



Thai Antipyretic Medicinal Plant Recognition Using CNNs Integrated into a LINE Chatbot

Walairach Nunsong¹ Surasit Sakda² Taravichet Titijaroonroj³ Donyarut Kakanopas^{4*}

^{1,2}*Faculty of Science and Technology, Rajamangala University of Technology Srivijaya,
Nakhon Si Thammarat, Thailand*

³*School of Information Technology, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand*

^{4*}*Faculty of Business Administration, Rajamangala University of Technology Srivijaya, Songkhla, Thailand*

*Corresponding author e-mail: donyarut.k@rmutsv.ac.th

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Abstract

This study developed a leaf-image recognition system for Thai antipyretic medicinal plants using deep convolutional neural networks (CNNs). Recognizing medicinal plants can be difficult because several species have similar leaf shapes and textures. An automatic recognition tool may help non-expert users identify medicinal plants more consistently. The main contributions are the collection of a 20-species Thai antipyretic herb leaf dataset, the evaluation of eight CNN architectures, and the integration of the selected model into a LINE Chatbot prototype. A new dataset of leaves from 20 medicinal plants for antipyretics found in southern Thailand was created. Data augmentation was applied to increase the number and variability of training images. Eight CNN architectures, namely AlexNet, ResNet, VGG, DenseNet, GoogLeNet, EfficientNet, MobileNet, and SqueezeNet, were evaluated for recognizing 20 Thai antipyretic herb species. Lastly, a CNN architecture, which is the best performing, was integrated with a LINE Chatbot for practical application. The experimental results showed that SqueezeNet achieved the highest accuracy of 92.8% with a processing time of 0.004 seconds per image. The SqueezeNet model was therefore selected for integration into the LINE Chatbot prototype.

Keywords: Convolutional neural network (CNN), Herbal plant recognition, Image classification, Thai herb leaf recognition, Thai medicinal plant

INTRODUCTION

Medicinal plants are commonly used in traditional Thai medicine. During the COVID-19 pandemic, plants with antipyretic properties, such as Andrographis and Ginger, received increased attention from government agencies and the public. This increased interest motivated the present study to focus specifically on Thai medicinal plants traditionally used to reduce fever. Accurate identification of these plants remains challenging because many species share similar visual characteristics, and distinguishing them often requires expert knowledge [1], [2], [3]. These challenges have encouraged the development of image-based methods to support plant identification. Among the observable plant features, leaves provide useful visual information, including shape, color, margin, and texture. Therefore, leaf images are commonly used for plant recognition [4]. However, inter-class similarity and intra-class variation can still reduce identification accuracy.

Previous studies have applied both conventional machines learning and deep learning to medicinal plant recognition. Some studies used manually extracted shape, color, and texture features with conventional classifiers [5], while others applied visual geometry group 16-layer network (VGG16), convolutional neural networks (CNNs), CNN-recurrent neural network (RNN) models, and established CNN architectures [6], [7], [8], [9], [10]. Although these studies reported promising results, they focused on medicinal plants from Indonesia, Vietnam, Malaysia, and India. However, a key research gap remains. Thai medicinal plants traditionally used to reduce fever have received limited attention in image-based recognition studies.

Research on Thai medicinal plants remains limited. Mettripun [11] classified eight Thai herb species using image-region features and an artificial neural network, while Pornpanomchai et al. [12] used 13 leaf features and k-nearest neighbors (k-NN) to recognize 32 herb species. Pornudomthap et al. [13] developed a transfer-learning framework and an Android application for identifying 20 Thai herbs. However, these studies addressed general medicinal herb categories rather than plants specifically associated with antipyretic use. Within the reviewed literature, a dedicated dataset and systematic comparison of multiple CNN architectures for Thai antipyretic herb recognition have not been reported.

Accordingly, this study aims to identify an effective CNN architecture for recognizing 20 Thai antipyretic medicinal plants from leaf images, considering both recognition performance and processing time. As illustrated in Figure 1, the research workflow begins with leaf-image collection and preparation, followed by data augmentation and division of the dataset into training and testing sets. Eight CNN architectures are then trained and evaluated, and the best-performing model is integrated into a LINE Chatbot as a proof of concept. This workflow represents the three main contributions of the study: a newly collected leaf-image dataset, a systematic comparison of eight CNN architectures, and a practical demonstration of model deployment through LINE Chatbot.

The objective of this study is to evaluate CNN architectures for recognizing 20 Thai antipyretic medicinal plants from leaf images and to identify the model that provides the best balance between recognition performance and processing time.

The main contributions are three parts. First, a new leaf-image dataset covering 20 Thai antipyretic medicinal plants was collected and organized. Second, eight CNN architectures—AlexNet, ResNet, VGG, SqueezeNet, DenseNet, GoogLeNet, MobileNet, and EfficientNet—were systematically evaluated using the same dataset and evaluation

protocol. Third, the best-performing model was integrated into a LINE Chatbot as a proof of concept to demonstrate its practical deployment for herb identification.

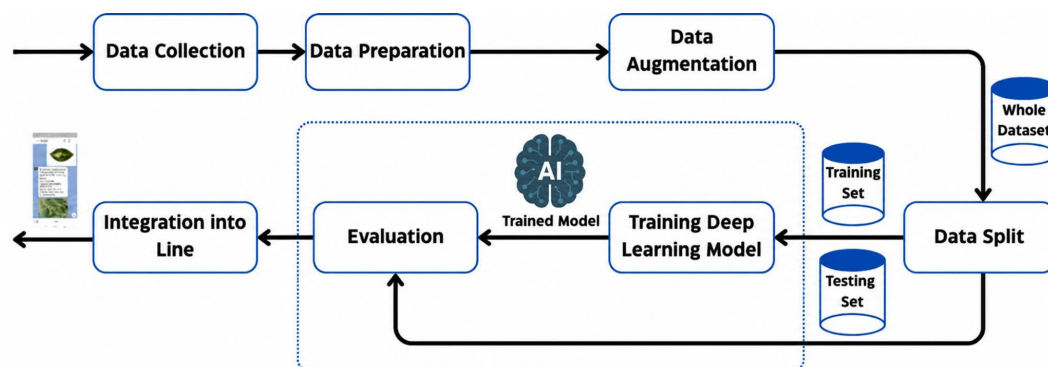


Figure 1: Workflow diagram illustrating the steps involved in developing the deep-learning for medicinal plant recognition system for Thai antipyretic.

1. Visual Characteristics of Thai Antipyretic Herb Leaves

Traditional Thai medicinal plants are commonly identified by folk healers using a combination of leaf appearance, smell, and taste. However, this study considers only visual information from leaf images. This makes recognition challenging because some herbs have similar appearances and are normally distinguished using non-visual characteristics and the experience of practitioners.

The 20 antipyretic herb classes exhibit both considerable morphological variation and subtle inter-class differences. As summarized in Table 1, their leaves vary in shape, apex, base, margin, and color [14], [15]. Some classes differ clearly in their overall dimensions and shapes, while others share similar visual characteristics and require closer examination of the leaf apex, base, and margin.

A locally specific example is *Cordyline fruticosa*, which folk healers in southern Thailand distinguish into two forms known as Mak Phu and Mak Mia. Mak Phu has short, narrow leaves, whereas Mak Mia has large, broad leaves. Including these locally recognized forms creates a fine-grained recognition challenge. Therefore, this dataset differs from existing foreign medicinal-leaf datasets in both its species composition and its representation of Thai antipyretic herbs and locally recognized botanical distinctions.

Table 1: Botanical characteristics of leaves used to identify Thai herbal plants for antipyretics

Local name	Scientific name	Leaf shape	Leaf apex	Leaf base	Leaf margin	Leaf color
Thung Fa	<i>Alstonia macrophylla</i>	oblanceolate	cuspidate	acute	entire	green
Chalut	<i>Alyxia reinwardtii</i> Blume	oblong	obtuse	oblong	entire	green
Fa Thalai Chon	<i>Andrographis paniculate</i>	ovate	acute	obtuse	entire	green
Mao Khai Pla	<i>Antidesma ghaesembilla</i> Gaertn	ovate	obtuse	obtuse	entire	green
Ma Phueang	<i>Averrhoa carambola</i>	lanceolate	acute	obtuse	entire	green
Chingchi	<i>Capparis micracantha</i>	elliptic	acute	obtuse	undulate	green
Kok Kra Om	<i>Cardiospermum halicacabum</i>	trifoliolate	acute	obtuse	lobed	green
Khwi Nin	<i>Cinchona succirubra</i>	ovate	acute	obtuse	entire	green

Table 1: Botanical characteristics of leaves used to identify Thai herbal plants for antipyretics (Cont.)

Local name	Scientific name	Leaf shape	Leaf apex	Leaf base	Leaf margin	Leaf color
Mak Phu	<i>Cordyline fruticosa</i>	lanceolate	acute	attenuate	entire	fuchsia
Mak Mia		linear	cuspidate	cuneate	entire	fuchsia
Kum Num	<i>Crateva religiosa</i>	oval	acuminate	acute slightly distorted	entire	green
Lai Phueak	<i>Eurycoma longifolia jack</i>	oblong	cuspidate	acute	entire	green
Ma Duea Chum Phon	<i>Ficus racemasa</i>	elliptic	cuspidate	obtuse	undulate	green
Cha Muang	<i>Garcinia cowa Roxb</i>	oblong	cuspidate	obtuse	entire	green
Bai Ngoen	<i>Graptophyllum pictum</i>	elliptic	cuspidate	attenuate	undulate	green-white pattern
Khon Tha	<i>Harrisonia perforate</i>	elliptic	obtuse	acute	lobed	green
Thaoyaimom	<i>Clerodendrum</i>	linear	cuspidate	cuneate	entire	green
Nom Maeo	<i>Uvaria siamensis</i>	lanceolate	acuminate	obtuse	entire	green
Boraphet	<i>Tinospora crispa</i>	cordate	acute	cordate	entire	green
Yanang	<i>Tiliacora triandra</i>	lanceolate	acute	obtuse	entire	green

METHODS

This study developed a CNN-based workflow for recognizing Thai antipyretic herb leaves and integrating the selected model into a LINE Chatbot, as shown in Figure 1. The process begins with data collection, where thirty images of each of twenty different herbal plant species were captured. Next, data augmentation techniques are applied to increase the diversity of the training data. After augmentation, the dataset is prepared by splitting the images into training and testing sets. The CNN models were trained using the training set and evaluated using the testing set. Finally, the trained model is integrated into a LINE Chatbot platform, providing an easy-to-use tool for identifying Thai medicinal plants.

1. Data Collection

The twenty species of Thai medicinal plants selected for their antipyretic properties were based on [14], [15]. In addition, these herbs are commonly found in southern Thailand and are traditionally used as antipyretics, according to discussions with Thai traditional medicine practitioners in the provinces where the data were collected. Herb samples were gathered between October 2022 and February 2023 from the southern provinces of Trang and Nakhon Si Thammarat. The local and scientific names of the herbs were verified by a specialist in Thai traditional medicine.

The selected antipyretic plants include *Alstonia macrophylla*, *Alyxia reinwardtii* Blume, *Andrographis paniculata*, *Antidesma ghaesembilla* Gaertn, *Averrhoa carambola*, *Capparis micracantha*, *Cardiospermum halicacabum*, *Cinchona succirubra*, *Cordyline fruticosa* (Mak Phu), *Cordyline fruticosa* (Mak Mia), *Crateva religiosa*, *Eurycoma longifolia* Jack, *Ficus racemosa*, *Garcinia cowa* Roxb, *Graptophyllum pictum*, *Harrisonia perforata*, *Tacca leontopetaloides*, *Tiliacora triandra*, *Tinospora crispa*, and *Cyathostemma micranthum siamensis*.

Leaves from these twenty herbal plant species were collected, with thirty images captured for each species, resulting in a total of 600 images for this study. Each leaf was placed on a white paper background to minimize background noise and improve recognition accuracy. Images were taken using a Huawei Nova5T smartphone, with resolutions ranging from 577×443 pixels to 4000×3000 pixels. Example images for each herb species are shown in Figure 2.

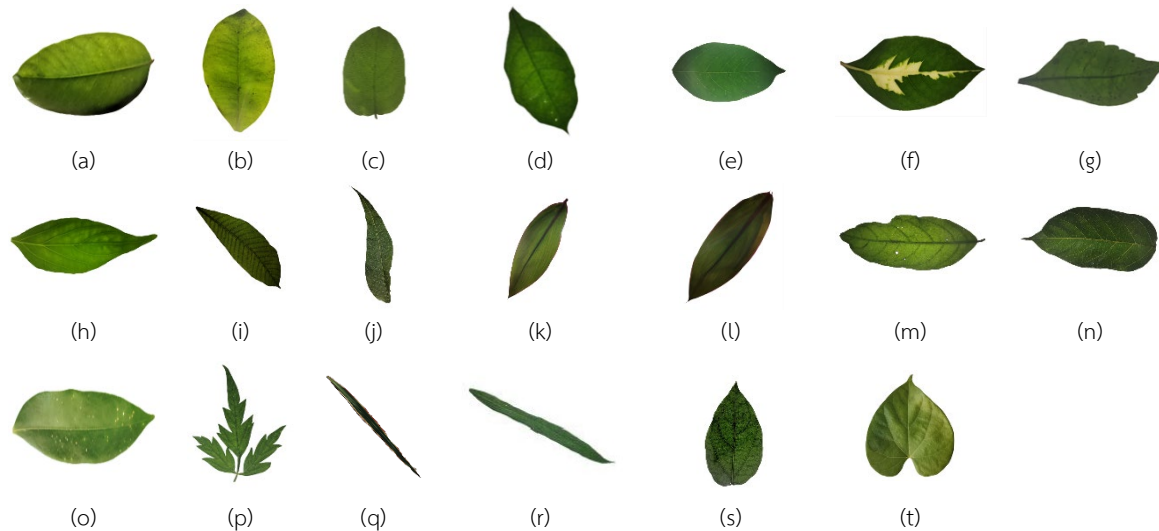


Figure 2: Example of the dataset images (a) *G. cowa* Roxb, (b) *A. reinwardtii* Blume, (c) *A. ghaesembilla* Gaertn, (d) *C. succirubra*, (e) *A. carambola*, (f) *G. pictum*, (g) *H. perforata*, (h) *A. paniculata*, (i) *A. macrophylla*, (j) *C. religiosa*, (k) *C. fruticosa* (Mak Mia), (l) *C. micranthum siamensis*, (m) *C. micracantha*, (n) *F. racemosa*, (o) *E. longifolia* Jack, (p) *C. halicacabum*, (q) *C. fruticosa* (Mak Phu), (r) *T. leontopetaloides*, (s) *T. triandra*, and (t) *T. crispa*

2. Data Augmentation

CNN models generally require sufficient training images; however, the original dataset in this study was limited. Therefore, data augmentation was applied before model training. Data augmentation is widely used to increase the sample of the training images and their variety. This process can improve model robustness to translation, rotation, and scale variations. Leaf images may vary in orientation, position, and scale during image capture. In general, human photography often lacks precise control over the direction or position of an image. To address this limitation, training computers to recognize various patterns becomes essential. To enhance the dataset and improve recognition accuracy, data augmentation techniques are applied. Specifically, four methods are utilized: (i) horizontal flipping, (ii) rotation, (iii) zooming in, and (iv) zooming out, as illustrated in Figure 3. All augmented images are resized to a resolution of 577×443 pixels. Following this process, each species dataset contains 150 images, including the original and the augmented versions.

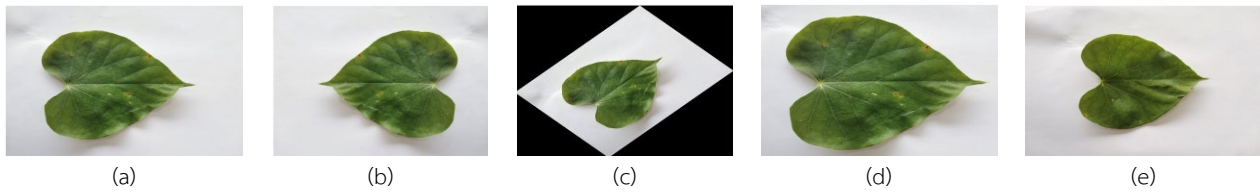


Figure 3: Example of augmented images (a) Input image (b) flipping with horizontal axis, (c) rotation with 45 degrees, (d) zooming in, and (e) zooming out

3. Dataset Preparation

Model performance was evaluated using 5-fold cross-validation. This approach reduces dependence on a single train-test split. In this study, 5-fold cross-validation is employed, as it is commonly used to provide reliable estimates of testing error rates while minimizing significant variation or bias [16]. After applying data augmentation, each species dataset consists of 150 images, including the original image and its augmented versions. The complete dataset comprises 3,000 images. These images are split into training and testing sets in an 80:20 ratios, resulting in 2,400 images for training and 600 images for testing. For each fold, augmented versions derived from the same original image were not shared between the training and testing sets. This setting allowed each model to be evaluated across multiple data splits after augmentation.

4. Recognition using CNN

Eight CNN architectures were evaluated for classifying Thai antipyretic herb leaf images. The models tested included AlexNet [17], ResNet [18], VGG [19], SqueezeNet [20], DenseNet [21], GoogLeNet [22], MobileNet [23], and EfficientNet [24]. Among these, SqueezeNet achieved the highest accuracy as reported in the Experimental Results subsection and was selected for chatbot integration. SqueezeNet is a lightweight CNN architecture designed to achieve high accuracy while significantly reducing the model size. Introduced by researchers Iandola et al. in 2016 [20], SqueezeNet aims to provide an efficient alternative to larger models like AlexNet without compromising performance. This characteristic is relevant to chatbot deployment, where fast model response and compact implementation are desirable. The core innovation in SqueezeNet is the Fire module, which consists of two main layers: a “squeeze” layer and an “expand” layer. The squeeze layer uses 1x1 filters to reduce the number of input channels, acting as a bottleneck. The expand layer then applies a mix of 1x1 and 3x3 filters to process the reduced feature maps. This approach minimizes the number of parameters while preserving accuracy. SqueezeNet achieves model compression through three strategies: (1) replacing 3x3 filters with 1x1 filters, (2) reducing the number of input channels to 3x3 filters, and (3) downsampling late in the network to maintain high-resolution feature maps in early layers. With these techniques, SqueezeNet achieves comparable accuracy to AlexNet while reducing the model size by over 50 times, making it a suitable candidate for resource-constrained applications.



5. Integration of the CNN Model into the LINE Chatbot

This section describes the LINE Chatbot prototype developed for recognizing Thai antipyretic medicinal plants from leaf images. The prototype chatbot is deployed on the LINE Official Account (LINE OA) platform, specifically designed to identify Thai herb leaves and provide detailed information about them.

Chatbot platforms are widely used for user interaction and can support image-based services [25]. The chatbot includes auto-response messaging and support for multiple message formats. The auto-response messaging functionality allows the chatbot to respond to user queries and engage in real-time interactions without human involvement, enabling users to receive responses without manual intervention. Additionally, the platform supports various message formats, including text, images, and videos, enabling users to conveniently upload images of herb leaves for identification. Upon receiving an image, the chatbot employs CNN-based models to classify the herb and returns the predicted herb name and related information, including the herb's common and scientific names, alternative names, medicinal properties, and relevant images. Furthermore, the chatbot provides supplementary resources such as terms of use, details about the development team, and user manuals, which can be accessed through the LINE rich menu. These features show how the trained CNN model was connected to a LINE OA interface for herb identification and information delivery.

RESULTS AND DISCUSSION

1. Performance Evaluation

The performance of the deep CNN for Thai medicinal plant recognition is assessed using Accuracy, Precision, Recall, and F1-Score. These metrics are defined based on the terms True Positive (TP), False Negative (FN), False Positive (FP), and True Negative (TN), which describe the relationship between actual and predicted labels [26]. A True Positive (TP) occurs when the model correctly identifies a positive case, such as recognizing a plant species accurately. In contrast, a False Negative (FN) represents cases where the model fails to identify a positive instance, incorrectly predicting it as negative. A False Positive (FP) is when the model incorrectly predicts a positive label for a negative case, such as misidentifying another plant species as the target species. Lastly, a True Negative (TN) occurs when the model correctly identifies a negative instance, such as determining that a plant does not belong to a specific species.

Precision measures the proportion of correctly predicted positive cases out of all predicted positives, reflecting the model's ability to avoid false positives. Recall evaluates the proportion of actual positives correctly identified by the model, indicating its ability to minimize false negatives. F1-Score is the harmonic mean of Precision and Recall, offering a balanced metric that is especially useful when dealing with imbalanced data. Finally, Accuracy quantifies the proportion of correctly classified instances, both positive and negative, relative to the total number of instances. Together, these metrics provide a comprehensive evaluation of the model's performance, capturing its strengths in recognizing relevant cases while minimizing misclassifications.

2. Experimental Results

2.1 CNNs Performance Evaluation Results

The CNN architectures were evaluated for Thai antipyretic herb recognition. The training parameters were configured separately for each architecture. Stochastic gradient descent (SGD) was used for AlexNet, VGG, SqueezeNet, GoogLeNet, MobileNet, and EfficientNet, with learning rates of 0.07921, 0.03209, 0.02954, 0.03166, 0.03593, and 0.07780, respectively. Adam was used for ResNet and DenseNet, with learning rates of 0.00035 and 0.08345, respectively. Momentum was set to 0.9 for the SGD-based models, while weight decay was set to 0 for all models. All experiments were conducted on a system equipped with an Intel Core i7 central processing unit (CPU), an NVIDIA RTX 3090 graphics processing unit (GPU), and 32 GB of RAM. All eight CNN architectures were initialized with ImageNet-pretrained weights and subsequently fine-tuned on the collected Thai antipyretic herb dataset.

Table 2: Comparison of recognition performance, inference time, and computational complexity among eight CNN architectures.

Architecture	Precision (%)	Recall (%)	F1 (%)	Accuracy (%)	Inference Time (Sec.)	Parameter sizes	GFLOPS
AlexNet	82.10 ± 0.020	72.20±0.032	72.40±0.033	72.20±0.033	0.001	61.1M	0.71
ResNet	84.60 ± 0.019	78.60±0.028	79.10±0.027	78.60±0.027	0.004	68.9M	11.40
VGG	71.50 ± 0.056	67.40±0.028	65.40±0.030	67.50±0.027	0.002	138.4M	15.47
SqueezeNet	92.40 ± 0.036	92.80±0.021	92.40±0.029	92.80±0.020	0.004	1.2M	0.82
DenseNet	91.40 ± 0.012	89.90±0.019	89.70±0.019	89.90±0.019	0.025	8.0M	2.83
GoogLeNet	74.90 ± 0.034	65.90±0.034	64.60±0.043	65.80±0.034	0.012	6.6M	1.50
MobileNet	47.90 ± 0.078	22.50±0.038	19.80±0.033	22.50±0.038	0.009	3.5M	0.30
EfficientNet	89.60 ± 0.016	86.20±0.016	86.50±0.018	86.20±0.017	0.014	5.3M	0.39

The accuracy of each CNN architecture is summarized in Table 2. Based on the experimental results, the SqueezeNet model outperforms all others, achieving the highest precision, recall, F1-score, and accuracy on the newly created medicinal plant dataset. SqueezeNet achieves an impressive 92.8% accuracy for herb recognition with a processing time of 0.004 seconds per image.

In comparison, AlexNet demonstrates the shortest processing time of 0.001 seconds, making it the fastest model tested. Although AlexNet achieved the shortest inference time, its accuracy was substantially lower than that of SqueezeNet. This difference indicates that SqueezeNet provided the strongest balance between accuracy and processing time among the evaluated models.

The number of parameters reflects the model size and memory requirements, whereas billions of floating-point operations (GFLOPs) indicate the computational operations required for a forward pass. VGG and ResNet had the highest computational complexity, with 138.4M parameters and 15.47 GFLOPs, and 68.9M parameters and 11.40 GFLOPs, respectively. However, their accuracies were lower than those of SqueezeNet, indicating that larger and more computationally demanding models do not necessarily achieve better recognition performance.

SqueezeNet achieved the highest accuracy of 92.8% with only 1.2M parameters and 0.82 GFLOPs. DenseNet also achieved high accuracy but required 8.0M parameters and 2.83 GFLOPs. Although MobileNet had the lowest

GFLOPs, its recognition accuracy was substantially lower. These results show that SqueezeNet provided the best balance between recognition performance and computational complexity. Parameter count and GFLOPs also did not directly correspond to inference time because latency can be affected by memory access, GPU parallelism, and architecture-specific operations.

Moreover, we employed the gradient-weighted class activation mapping (Grad-CAM) technique, as described in [27], to highlight significant areas within images that contribute to model differentiation. This method visualizes the most critical regions in red/yellow and less important areas in blue. An example in Figure 4 illustrates activation maps generated for herb leaf images using eight different architectures. These include species such as *C. micranthum siamensis*, *T. leontopetaloides*, *G. pictum*, and *H. perforata*. For *C. micranthum siamensis* and *T. leontopetaloides*, SqueezeNet demonstrated superior performance by accurately identifying the correct class. The Grad-CAM results suggest that SqueezeNet attended more consistently to leaf regions than several other evaluated models.

In the case of *G. pictum*, the unique texture of the leaf surface serves as a key discriminating feature. As shown in Figure 4, under the column “*G. pictum*,” SqueezeNet effectively highlights the texture area, which may have contributed to the correct prediction. In contrast, other CNNs either focus on the entire leaf area (e.g., AlexNet, DenseNet, EfficientNet, VGG, MobileNet) or mistakenly emphasize the background (e.g., GoogLeNet and ResNet), which reduces their prediction accuracy.

For *H. perforata*, the distinguishing feature lies in the wrinkles along the leaf edges. SqueezeNet successfully concentrates on these wrinkles, whereas other CNNs incorrectly focus on irrelevant regions, which may be related to their incorrect predictions in these examples. These examples provide visual support for the quantitative performance of SqueezeNet. Its attention to leaf-related regions may partly explain its higher accuracy in this dataset.

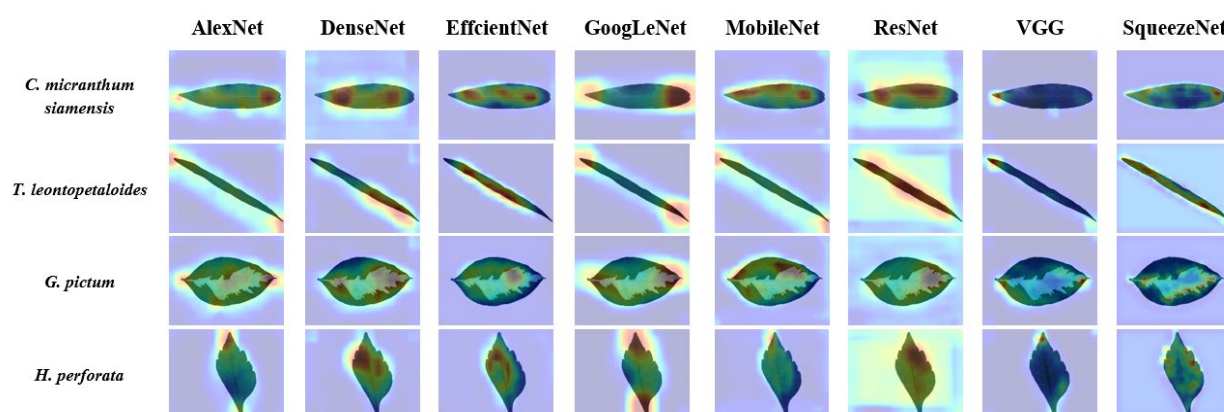


Figure 4: Grad-Cam's visualization of Thai herb leaf identification through eight CNNs.

2.2 Prototype of LINE Application

As described in the “Recognition using CNN” subsection, the model with the highest recognition accuracy was used to develop a LINE Chatbot prototype. The SqueezeNet model was integrated into the LINE OA platform to

test the feasibility of chatbot-based herb recognition. This application works on the LINE platform through LINE OA. The application has two main functions: image-based leaf recognition and result display. To start using the chatbot, you add it as a friend on LINE OA. After adding the LINE OA account, the main menu is displayed, as shown in Figure 5(a). This menu has three options: (i) how to use the application, (ii) identifying the Thai herb leaf, and (iii) information about the team that made the app. Under how to use the application, as shown in Figure 5(b), there are two main points: (i) what each menu option does and (ii) restrictions on use. Users can send one image at a time, which should be of a leaf. The chatbot knows 20 types of Thai herb leaves for antipyretics.

Identifying the Thai herb leaf option has two parts: (i) instructions on how to use it, and (ii) recognizing the leaf from the given image. The chatbot first displays usage instructions, as shown in Figure 5(c). After a user submits a leaf image, the predicted result is displayed, as shown in Figures 5(d) and 5(e). The last option, also known as information about the team that made the app, on the main menu introduces the team and gives contact information, as shown in Figure 5(f). The chatbot uses the SqueezeNet architecture because it achieved the highest accuracy among the evaluated CNN models.



Figure 5: Example of LINE Chatbot screen showing (a) main menu, (b) terms of use, (c) Thai herb leaf identification, (d) and (e) the predicted results, and (f) the developing team



2.3 Discussion

This study aimed to develop and evaluate a CNN-based method for recognizing Thai antipyretic medicinal plants from leaf images. SqueezeNet achieved the highest accuracy among the evaluated architectures, with an accuracy of 92.8%. This finding suggests that a lightweight CNN can perform well on this controlled leaf-image dataset.

Compared to other models, SqueezeNet not only offered the highest precision, recall, and F1-score but also maintained a competitive processing speed (0.004 seconds per image). In contrast, AlexNet demonstrated the fastest processing time (0.001 seconds per image) but significantly lower accuracy at 72.2%. This result indicates that the fastest model was not necessarily the most accurate model in this experiment.

Models such as DenseNet and EfficientNet also achieved high accuracies (89.9% and 86.2%, respectively) but did not surpass SqueezeNet. MobileNet and GoogLeNet exhibited relatively poor performance, particularly MobileNet, which recorded an accuracy of only 22.5%. However, previous studies have reported performance for lightweight architectures such as MobileNetV2 and Ayur-PlantNet in medicinal plant recognition [28], [29]. Therefore, the relatively low performance of MobileNet in this study should be interpreted as specific to the dataset, model configuration, and training settings rather than as a general limitation of lightweight architectures.

To further understand the behavior of each model, Grad-CAM visualizations were generated. These visualizations revealed that SqueezeNet consistently focused on the most relevant parts of herb leaf images, such as the entire leaf shape in *C. micranthum siamensis* and *T. leontopetaloides*, surface textures in *G. pictum*, and the wrinkles along the leaf edges in *H. perforate*. In contrast, other models often misfocused on irrelevant background areas or broad regions, leading to decreased recognition performance. These observations provide a visual explanation that is consistent with the quantitative results. Its ability to accurately attend to important visual features while ignoring background noise contributes significantly to its superior classification performance.

Two factors help explain why SqueezeNet achieved higher recognition performance. First, the Grad-CAM results show that SqueezeNet focused on the surface texture of *G. pictum* and the leaf-edge wrinkles of *H. perforata*, while several other models focused on the entire leaf or background. Second, the SqueezeNet architecture uses Fire modules that combine 1x1 and 3x3 filters to capture channel and local spatial features. It also uses late downsampling to preserve fine texture and edge details. These characteristics may have helped SqueezeNet extract more relevant features for herb recognition.

The results indicate that SqueezeNet was suitable for the evaluated Thai antipyretic herb dataset under controlled imaging conditions. Integrating SqueezeNet into a LINE Chatbot demonstrates the feasibility of a user-accessible prototype for herb identification. This study provides an initial dataset and chatbot prototype for Thai antipyretic herb recognition from leaf images.

3. Limitation

This study focused on CNN-based models and did not compare them with multilayer perceptrons (MLPs), extreme gradient boosting (XGBoost), or other conventional classifiers. Direct comparisons require careful control of input features because CNNs learn features automatically, whereas conventional methods rely on predefined

representations. Future work will conduct a fair comparison using controlled feature representations and identical evaluation settings.

4. Data Availability

The dataset collected and analyzed during this study is not currently available in a public repository. However, it may be made available upon reasonable request by contacting the corresponding author, Donyarut Kakanopas, at donyarut.k@rmuts.ac.th. Each request will be considered individually, and access to the dataset will be granted subject to approval.

CONCLUSION

This study developed a CNN-based LINE Chatbot prototype for recognizing Thai antipyretic medicinal plants from leaf images. The key contributions include collecting a dataset of 20 Thai herbs, evaluating eight CNN architectures, and integrating the best model into a chatbot. Among the models tested, SqueezeNet achieved the highest recognition accuracy and was selected for prototype integration. However, two main limitations were identified: First, the dataset was collected under controlled conditions with plain backgrounds, limiting data variety. Second, the chatbot was developed in Thai to support local users; however, formal usability testing has not yet been conducted.

Future work should collect leaf images under natural backgrounds, increase the number of samples per species, and evaluate the chatbot with target users.

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