Such exploration may contribute to the development of drugs harnessing the potential of herbal medicinal plants.

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