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Research article

Herbal Plant Classification System Using Deep Learning Technology on a Mobile Application: A Case Study of Udai Charoen Subdistrict, Khuan Kalong District, Satun Province

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Abstract: This study aimed to develop a herbal plant classification system based on Deep Learning technology implemented on a mobile application, and to evaluate both the system's performance and user satisfaction. The application was developed using the Flutter framework for mobile development, PHP for data management, and TensorFlow for constructing the Deep Learning model. A total of 42 medicinal plants were collected, comprising 2,100 images. The system employed a Custom CNN Architecture consisting of four convolutional layers, and its performance was tested using the Adam optimizer. The results demonstrate that the herbal plant classification system achieved an accuracy of 85.7%. In addition, experts evaluated the system's performance at the highest level ($\bar{x}$ = 4.28, S.D. = 0.14), and users reported the highest level of satisfaction ($\bar{x}$ = 4.21, S.D. = 0.61). These findings indicate that the developed classification system is feasible for real-world use and can contribute significantly to the preservation of medicinal plants.

Keywords: Information system; deep learning; medicinal plants; classification; mobile application

1. Introduction

Thailand is recognized for its high biodiversity of medicinal plants, with more than 2,187 species documented for traditional therapeutic use [1]. However, knowledge regarding the utilization of medicinal plants is increasingly at risk of being lost due to limited transmission of traditional wisdom to younger generations, changes in community lifestyles, and the absence of systematic knowledge management frameworks [2]. Accurate identification of medicinal plant species is therefore a fundamental prerequisite for sustainable conservation and utilization [3, 4]. Nevertheless, species identification remains challenging, as it often requires individuals with specialized expertise [5]. Hence, the development of tools that can support the classification of medicinal plants has become critically important [6].

The emergence of Deep Learning technology, particularly Convolutional Neural Networks (CNNs) has demonstrated strong capabilities in efficient plant identification and classification [7, 8]. Recent studies indicate that Deep Learning can achieve high levels of accuracy across various plant recognition contexts [9].

For example, a 2024 study reported a classification accuracy of 95.87% for a herbal plant recognition system [10], while Waldchen [11] concluded that Deep Learning significantly outperforms traditional approaches. Mobile applications for plant identification are also gaining popularity, such as PlantNet, which has millions of users worldwide [12]. Additionally, research by Lee [13] demonstrated that Deep Learning models can effectively extract key leaf features for classification [14].

This trend aligns with the rapid expansion of Thailand's herbal plant industry, valued at 42.4 billion THB (USD 1.36 billion) in 2018, with an annual growth rate of 11% [15, 16]. Crucially, this research does not merely focus on mobile software engineering; rather, it establishes a rigorous applied computational and spatial science framework. By integrating localized Convolutional Neural Network (CNN) architectures with geobotanical spatial mapping, this study provides a scientifically validated approach to preserving and identifying complex herbal species under real-world community constraints. Given this context, the present study aims to develop a medicinal plant classification system using Deep Learning technology on a mobile application and to evaluate its performance and user satisfaction. The system is intended to serve as a practical, scientifically grounded tool supporting the conservation and sustainable use of medicinal plants in Udai Charoen Subdistrict, Khuan Kalong District, Satun Province.

2. Materials and Methods

2.1 Herbal Plant Data Collection

Data collection was conducted from March to April 2024 in Udai Charoen Subdistrict, Khuan Kalong District, Satun Province. We documented a total of 42 local medicinal plant species. We captured images of leaves and other relevant plant parts, yielding 2,100 images in total (50 images per species). The survey covered all nine villages in Udai Charoen Subdistrict, as illustrated in Figure 1(A). To ensure strict adherence to international ethical standards, all research team members completed official human research ethics training. The research protocol, fieldwork methodology, and evaluation instruments were reviewed and approved by the Institutional Review Board (IRB/IRD) of Songkhla Rajabhat University before the allocation of the research grant. Formal informed consent was obtained from all participating local sages and community members before conducting surveys and interviews. All data were strictly anonymized and protected to maintain participant confidentiality.

(A) (B)

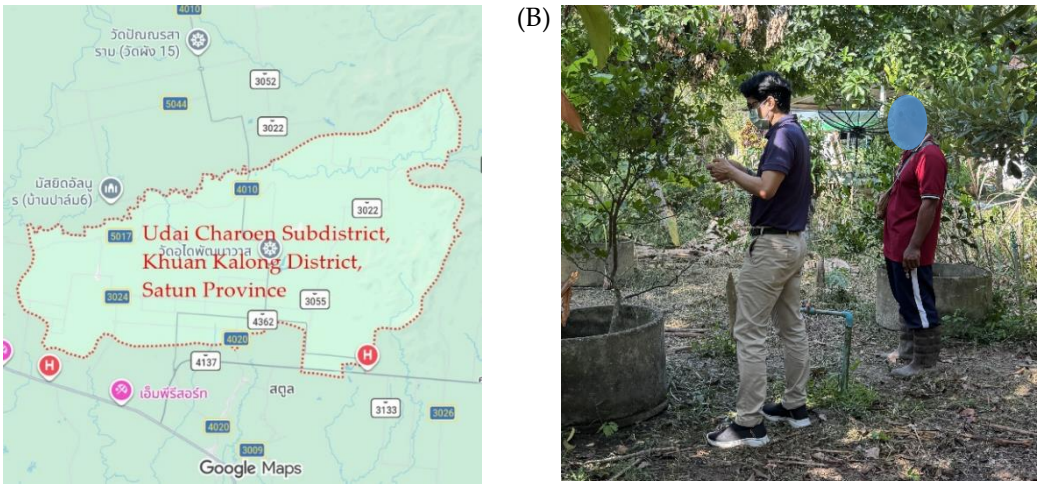


Figure 1. (A) Map of Udai Charoen Subdistrict, Satun Province; and (B) the research team conducting field data collection in the community.

The research team surveyed medicinal plants, recorded field data, and interviewed community members knowledgeable about herbal species, as shown in Figure 1(B). The team identified 42 species. Commonly found examples include Roselle, Ginger, and Turmeric, as illustrated in Figure 2.

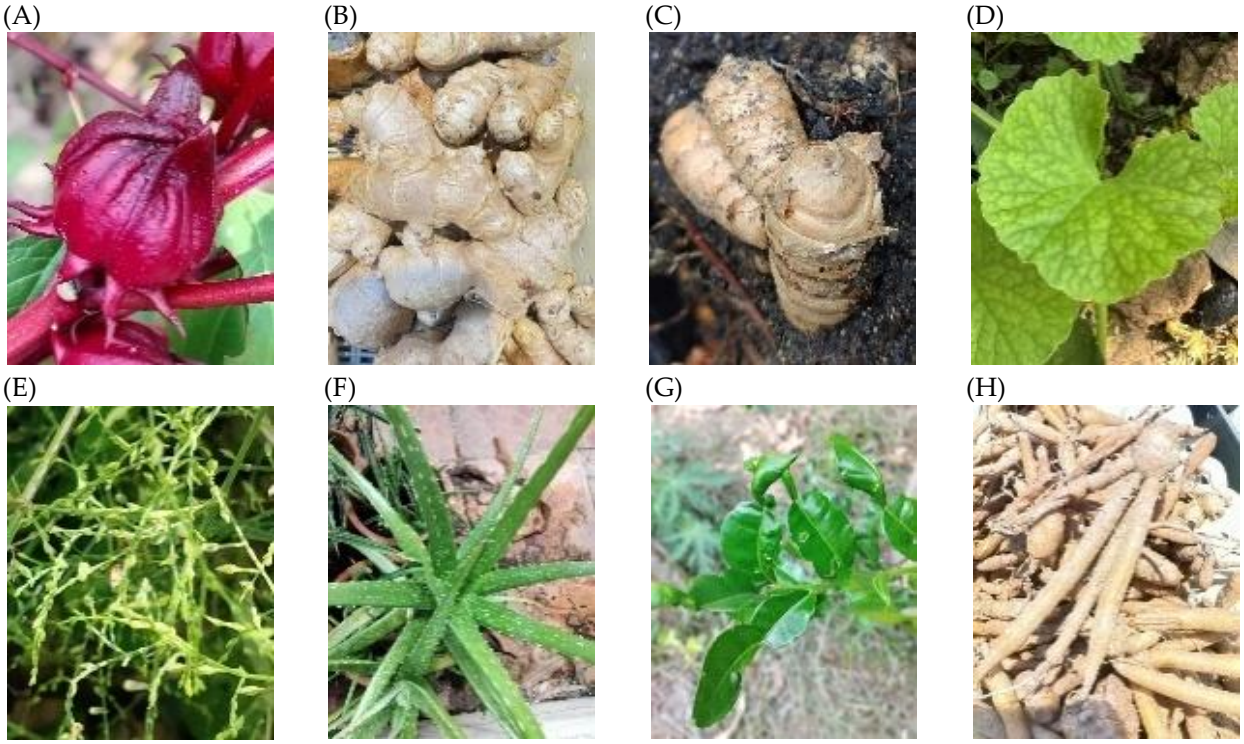


Figure 2. Representative medicinal plants found in the study area: (A) Roselle, (B) Ginger, (C) Turmeric, (D) Gotu kola, (E) Andrographis paniculata, (F) Aloe vera, (G) Kaffir lime leaf, and (H) Fingerroot.

2.2 Development of the Deep Learning Model

2.2.1 Data Preparation

All herbal plant images were resized to 224 × 224 pixels. Data Augmentation was applied to increase the diversity of the training dataset and to reduce overfitting. The general formulation of the Data Augmentation process is expressed in Equation (1):

$$\Gamma'(x,y) = T(I(x,y)) \quad (1)$$

where (I(x, y)) denotes the original image, (Γ′(x, y)) represents the transformed image, and (T) refers to the set of transformation functions used to generate augmented images [17]. These transformations included:

Random Horizontal Flip (p = **0.5)**

Random Rotation (θ ∈ [-**10°**, **10°])**

Random Zoom (z ∈ [**0.9**, **1.1])**

The dataset was enriched using these Data Augmentation techniques to increase sample variability, as illustrated in Figure 3.

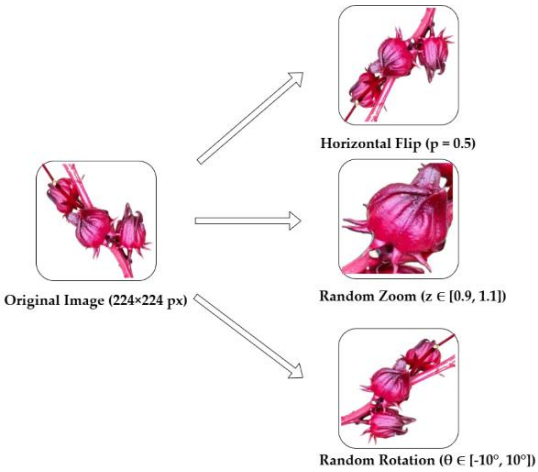


Figure 3. Data preparation using Data Augmentation techniques, including the original herbal leaf image, horizontally flipped image, rotated image, and zoomed image.

2.2 Model Architecture

A Custom CNN Architecture consisting of four convolutional blocks was employed because it effectively extracts discriminative features from plant images. Table 1 presents the overall model structure.

Table 1. Structure of the Custom CNN Architecture

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 224, 224, 3)	0
conv2d (Conv2D)	(None, 222, 222, 16)	448
max_pooling2d	(None, 111, 111, 16)	0
conv2d_1 (Conv2D)	(None, 109, 109, 32)	4,640
max_pooling2d_1	(None, 54, 54, 32)	0
conv2d_2 (Conv2D)	(None, 52, 52, 64)	18,496
max_pooling2d_2	(None, 26, 26, 64)	0
conv2d_3 (Conv2D)	(None, 24, 24, 128)	73,856
max_pooling2d_3	(None, 12, 12, 128)	0
dropout (Dropout)	(None, 12, 12, 128)	0
flatten (Flatten)	(None, 18432)	0
dense (Dense)	(None, 256)	4,718,848
dense_1 (Dense)	(None, 42)	10,794
Total params		4,827,082

The model contains 4,827,082 parameters, most of which reside in the first Dense layer (4,718,848 parameters). This is due to the fully connected mapping from the Flatten layer (18,432 neurons) to the Dense layer comprising 256 neurons. Figure 4 illustrates the model architecture.

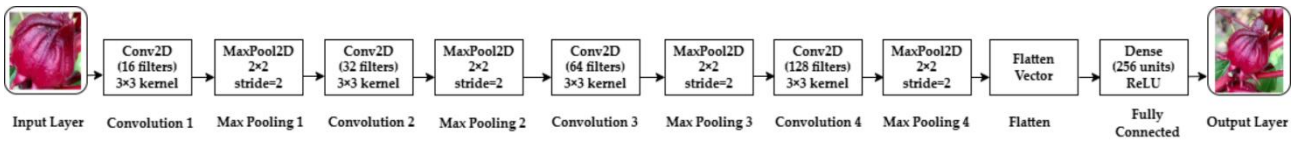


Figure 4. CNN model architecture (diagram showing the Custom CNN Architecture from the Input Layer to the Output Layer).

Based on the Custom CNN architecture described above, the model employs different activation functions across its layers. The ReLU activation function is used for all hidden layers (both convolutional and dense layers), while the Softmax function is applied in the output layer to generate probability distributions across the herbal plant classes, as shown in Equations (2) and (3) [18, 19].

$$\text{ReLU}(x) = \max(0, x) \quad (2)$$

$$Softmax(z_i) = \frac{e^{zi}}{\sum_{j=1}^{K} e^{zj}} \quad (3)$$

ReLU (Equation 2) enhances the model's nonlinearity and helps mitigate the vanishing gradient problem. Softmax (Equation 3) converts the network outputs into probability values that sum to 1 across all 42 medicinal plant classes.

2.2.3 Model Training

For model training, the Adam optimizer was selected for its efficiency and adaptive learning mechanism, making it suitable for multi-class classification tasks [20]. The learning rate was set to 0.001. The loss function used was Sparse Categorical Cross-entropy, appropriate for multi-class classification with 42 categories, as expressed in Equation (4):

$$L = -\Sigma i \; yi \log(\hat{y}i) \quad (4)$$

where (yi) denotes the ground truth label and ŷi represents the predicted probability. Prior studies support the choice of the Adam optimizer, such as [21], which proposed a Modified Adam Algorithm to enhance Deep Neural Network optimization, and [22], which improved the algorithm's overall performance. The dataset was split into 80% for training (1,680 images) and 20% for validation (420 images). Training was conducted for 15 epochs with Early Stopping applied.

2.3 Application Development

For application development, the Flutter framework was selected to build the Android application because of its high performance, support for native execution, and Hot Reload feature, which accelerates development. Android was chosen as the primary platform to accommodate user preferences in Udai Charoen Subdistrict, where most community members commonly use Android smartphones. The system adopts a multi-platform architecture consisting of: (1) Web Application (Admin): PHP, HTML, JavaScript, and MySQL; (2) Mobile Application (User/Member): Flutter Framework (Dart) for Android; and (3) Deep Learning Integration: TensorFlow Lite (26.1 MB), which is suitable for deployment on mobile devices. The decision to utilize TensorFlow Lite for mobile inference follows the guidelines outlined in [23], which examined the application of TensorFlow Lite and Transfer Learning for plant species classification. Findings from [24] support the real-time performance of TensorFlow Lite integrated with Flutter, demonstrating effective real-time plant disease detection on mobile platforms. The developed herbal plant classification system supports two image input modes: Real-time Camera Capture and Gallery Image Upload, as illustrated in Figure 5.

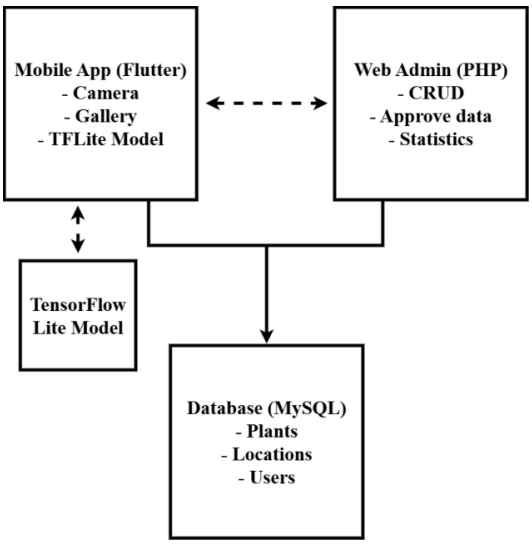


Figure 5. System Architecture showing interactions among the Mobile Application (Flutter), Web Admin Interface (PHP), Database (MySQL), and the TensorFlow Lite Model.

2.4 Performance Evaluation

2.4.1 Model Performance Evaluation

Standard evaluation metrics Accuracy, Precision, Recall, and F1-Score were employed, as shown in Equations (5)–(8) [25]:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (5)$$

$$\text{Precision} = TP / (TP + FP) \quad (6)$$

$$\text{Recall} = TP / (TP + FN) \quad (7)$$

$$\text{F1-Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (8)$$

where TP = True Positive, TN = True Negative, FP = False Positive, and FN = False Negative. Accuracy (Equation 5) measures the overall correctness of the model; Precision (Equation 6) evaluates how reliably the model predicts a given plant class; Recall (Equation 7) assesses the model's ability to capture all instances of that class; and F1-Score (Equation 8) represents the harmonic mean of Precision and Recall, reflecting the model's balanced performance.

2.4.2 System Evaluation by Experts

Three experts evaluated the system across five dimensions using a Likert Scale [26].

2.4.3 User Satisfaction Evaluation

User satisfaction was assessed among 50 participants across four dimensions using a Likert Scale [26]. The local Village Headman officially coordinated the user satisfaction training sessions and system evaluation workshops and recruited 50 community residents to test and evaluate the multi-platform system. Furthermore, the completed prototype is intended for long-term deployment, operational maintenance, and community utilization by the Udai Charoen Subdistrict Administrative Organization.

3. Experimental Results and Discussion

3.1 Results of the Herbal Plant Classification System Development

The developed herbal plant classification system was deployed as an Android application with a total size of 89.5 MB (including the 26.1 MB TFLite model). This size is considered appropriate for an AI-based mobile application, as many standard Android applications typically range from 50–100 MB. The system supports Android versions 5.0 and above. Figure 6 illustrates the application interface.

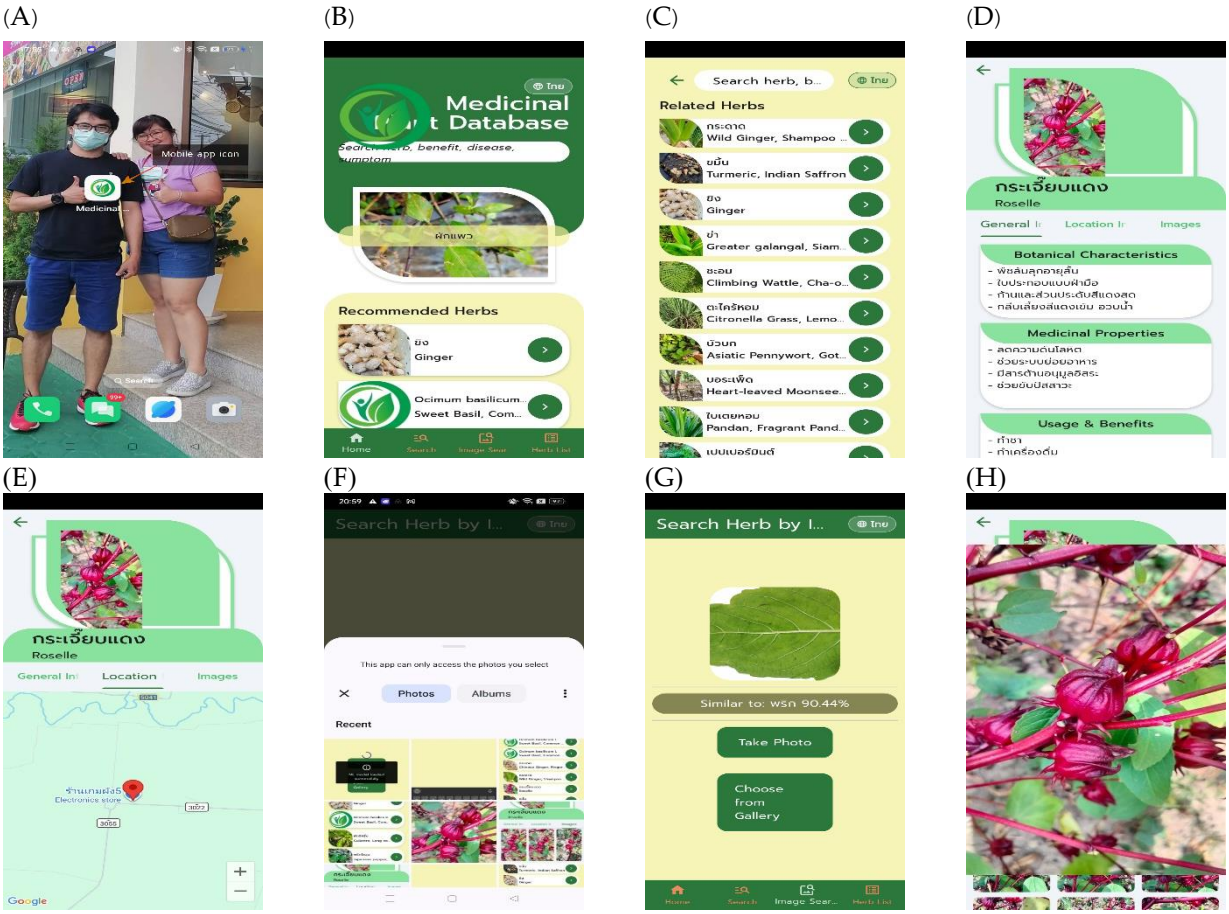


Figure 6. Mobile application interface: (A) Splash screen, (B) Main screen, (C) List of medicinal plants, (D) Classification result screen, (E) Details and map view, (F) Related image gallery, (G) Camera/Gallery input interface, (H) Real-time classification screen.

3.2 Classification Performance

Table 2. Classification performance of the herbal plant dataset

Metrics	Mean (%)	S.D.
Accuracy	85.7	3.2
Precision	87.3	4.1
Recall	84.9	3.8
F1-Score	86.1	3.5

The experimental results indicate that the Deep CNN architecture performs strongly in herbal plant classification, particularly when trained on properly prepared datasets. The evaluation results are illustrated in Figure 7, which consists of five components: (1) Performance Metrics Summary, (2) Confusion Matrix for 10 herbal plant classes, (3) Detailed class-wise performance table, (4) Training/Validation Accuracy curve over 15 epochs, and (5) Training/Validation Loss curve over 15 epochs.

(A)



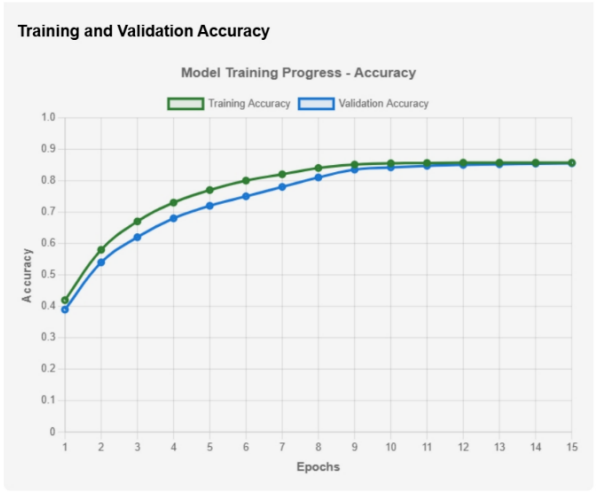
(B)

Actual / Predicted	Predicted Class									
	Roselle	Ginger	Turmeric	Yanang Leaves	Kao Song	Phak Seua	Kaffir Lime	Na Krud	Ya Phae	Others
Roselle (Hibiscus sabdariffa)	18	0	1	0	0	0	0	0	1	0
Ginger (Zingiber officinale)	0	19	1	0	0	0	0	0	0	0
Turmeric (Curcuma longa)	1	0	17	0	1	0	0	0	1	0
Yanang Leaves (Tiliacora triandra)	0	0	0	18	0	1	0	0	0	1
Kao Song (Dracaena loureiri)	0	0	0	0	17	0	1	1	0	1
Phak Seua (Gynura divaricata)	0	0	0	1	0	18	0	0	0	1
Kaffir Lime (Citrus hystrix)	0	0	0	0	0	0	18	0	0	2
Na Krud (Hyptis suaveolens)	0	0	0	0	1	0	0	19	0	0
Ya Phae (Chromolaena odorata)	1	0	0	0	0	0	0	0	18	1
Others (Mixed Species)	0	1	1	1	1	1	1	0	0	14

(C)

Medicinal Plant Species	Scientific Name	Precision (%)	Recall (%)	F1-Score (%)	Support	Plant Family
Roselle	*Hibiscus sabdariffa*	**86.0**	**86.0**	**86.0**	50	Malvaceae
Ginger	*Zingiber officinale*	**90.0**	**90.0**	**90.0**	50	Zingiberaceae
Turmeric	*Curcuma longa*	**84.0**	**84.0**	**84.0**	50	Zingiberaceae
Centella	*Centella asiatica*	**88.0**	**88.0**	**88.0**	50	Apiaceae
Andrographis	*Andrographis paniculata*	82.0	82.0	82.0	50	Acanthaceae
Aloe Vera	*Aloe vera*	**86.0**	**86.0**	**86.0**	50	Asphodelaceae
Kaffir Lime	*Citrus hystrix*	**92.0**	**92.0**	**92.0**	50	Rutaceae
Fingerroot	*Boesenbergia rotunda*	80.0	80.0	80.0	50	Zingiberaceae
Phyllanthus	*Phyllanthus amarus*	82.0	82.0	82.0	50	Euphorbiaceae
Others (Average)	*Mixed Species*	78.5	78.5	78.5	1,600	Various

(D)



(E)

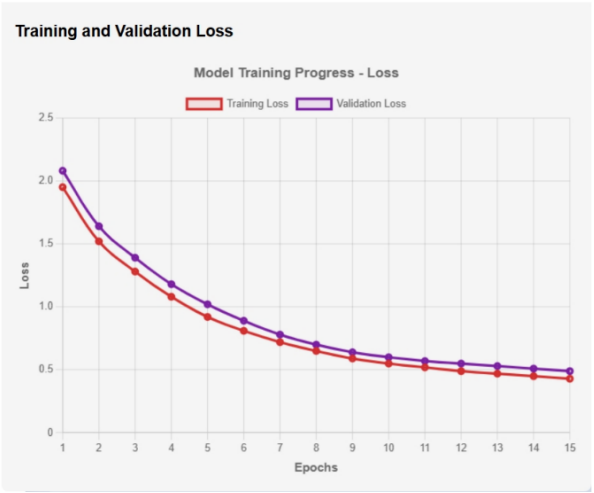


Figure 7. CNN model performance evaluation results: (A) Performance Metrics Summary; (B) Confusion Matrix for 10 selected representative herbal plant classes (intentionally displayed for optimal visual readability due to standard page layout constraints); (C) Class-wise performance table; (D) Training/Validation Accuracy over 15 epochs; and (E) Training/Validation Loss over 15 epochs.

3.3 Response Time

Table 3. Average system response time

Component	Average Time (seconds)	S.D.
Image capture and processing	2.3	0.4
Inference and result display	1.8	0.3
History logging	1.2	0.2

3.4 System Performance Evaluation

Three experts evaluated system performance, as shown in Table 4.

Table 4. Expert evaluation of system performance (n = 3)

Evaluation Item	$\bar{x}$	S.D.	Level
1. Usability	4.33	0.15	Highest
2. Efficiency	4.20	0.10	High
3. Security	4.33	0.17	Highest
4. Reliability	4.40	0.12	Highest
5.Functional completeness	4.13	0.17	High
Overall	**4.28**	**0.14**	**Highest**

3.5 User Satisfaction Evaluation

User satisfaction was assessed among 50 participants, as presented in Table 5.

Table 5. User satisfaction evaluation (n = 50)

Evaluation Item	$\bar{x}$	S.D.	Level
1. Usability	4.35	0.62	Highest
2. Efficiency	4.22	0.55	Highest
3. Security	4.10	0.68	High
4. Reliability	4.18	0.59	High
Overall	**4.21**	**0.61**	**Highest**

In addition to the mobile application for end users, a Web Administration module was developed to enable system administrators to manage medicinal plant data efficiently. The Web Admin system supports end-to-end operations, including data creation, editing, deletion, analysis, and report generation, as illustrated in Figure 8. It was developed using a PHP framework integrated with a MySQL database, providing stable, secure data management. The system features multi-level user access control and an automatic backup mechanism to prevent data loss.

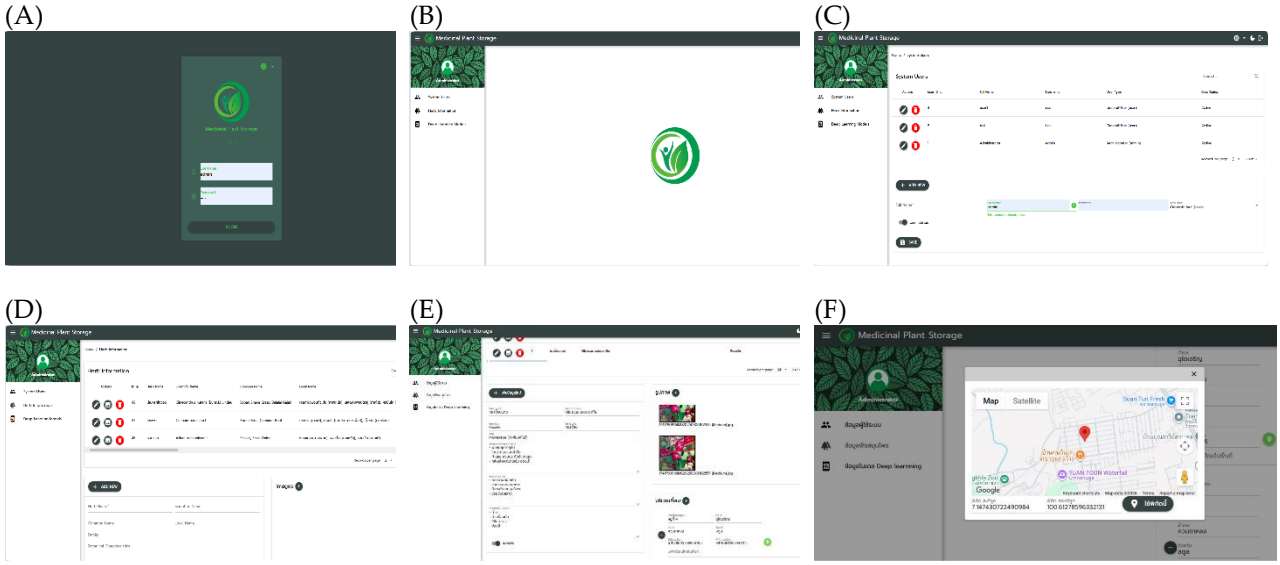


Figure 8. Web Admin interface: (A) Login screen ("Medicinal Plant Species System"), (B) Loading screen, (C) Dashboard showing all medicinal plant records, (D) CRUD operations interface, (E) Detailed plant information with editing functions, and (F) Map interface displaying the spatial distribution of medicinal plants.

4. Discussion

The findings of this study demonstrate that the developed medicinal plant classification system achieved an accuracy of 85.7%, which is considered suitable for real-world applications. Compared with the analysis in Mulugeta et al. [27], which reported that CNN-based medicinal plant classification systems typically achieve accuracies ranging from 80% to 95%, the proposed model's performance falls within the academically acceptable range. Although the accuracy obtained in this study is lower than that reported by Kavitha et al. [28], which successfully identified six medicinal plant species with 93% accuracy, it is important to recognize that the present study posed a substantially more complex classification problem involving 42 species. Based on evaluations under real-world usage conditions, image quality most strongly influenced model performance. Poor illumination, excessive brightness, morning dew on leaves, and wilted or damaged leaf surfaces decreased classification accuracy. Analysis of the Confusion Matrix further revealed varying accuracies among classes: ginger (Zingiber officinale) achieved 90% accuracy, whereas gotu kola (*Centella asiatica*) achieved only 88%. This discrepancy may be attributed to the morphological characteristics of gotu kola, particularly its round leaf shape, which resembles that of several other plant species. The decision to employ a Custom CNN Architecture instead of Transfer Learning was motivated by the need to control model size for deployment on mobile devices. The final model size of 26.1 MB enabled smooth and efficient operation even on devices with limited computational resources. This aligns with the findings of Zhang and Liu [23], which reported that TensorFlow Lite can effectively reduce model size while maintaining adequate performance. Nonetheless, future work may require comparative experiments with lightweight architectures such as MobileNet-Lite or EfficientNet-Lite to assess optimization strategies and potential performance improvements further. Field testing and system evaluation were conducted in collaboration with the local community in Udai Charoen Subdistrict to ensure that the collected data and user feedback reflected authentic, real-world usage conditions, as illustrated in Figure 9.



Figure 9. Field testing activities of the herbal plant classification system in Udai Charoen Subdistrict: (A) surveying and collecting herbal plant samples in local gardens; (B) testing plant image capture using the mobile application; (C) demonstrating system usage to interested community members; and (D) evaluating user satisfaction and gathering feedback from participants.

Findings from the field testing indicate that most users learned to operate the system within 5–10 minutes, particularly adolescents and working-age adults already familiar with smartphone technology. However, some elderly users required additional assistance in capturing images from appropriate angles for accurate analysis. User feedback included suggestions to provide clearer photo-taking guidelines, add more information on the medicinal properties of plants, and increase the font size for improved readability. The expert evaluation results showed an overall mean score at the highest level ($\bar{x}$= 4.28, S.D. = 0.14), with particularly strong ratings in applicability for practical use ($\bar{x}$= 4.40). In contrast, general users reported a slightly lower overall satisfaction level ($\bar{x}$= 4.21, S.D. = 0.61). This discrepancy highlights a remaining gap between user expectations and actual user experience. Several users recommend adding features such as searching by local plant names and providing more sample images of plants under varying conditions.

The use of the Flutter Framework for Android application development contributed to efficient development processes, supported by the simplicity of the Dart programming language and the convenience

of the Hot Reload tool. Experimental results showed that the application required an average processing time of 1.2 seconds per image on mid-range Android devices (4GB RAM, Android 8.0 or above), which is considered sufficiently fast for practical use. A key limitation identified in this study is that the system performs poorly when classifying plants with wilted, damaged, or otherwise suboptimal leaves; high-quality images remain essential for accurate classification. Additionally, the dataset is limited to 42 medicinal plant species found specifically within Udai Charoen Subdistrict. The current application supports only Android devices, preventing access among users with iOS devices. This study illustrates the potential of AI technologies as vital tools for preserving local wisdom, particularly among younger generations who are more accustomed to digital technology. A tool that enables convenient and accurate identification of medicinal plants can enhance access to herbal knowledge, thereby sustainably bridging traditional wisdom and modern technology.

5. Conclusion

This study successfully developed a medicinal plant classification system based on Deep Learning technology deployed on an Android mobile application. The system covers 42 medicinal plant species found in Udai Charoen Subdistrict, Satun Province. The developed model achieved 85.7% accuracy using a Custom CNN Architecture comprising four convolutional layers, with a model size of 26.1 MB, an appropriate size for mobile deployment. The application, built using the Flutter Framework for Android, has a total size of 89.5 MB and supports installation from Android 5.0 (API level 21) onward, accommodating the majority of Android devices currently in use. The system enables real-time classification through both live camera capture and image upload from the device gallery, requiring an average processing time of 1.2 seconds per image. System performance evaluation results demonstrated that experts rated the system at the highest level ($\bar{x}$= 4.28, S.D. = 0.14), particularly in terms of applicability for practical use ($\bar{x}$= 4.40). General users also reported high levels of satisfaction ($\bar{x}$= 4.21, S.D. = 0.61), indicating the system's potential for real-world implementation. The final system consists of three core components: (1) the Android mobile application for end users; (2) the web-based administration system for data management; and (3) a MySQL database connected to the TensorFlow Lite model. This modular system architecture enhances flexibility for future improvements and feature expansion. The findings of this study highlight the feasibility of applying AI technologies to support the preservation of local herbal plant knowledge, particularly at a time when traditional wisdom is at risk of disappearing along with older community experts. The developed system serves as an important tool for transferring knowledge to younger generations and promoting the sustainable utilization of medicinal plants. Nevertheless, the study identified several limitations, including the need for high-quality images for accurate analysis, the dataset's limited scope to the study area, and the application's current availability only on the Android operating system.

5.1 Recommendations for Future Development

5.1.1 The number of images should be increased to approximately 200 images per plant species to enhance classification accuracy. Future work should also compare performance across alternative lightweight architectures such as MobileNet-Lite or EfficientNet-Lite.

5.1.2 The database should be expanded to include medicinal plant species from additional geographic areas.

5.1.3 An Over-the-Air (OTA) model update system should be implemented to allow model updates without requiring users to reinstall the application. Offline functionality should also be enhanced to support users in areas with unstable internet connectivity.

5.1.4 An iOS version of the application should be developed to broaden accessibility. Additionally, the user interface should be adapted to accommodate users across all age groups.

5.1.5 Modern performance optimization techniques recommended within the TensorFlow ecosystem [29] should be applied, alongside algorithmic enhancements in line with the guidelines of Wang [30] to improve model capability further.

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