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Automated identification of pattani local medicinal herbs based on deep learning techniques

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ABSTRACT

Despite Pattani's rich biodiversity, there is a significant lack of digital datasets and automated tools to preserve local ethnomedicinal knowledge. Traditionally, herbal medicine plays a significant role in healthcare systems, especially in regions with rich biodiversity, such as Pattani, Thailand. However, the manual identification of medicinal herbs is often labor-intensive and disposed to inaccuracies. This study introduces an automated system for identifying Pattani's local medicinal herbs (Etlingera elatior, Euphorbia hirta, and Leucas aspera) using Deep Learning methods, specifically Convolutional Neural Networks (CNNs). The system uses image processing techniques to improve the accuracy and confidence in herb identification. The system uses a Convolutional Neural Network (CNN) architecture comprising feature-extraction layers with ReLU activation and max pooling, followed by a fully connected softmax classifier. Data augmentation techniques were employed to enhance model generalization on the collected dataset. It additionally protects traditional knowledge through scientific validation. Collecting and pre-processing a dataset of 600 images and using CNNs yielded an overall test accuracy of 97%. Such performance reinforces the system's capabilities in healthcare for traditional practitioners and pharmaceutical researchers who need precise herb identification. Integrating technology and local knowledge to use and conserve Pattani's medicinal plants and to harness local medicinal plant knowledge is a crucial step this research takes.

Keywords: Deep learning, Pattani herbal medicine, Convolutional neural networks, Image processing, Herb identification

INTRODUCTION

Plants are undeniably essential to human life, with the most important benefits including food, medicine, spices, clothing, shelter, and even fertilizers. Besides these uses, they contribute to climate change mitigation by sequestering carbon dioxide and regulating ecosystems [1, 2]. The aforementioned ways in which plants sustain human life and help restore the balance of the ecosystem prove that they are important for human life and the environment. Plants perform this dual role, sustaining human life and simultaneously maintaining the environment, underscoring the need to conserve plant diversity and practice sustainable ways. In particular, medicinal plants have been of great importance to all health care systems. The World Health Organization (WHO) reports that in most developing countries, traditional medicine accounts for over 80% of healthcare for the population. Ever since, these plants have been used for their therapeutic benefits, primarily for pain and illness management in medicine [1, 3]. Many plant materials have great potential for anti-microbial therapy, as numerous plant substances exhibit remarkable anti-microbial properties. These natural products offer promising prospects for the design of biocompatible medicinal products to manage microbial infections. In an era marked by rising antibiotic resistance, the search for new plant-based therapeutic agents has become increasingly critical, offering potential alternatives to conventional antibiotics. Additionally, plant-based drugs are often more biocompatible, reducing the likelihood of adverse side effects commonly seen with synthetic drugs [1,2]. Exploring medicinal plants for these properties is crucial in the ongoing search for new anti-microbial treatments that are both effective

and safe for long-term use. The alarming acceleration of plant species extinction, now occurring at 100 to 1,000 times the natural rate, represents a severe threat to valuable medicinal resources. Estimates suggest that Earth loses a potential medicinal plant species every two years. It is predictable that between 50,000 and 80,000 plant species worldwide are used for therapeutic purposes, but approximately 15,000 are endangered due to unsustainable harvesting and habitat loss. As a result, 20% globally wild herbal resources have already been exhausted [2, 4, 5].

Traditional herbal medicine, rooted in plant-based therapies, has long been a vital component of healthcare in many cultures, particularly in regions with rich biodiversity, such as Pattani, Thailand. Pattani's unique ecological landscape has fostered a deep tradition of medicinal herb usage, passed down through generations [6]. For Example, Etlingera elatior, commonly known as torch ginger, is a tropical plant with large, showy flowers. It's widely used in Southeast Asia for both attractive and medicinal purposes [7]. In the past, the flowers, leaves, and stems of Etlinga elatior have been used to treat inflammation, digestive issues, and high blood pressure [8]. The plant has been shown to contain anti-inflammatory and antioxidant compounds [9], and some literature reports antibacterial and anti-fungal activities [10]. Apart from medicinal usage, the flower buds are a well-known ingredient in Thai and Malaysian cooking. They are commonly used in salads, soups, and curries [11]. Euphorbia hirta, popularly known as asthma weed, is a tropical, annual herb. It has long been used in traditional medicine and for respiratory conditions such as asthma and bronchitis [12]. Many cultures have adopted the use of this weed for the formal treatment of specific ailments like coughs and even digestive disorders, particularly dysentery and diarrhea [13, 14]. Phytochemical studies indicate anti-microbial, anti-fungal, and anti-inflammatory activities [13, 14]. The latex of some plants, like this one, has been used in folk medicine externally to treat skin diseases and boils [15]. Also known as thumbai, Leucas aspera is reported to grow in southern Asia. The plant is well-received for its beneficial features as described in Ayurveda and folk medicine [16]. Respiratory challenges such as coughs, colds, and even asthma are not the only issues this herb addresses. Minor skin infections, inflammation, insect bites, and even wounds are also addressed [17]. Also, it has been proven to help lower fevers and inflammation [19]. Certain digestive tract disorders, such as indigestion and loss of appetite, are also relieved with this herb. These potential traits, to a chooser of wishing to adhere to exotic therapeutic systems, present an almost insurmountable barrier. The process of 'diagnosis' as above is overly burdensome, prone to error, and far too reliant on a system of functioning oral histories. In a situation like this, massive shifts mean the cultures in question risk losing an awful lot of information. This is to say, the maw distortions that seek to injure the people's relationship with this land and with these plants [20]. The exhaustion of old Relay systems and a top lip brought on the policies; it is folly to cling to old paths. Quite several new, sustainable options exist [21].

Digital technology solutions, most especially deep learning, are possible. CNN, as the backbone of many successful image classification projects, is therefore well-suited to improving automation and accuracy in herb identification [22,23]. This leads to the development of a system for identifying the three major ethnomedicinal plants in Pattani-Etlingera Elatior, Euphorbia Hirta, and Leucas Aspera-using images [24]. The developed system aims to integrate image processing techniques with Convolutional Neural Networks (CNNs) to address the dichotomy between herbal and scientific practices.
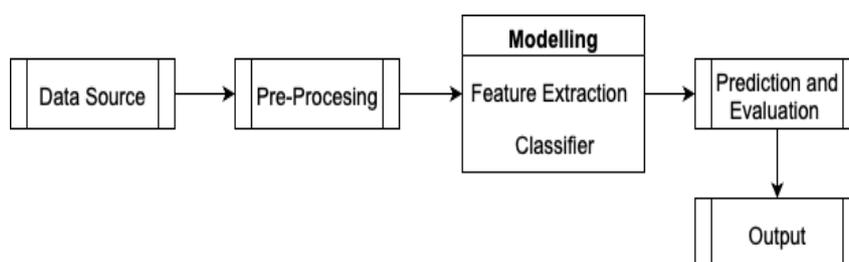
Research proposes a technology-based model that offers better ease of use, computational efficiency, and accuracy while reducing user costs for identifying herbal plants [26]. the addition of deep learning to this process simplifies the task while providing scientific relevance to traditional practices and knowledge, strengthening its adoption in the contemporary healthcare system. The significance of this approach lies in its potential for adoption across other areas of pharmaceutical and medical research, thereby increasing the understanding and use of medicinal plants globally and locally. Thus, CNNs represent not only a technical advance but also an important step in preserving cultural heritage while extending its value within contemporary science [22, 23]. This research contributes beyond standard CNN image classification by addressing a specific gap in regional biodiversity informatics. While many studies focus on common global crops, this study establishes a novel digital baseline for Pattani-specific ethnomedicinal plants, effectively acting as a digital preservation tool for vanishing local wisdom. It validates that lightweight CNN architectures can be effectively deployed for region-specific botanical conservation [25].

Deep learning has seen widespread adoption in botany. For instance, generic CNNs have been successfully used to classify crop diseases [24]. Similarly, [3] demonstrated the efficacy of deep learning for medicinal plant recognition in broader contexts. However, few studies focus on the specific micro-climatic flora of Southern Thailand, creating a gap that this research addresses. The proposed system is intended to serve as a digital assistant for pharmacy students, local researchers, and traditional practitioners who need rapid, accurate field verification of plant species.

Therefore, the specific objectives of this research are: (1) To curate a verified image dataset of *Etlingera*

elatior, *Euphorbia hirta*, and *Leucas aspera* from the Pattani region. (2) To design and validate a CNN architecture suitable for classifying these specific ethnomedicinal herbs. (3) To provide a digital tool that assists traditional healers and medical students in accurately identifying these species.

The remainder of the paper is organized as follows. describes the proposed methodology in detail. Presents the results obtained and a discussion. Finally, presents the conclusions.

MATERIAL AND METHODS

This section outlines the methodology used to develop and implement the Convolutional Neural Network (CNN) model for identifying three specific medicinal herbs native to Pattani: Etlingera elatior, Euphorbia hirta, and Leucas aspera. The methodology includes the following phases: data collection, pre-processing, model development, and evaluation (Figure 1).

Figure 1 Methodological process study.

1. Data source

For this study, images of three medicinal herbs native to Pattani (Etlingera elatior, Euphorbia hirta, and Leucas aspera) were collected with smartphones. Images were captured with standard smartphone cameras (12 MP) via random sampling in the herbs' natural habitats across the Pattani region. These were subsequently resized to 160x120 pixels. To address the limited dataset size, data augmentation (rotation, zooming) was applied to the training set at a 1:1 ratio. A dataset comprising 600 images was collected to train the CNN model. Images of the selected herbs were captured with a smartphone camera under natural lighting to preserve their visual features. Each herb was represented by 200 images, ensuring variability in lighting, angles, and plant conditions to enable generalization in the model. The images were collected from various locations in Pattani to capture the diversity of plants in their natural habitats. Species manually identified the images to provide supervised learning input for the CNN model. During data collection, geographic and environmental metadata, including time of day and prevailing weather conditions, were systematically recorded to enhance data quality and ensure the replicability of the study.

2. Data acquisition

This dataset structure ensures the model has organized and labeled data for both training and testing, which is essential for supervised learning tasks such as image classification. By splitting the data into training and test sets, the model's performance can be evaluated on unseen data, helping gauge its real-world effectiveness.

Width: 160
Height: 120
Number of Classes: 3
List of Training Image Paths:
    ['train/Etlingera elatior', 'train/Euphobia hirta L', 'train/Leucas aspera']
List of Test Image Paths:
    ['test/Etlingera elatior', 'test/Euphobia hirta L', 'test/Leucas aspera']

Figure 2 Bring Data and Set image.

Figure 2 shows the details of the images and of the dataset: Image Dimensions: the images used in this dataset have a height of 120 pixels and a width of 160 pixels. This consistent image size is essential for feeding the images into the CNN model, as it requires inputs of the same dimensions to perform feature extraction efficiently. Number of Classes: the dataset contains images of three herb classes (Etlingera elatior, Euphorbia hirta L., and Leucas aspera), which represent the three medicinal herbs the CNN model is trained to classify. Training Image Paths: the list of directories where the images for each herb species are stored for training the CNN model. The images are separated into three folders, one for each herb class, allowing the model to learn from labeled data. Test Image Paths: similarly, the test image paths refer to the directories containing images for each herb species used for testing the model's performance. These images are not seen by the model during training and are used to evaluate the CNN's accuracy and generalization.

3. Image Processing

3.1 Pre-Processing
The collected images were subjected to a series of pre-processing steps to ensure they were

standardized and enhanced their suitability for analysis with the CNN model. These steps included: (i) Resizing: all images were scaled to a consistent size of 160x120 pixels to regulate input dimensions for the CNN model. This facilitates a balance between computational efficiency and the recording of crucial visual attributes. (ii) Normalization: All pixel values of each image were normalized within the range of 0 and 1 to ensure the effectiveness of the model and the learning process is not impeded. The model's convergence speed and stability are enhanced. (iii) Augmentation: in a bid to improve the model's performance and increase the variety of the dataset, data augmentation strategies were implemented. This included applying random rotations, flips, zooms, and shifts. These techniques were applied to help the model recognize herbs under different angles and at different scales. (iv) Data Splitting: the set of data that underwent pre-processing was split into two parts, with the model having a 20% test set, while the remaining 80% was used to train the model. This ensures that the model is assessed on data that was not available to him during the training phase. (v) Conversion to NumPy Arrays: The processed images were converted into NumPy arrays, which are highly efficient for numerical computations. This format facilitates fast data manipulation during training and inference.

Table 1 Attributes of selected medicinal herbs with visual representations.

Herb Types	Length (cm.)	Width (cm.)	Color	Image
Etlingera elatior	30 - 40	15 - 20	Reddish pink	
Euphorbia hirta L	15 - 20	1 - 1.5	Light brown, green	
Leucas aspera	30 - 60	0.39 - 0.79	Green	

Table 1 displays the attributes of three medicinal herbs: Etlingera elatior is a herbaceous plant with a single underground rhizome and reddish-pink bracts. Euphorbia hirta L. is very branchy, with square-shaped trunks and branches covered in long hairs, and Leucas aspera is Resistant branching, with rectangular, furry branches. Each row corresponds to a specific herb and includes key details such as the plant's physical attributes, leaf measurements, color, and an accompanying image.

3.2 Numeric transformation of images

Image numeric transformation is an important pre-processing step for Machine Learning. It involves assigning numeric values to raw pixel data to enable the application of Machine Learning methods, especially Convolutional Neural Networks (CNNs). The transformation invariably includes normalizing pixel values, which reduces the data range to a standard interval, typically 0 to 1, to minimize the effect of excessive pixel intensity variation. In addition, the model determining image classification is structured so that the images as labels are stored in a model-compatible format, e.g., multi-class classification tasks are one-hot encoded as illustrated in Table 2:

Table 2 Data structure for training and testing images with deep learning model.

Data type	Total images	Image dimensions	Label Shape
x_train	480	160 x 120 x 3	(480, 3)
y_train	480	N/A	(480, 3)
x_test	120	160 x 120 x 3	(120, 3)
y_test	120	N/A	(120, 3)

```
x_train shape: (480, 160, 120, 3)
y_train shape: (480, 3)
x_test shape: (120, 160, 120, 3)
y_test shape: (120, 3)
Sample values from x_train: |
[[[9.83116435e-11 1.38192804e-10 1.13151141e-10]
  [7.51249410e-11 1.26135699e-10 1.01094057e-10]
  [4.82283519e-11 1.09441269e-10 8.25446864e-11]
  ...
  [1.11296207e-11 7.04876019e-11 5.93579838e-11]
  [3.70987399e-12 5.75030405e-11 5.00832951e-11]
  [2.78240504e-11 8.16172130e-11 7.14150683e-11]]
 [[1.06658862e-10 1.43757603e-10 1.20570900e-10]
  [8.43996192e-11 1.27063166e-10 1.03876456e-10]
  [6.02854502e-11 1.15006081e-10 8.90369653e-11]
  ...
  [2.78240504e-11 8.06897466e-11 7.60524074e-11]
  [2.68965822e-11 7.88348137e-11 7.41974676e-11]
  [2.78240504e-11 7.97622801e-11 6.77051956e-11]]
 [[1.07586329e-10 1.42830137e-10 1.22425833e-10]
  [8.90369653e-11 1.31700512e-10 1.07586329e-10]
  [7.32700012e-11 1.19643434e-10 9.73841702e-11]
  ...
  [1.76219005e-11 4.82283519e-11 1.48394960e-11]]]
Sample values from y_train:
[ True False False ]
```

Figure 3 Sample data and label representation after numeric transformation.

As shown in Table 2, the training images are 160 x 120 pixels and have 3 channels (RGB). These training images total 480, and each image is labeled with a category indicating its membership in one of three categories. The validation images, which are also 160 x 120 pixels, are used to test the model. There are 120 test images, and, as with the training images, each is labeled with one of three possible classes. The image data has undergone several significant transformations. These transformations serve as the primary data preparation steps for training CNNs, enabling efficient image processing and focusing on the recognition of internal configurations and elemental features. By normalizing the pixel values, the model avoids being

influenced by the magnitude of raw pixel intensities and can better generalize across varying conditions. As a result, this pre-processing step enhances the model's ability to capture meaningful representations, leading to improved performance during both training and testing. Ultimately, the numeric transformation of image data is critical for ensuring the accuracy and efficiency of Machine Learning models in image classification tasks. These operations are typical pre-processing steps commonly employed in (see Figure 3).

As shown in Table 2, each training image has a width of 160 pixels, a height of 120 pixels, and 3 channels (RGB), and the training labels correspond to 480 images, with each label indicating one of the three classes. While the test images, which have the same dimensions as the training images, are used for model validation, the test labels correspond to 120 images, each labeled with one of the three classes. Several essential processes have been undertaken on the image data. This transformation is foundational to CNN training, enabling the model to process image data effectively and focus on identifying underlying patterns and features. By normalizing the pixel values, the model avoids being influenced by the magnitude of raw pixel intensities and can better generalize across varying conditions. As a result, this pre-processing step enhances the model's ability to capture meaningful representations, leading to improved performance during both the training and testing phases. Ultimately, the numeric transformation of image data is critical for ensuring the accuracy and efficiency of Machine Learning models in image

classification tasks. These operations are typical pre-processing steps commonly employed.

In Figure 4, sample values from x_train are shown: the numbers represent the pixel values from the x_train dataset. These values have been normalized or transformed to a range close to zero, which is typical in Machine Learning to improve model convergence. The values are very small, likely due to a normalization process (e.g., dividing by 255), which is commonly used to scale pixel values from 0–255 (for RGB images) to a range of 0-1 or close to 0. With respect to the Sample values in y_train, the samples correspond to the images' labels. In this case, the labels are [True, False, False], which means the image belongs to the first class (since True corresponds to the first label).

4. Modelling

The core step of this study is the Convolutional Neural Network (CNN) Model. CNNs are specifically designed for image classification and are used here to learn patterns and features that differentiate the herbs, as illustrated in Figure 4.

The CNN architecture employed in this study comprises the feature extraction and classifier stages, as explained below. A lightweight CNN architecture was deliberately chosen over complex pre-trained models (like ResNet or VGG) to minimize computational cost. This design ensures the model remains suitable for deployment on resource-constrained mobile devices used by local practitioners in Pattani.
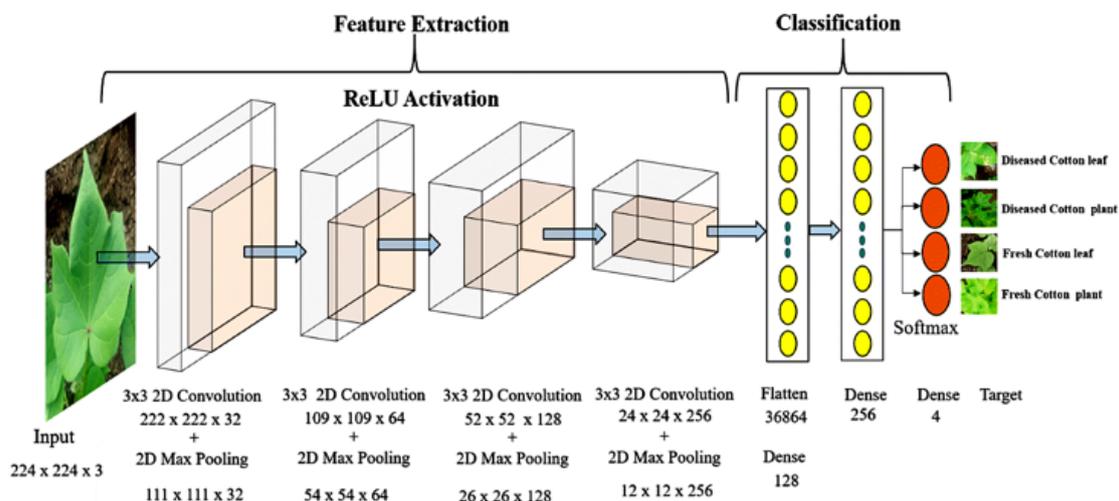
Figure 4 Convolutional Neural Network (CNN) Processes (Rai et al.).

4.1 Feature extraction

Feature Extraction includes (i) Input Layer: the input layer receives the pre-processed images (160x120 pixels, 3 channels for RGB). (ii) Convolutional Layers: The network utilizes two convolutional layers. The first layer applies 128 3x3 filters to capture basic features such as edges and textures. The second layer uses 64 3x3 filters to identify more complex structures. Each layer uses the Rectified Linear Unit

(ReLU) activation function, enabling the model to capture important features of herb images and to incorporate nonlinearity, helping it learn complex relationships [28]. (iii) Max-Pooling Layers: a max-pooling layer with a 2x2 window after each convolutional layer [29] is applied to reduce the spatial dimensions of the feature maps [30]. This pooling layer simplifies the representation while retaining the most important information, helping

reduce computational load and the risk of overfitting. (iv) Dropout Layer: A dropout rate of 0.25 is introduced after the max-pooling layers to avoid overfitting without a pattern turning off neurons throughout the training phase, forcing the network to generalize better [31].

4.2 Classifier

The Classifier stage includes: (i) the Dense Layer, an inbuilt function of the TensorFlow.js library, is used to create fully connected layers. In these layers, each output depends on all inputs, enabling the model to capture complex relationships among features. The model used includes a Dense Layer with 16 neurons. This fully connected layer is crucial for extracting and representing high-level patterns in the data by learning combinations of the features detected by earlier layers [32, 33]. (ii) Flattening Layer: after the convolutional and pooling layers, the feature maps generated by these operations are transformed into a one-dimensional vector, or flattened, to serve as input for the fully connected layers. This step ensures that the learned spatial features from the earlier layers can be processed by the dense layers [34]. (iii) Dense Layers (Fully Connected): The model is now capable of classifying the data it was trained on, as the last output layer classifies the data into one of the three herb classes using the Softmax activation function. The Softmax layer transforms the outputs into probabilities, assigning each output neuron (corresponding to each herb class) a score, with the highest score indicating the class the model is most confident it belongs to. The output layer has three herb species, and, as expected, each is associated with a separate neuron. The model can predict the associated herb species by estimating the class with the highest probability using Softmax. The classifier was trained on a pre-processed dataset, and the model's backbone consists of convolutional layers followed by ReLU activations and pooling layers that compress the most important features of the input images. Through this layered process, the model learns to recognize the unique characteristics of each medicinal herb species, effectively making predictions based on the given input [28].

4.3 Experimental Setup

The CNN model was implemented using TensorFlow.js, enabling direct execution in web-based environments. The training process utilized the Adam optimizer with a learning rate of 0.001 to ensure efficient convergence. A batch size of 32 was selected to balance memory efficiency with training stability. The model was trained for 10 epochs using Categorical Cross-entropy as the loss function, with a 20% validation split to monitor for overfitting.

5. Prediction and evaluation

The Confusion Matrix is a fundamental tool in Machine Learning for evaluating the performance of classification models. It offers detailed insights into how effectively the model distinguishes among different classes within a dataset. Although it is widely applied in binary classification tasks, its usefulness extends equally to more complex multi-class classification problems. It provides valuable insights into a model's ability to categorize instances across different classes within a dataset. While it finds prominent applications in binary classification, its utility extends seamlessly to multi-class classification. The Confusion Matrix, shown in Figure 5, helps compare the predicted labels (model output) with the actual (true) labels in a classification task.

Figure 5 Confusion matrix for classification model evaluation [37].

Here's an overview of the functioning of a Confusion Matrix within the context of research:

5.1 Confusion Matrix Component

True Positive (TP): instance in which the model where the positive class was predicted correctly by the model [37]. Example: if the actual class is positive (e.g., herb correctly identified as Etlingera elatior), and the model also predicts it as positive, it's counted as a true Positive. True Negative (TN): cases in which the model correctly predicted the negative class. Example: If the actual class is negative (e.g., the herb is not Etlingera elatior), and the model predicts it as negative, it's counted as a True Negative.

False Positive (FP): cases in which the model incorrectly assigned the positive class. Example: if the actual class is negative (e.g., the herb is Leucas aspera), but the model incorrectly classifies it as positive (e.g., predicting Etlingera elatior), the outcome is a False Positive. This is also called a Type I Error. False Negative (FN): Cases in which the model incorrectly predicts the negative class [37]. Example: If the actual class is positive (e.g., herb is Etlingera elatior), but the model predicts it as negative (e.g., predicts it as Leucas aspera), it's a False Negative. This is also called a Type II Error.

The effectiveness of a classification model is measured by multiple metrics that provide an all-inclusive evaluation of predicted outcomes. These metrics serve as primary indicators of the model's utility, not only in observations but also in the formulation and recognition of intricate features in the provided dataset. One of the primary ingredients, the Confusion Matrix, yields the vital information necessary to calculate model performance parameters

such as Precision, Recall, F1-Score, and Accuracy. Any metric for the above-enunciated thrusts focuses on the segment of the model's effectiveness, thereby enhancing understanding of the contours of its limitations.

Precision assigns a value to the model's ability to predict the very issue of concern within the scope of the research. Each metric captures a different dimension of the model's performance. Precision measures the model's predictive ability within the research domain. In this case, the model is said to have successfully predicted a concern. Recall measures the issue of concern that a model predicts about. The F1-Score metric captures the model's performance in both Precision and Recall by taking the harmonic mean of both. Accuracy: is the total count of correctly predicted results of the model without distinguishing between the classes. After training, the model is equipped with a Convolutional Neural Network (CNN) capable of classifying unlabeled images. Each input image is processed through a sequence of bends and twists across the network's layers. Each layer pass focuses the model on a set of features and computes many of them, starting at the lower levels of the hierarchy and working up to the top, analyzing increasingly complex structures. At the last layer, the culmination of all this work is a probability distribution indicating the likelihood that the image belongs to each of the selected herb species. The trained CNN model was evaluated on 20% of the dataset specifically reserved for this purpose. The model's effectiveness was evaluated using performance metrics such as Accuracy, Precision, Recall, and F1-score. A Confusion Matrix was generated to evaluate the model's ability to classify the three herb species correctly and to analyze potential misclassifications. Cross-validation was also used to confirm that the model generalized effectively across different data splits. Finally, the system generates the predicted herb species. This output could be displayed as the herb's name, or, in a real-world application, include additional information such as its medicinal properties or uses.

RESULTS AND DISCUSSION

This section navigates the intricate aspects of this research and presents the practical application of the methodologies outlined previously, revealing the empirical findings and pivotal insights derived from rigorous data analysis and model evaluation. These practices are among the many aspects of data synthesis and analysis that aid in crafting and fine-tuning custom models. Employing the described practices in diachronic analysis yields practical strategies within the contextual frameworks outlined. The model undergoes multiple training cycles before being authenticated and definitively evaluated. The

explanations for each of these are developed alongside the various algorithmic approaches to the model's training and evaluation. Each model is built on the previous one, allowing all models to function simultaneously while new features are added to the pipeline. The model described is architecture-agnostic; thus, the predictions bound the total output of each model based on structural constraints. In deep learning and data mining, this dataset structure allows the model to use the available training and test data in a sequential order. The initial training cycle is based on the model using one of the previous output structures. The primary backbone does not change; it simply gains new configurable parameter sets. The additional data available allows the model in the evaluation sets to narrow the guess range, thus enabling the layer of structural constraints within each model to perform its primary function.

1. Deep learning model design

The CNN architecture was designed using a Sequential model in Deep Learning. A Sequential model is a linear stack of layers where the output of one layer serves as the input to the next. The model comprises convolutional layers, pooling layers, dense layers, dropout for regularization, and a final fully connected layer for classification.

Table 3 summarizes the model layers and parameters. Each row corresponds to a specific layer in the Neural Network architecture, and the columns indicate the output shape, the layer type, and the number of parameters (weights and biases) to be learned by the model. This structure is crucial for understanding how the model processes input data and transforms it through various stages of convolution, pooling, flattening, and dense layers to generate final predictions.

Table 3 Sequential model.

Layer (type)	Output Shape	Param
conv2d (Conv2D)	(None,158,118,128)	3,584
max_pooling2d (MaxPooling2D)	(None, 79, 59, 128)	0
conv2d_1 (Conv2D)	(None, 77, 57, 64)	73,792
max_pooling2d_1 (MaxPooling2D)	(None, 38, 28, 64)	0
dropout (Dropout)	(None, 38, 28, 64)	0
dense (Dense)	(None, 38, 28, 16)	1,040
flatten (Flatten)	(None, 17024)	0
dense_1 (Dense)	(None, 3)	51,075

Total params: 129,491 (505.82 KB)
Trainable params: 129,491 (505.82 KB)
Non-trainable params: 0 (0.00 Byte)

The model can be described as follows: (i) Conv2D Layer (conv2d): The first layer is a 2D convolutional layer, which applies 128 filters of size 3x3 to the input image. Output Shape: (None, 158, 118, 128), where None denotes the batch size (flexible and not predefined), 158 is the height, 118 is the width, and 128 is the number of filters (or channels). Parameters: there are 3,584 parameters, which are calculated as (3x3x3x128) + 128, where the first term comes from the filter size, input channels, and output channels, and the second term is the bias.

(ii) MaxPooling2D Layer (max_pooling2d): The second layer is a max-pooling layer, which reduces the spatial dimensions (height and width) by a factor of 2. Output Shape: reduced to (None, 79, 59, 128), indicating halved height and width, with the same number of channels (128). Parameters: this layer has 0 parameters because max pooling reduces dimensionality without any learnable weights.

(iii) Conv2D Layer (conv2d_1): a second 2D convolutional layer, similar to the first one but with 64 filters of size 3x3. Output Shape: (None, 77, 57, 64), indicating the new dimensions and the number of filters. Parameters: 73,792, calculated similarly to the first layer as (3x3x128x64) + 64.

(iv) MaxPooling2D Layer (max_pooling2d_1): A second max-pooling layer reduces the spatial dimensions again by a factor of 2. Output Shape: this reduces the shape to (None, 38, 28, 64). Parameters: again, no parameters, as it just reduces dimensions.

(v) Dropout Layer (dropout): A dropout layer with a 50% dropout rate is used to prevent overfitting by randomly setting half of the neurons to zero during training. Output Shape: the shape remains the same, (None, 38, 28, 64), as dropout does not affect the dimensions. Parameters: No parameters, as dropout does not have weights.

(vi) Dense Layer (dense): a fully connected (dense) layer with 28 neurons. Output Shape: this reshapes the output to (None, 38, 28, 16). Parameters: 1,040 for this layer.

(vii) Flatten Layer (flatten): the flatten layer reshapes the multi-dimensional tensor into a one-dimensional tensor for input into the dense layer. Output Shape: the output is flattened to (None, 17,024). Parameters: No parameters, as it only reshapes the tensor.

(viii) Dense Layer (dense_1): The final dense layer is the output layer with 3 neurons, related to the three classes in the classification task. Output Shape: (None, 3), representing the final class probabilities. Parameters: there are 51,075 parameters for this layer.

Total Parameters: 129,491 parameters in total, which includes both trainable weights and biases. Trainable Parameters: All 129,491 parameters are trainable, meaning they will be updated during training. Non-trainable Parameters: there are none, meaning all parameters are trainable.

2. Confusion matrix training

The confusion matrix serves as a visual representation of our classification model's performance, particularly focusing on three distinct herb classes: "Erlingera elatior", "Euphobia hirta", and "Leucas aspera". (see Figure 6). Erlingera elatior: impressively, the model achieved flawless classification, achieving an impeccable Accuracy of 100%. No instances of "Erlingera elatior" were misclassified. Euphobia hirta: the model demonstrated commendable Precision by correctly identifying 95% of the "Euphobia hirta" instances. However, a minor hiccup was observed where 5% of the true "Euphobia hirta" instances were mistakenly predicted as "Leucas aspera". Leucas aspera: mirroring the performance with "Erlingera elatior", the model exhibited perfect classification for "Leucas aspera", again with a 100% Accuracy rate. In summation, the classification model exhibited stellar performance on the training dataset. While "Erlingera elatior" and "Leucas aspera" were identified with unerring accuracy, there was a slight margin of error with "Euphobia hirta". Nevertheless, the overall high accuracy indicates the model's robust ability to distinguish between these herb classes during training. Figure 6 provides a clear visual breakdown of these results, further emphasizing the model's effectiveness.
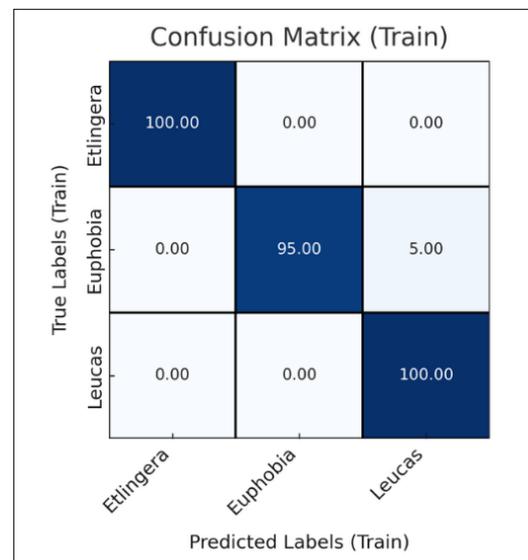
Figure 6 Confusion matrix training.

3. Confusion matrix testing (validation)

The Confusion Matrix in Figure 6 provides a detailed visual representation of the classification model's performance on the test dataset, specifically for three herb classes: "Erlingera elatior", "Euphobia hirta", and "Leucas aspera". Erlingera elatior: the model demonstrated impeccable performance for this class on the test set, accurately classifying "Erlingera elatior" with a success rate of 100%. No instances were misclassified. Euphobia hirta: the model correctly

classified 90% of the instances as "Euphobia hirta". However, 7.50% of the true instances "Euphobia hirta" were misclassified as "Leucas aspera". This indicates a small overlap or similarity between these two classes that the model occasionally confuses. Additionally, 2.50% of the true instances "Leucas aspera" were incorrectly predicted as "Euphobia hirta". Leucas aspera: aside from the minor misclassification with "Euphobia hirta" mentioned above, the model achieved a perfect 100% classification rate for "Leucas aspera" in the test set. The classification model performed well on the test dataset, correctly identifying "Erlingera elatior" and "Leucas aspera" with minimal errors. There was a slight increase in misclassification for "Euphobia hirta" in the test set compared to the training set, suggesting a potential area for improvement in the model. However, the overall accuracy remains high, indicating effective generalization to unseen data. For a more granular breakdown of these results, readers are encouraged to refer to Figure 7, which visually captures the nuances of the model's performance across different classes.

The model achieved 100% accuracy on the testing set for Etlingera elatior and Leucas aspera. This high performance is attributed to the distinct visual characteristics of these species (e.g., the bright pink bracts of Etlingera) compared to the background. However, we acknowledge that this accuracy is conditional on the current dataset. In real-world scenarios with varying lighting or occlusion, performance may fluctuate, highlighting the need for continuous data validation.

4. Classification report for the training set

Table 4 provides a comprehensive analysis of the classification model's performance metrics for distinguishing among three herbs: Etlingera elatior, Euphorbia hirta, and Leucas aspera. The evaluation metrics used to assess the model's performance include Precision, Recall, F1-Score, and Support.
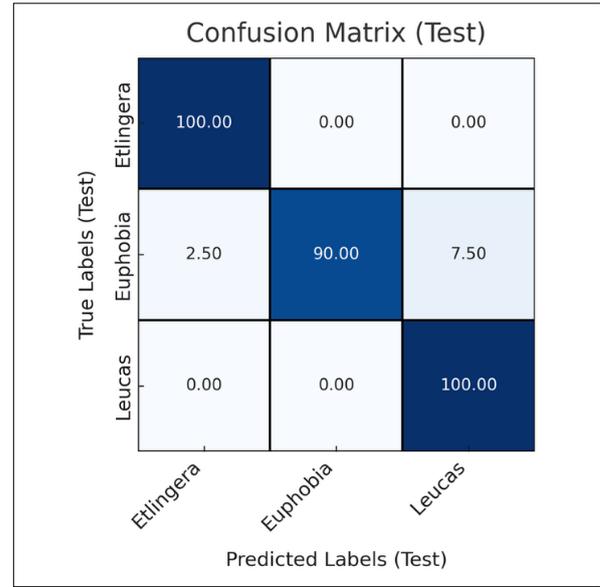

Figure 7 Confusion matrix testing.

Table 4 Model performance on training set.

Training Classification				
Herb/Measurement	Precision	Recall	F1-Score	Support
Etlingera elatior	1.00	1.00	1.00	160
Euphorbia hirta	1.00	0.95	0.97	160
Leucas aspera	0.95	1.00	0.98	160
Overall Metrics				
Accuracy			0.98	480
Macro Average	0.98	0.98	0.98	480
Weighted Average	0.98	0.98	0.98	480

The model has achieved outstanding results for the Etlingera elatior class, scoring 1 (perfect) on Precision, Recall, and F1-Score, indicating that every prediction for Etlingera elatior is correct and that the model successfully classifies every herb of this type in the training set. For the Euphorbia hirta class, the model achieved a precision of 1.00, indicating that all predictions for this class were correct. The Recall, on the other hand, which is lower in this case, is 0.95, indicating that the model captured 95% of the Euphorbia hirta samples in the training set. The F1-Score, which is the average of Precision and Recall, is 0.97 in this case. For the class Leucas aspera, the model achieved a precision of 0.95, meaning that 95% of its predictions for this herb were correct. The Recall score is 1.00, indicating that the model captured all true instances of Leucas aspera. The F1-Score is 0.98, indicating the model has achieved high accuracy for this herb class.

The model has achieved an overall accuracy of 0.98, meaning that it has correctly classified 98% of the samples in the training set. The results for Precision, F1 Score, Recall, and the F1 Score Ratios for both the Macro Average and the Weighted Average

are consistently 0.98, highlighting the model's robust performance across all herb classes and its ability to account for potential class imbalances. The Support metric indicates that there were 160 samples for each herb in the training set, ensuring a balanced dataset for the classification task. These metrics, along with the visual representation in Figure 7, provide a comprehensive overview of the model's effectiveness in distinguishing between the three herb species during the training phase.

5. Classification report for the testing set

A comprehensive analysis of the performance metrics for the classification model tested is provided in Table 5, specifically focusing on three herb species: Etlingera elatior, Euphorbia hirta L., and Leucas aspera. The metrics used to assess the model's effectiveness include Precision, Recall, F1-Score, and Support.

Table 5 Model performance on testing set.

| Testing Classification			
Herb/Measurement	Precision	Recall	F1-Score	Support
Etlingera elatior	0.98	1	0.99	40
Euphorbia hirta	1	0.9	0.95	40
Leucas aspera	0.93	1	0.96	40
Overall Metrics			
Accuracy	0.97			120
Macro Average	0.97	0.97	0.97	120
Weighted Average	0.97	0.97	0.97	120

For the Etlingera elatior class, the model obtains a Precision of 0.98, indicating that 98% of its predictions for this herb are accurate. The Recall of 1.0 indicates that the model correctly identifies all actual instances of Etlingera elatior in the dataset. The F1-Score, which combines Precision and Recall, stands at an impressive 0.99. In the Euphorbia hirta class, the model achieves a Precision of 1.0, meaning that all predicted instances of this herb are correct. However, the Recall value is slightly lower at 0.9, indicating that the model captures 90% of the actual Euphorbia hirta samples in the dataset. The F1-Score for this herb is 0.95, reflecting a balance between the high Precision and the slightly lower Recall. For the Leucas aspera class, the model has a Precision of 0.93, signifying that 93% of its predictions for this herb are accurate. The Recall score remains flawless at 1.0, indicating that the model captures all true occurrences of Leucas aspera in the analyzed data. The value of the corresponding F1-Score for this specific class is 0.96.

In general, the model achieved an Accuracy of 0.97, meaning it correctly classified 97% of the dataset. The Precision, Recall, and F1-Score Macro Average, as well as Weighted Average, all equal 0.97. These metrics are the model's key herb-class performance metrics, serving as a reasonable worst-case guardrail against class imbalance in model performance. The Support value represents the number of samples in the dataset for each herb class and is 40 per herb. This Support value is consistent across classes, indicating that the model's

Support metrics were class-balanced. This evaluation suggests that the model was robust enough to classify the three herbs properly and can therefore be used to identify herbs using this dataset. Readers who wish to see more illustrative data on these findings should consult Figure 8, which shows the model's performance across the various herb classes.
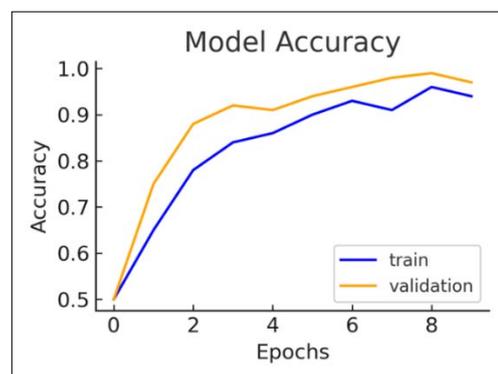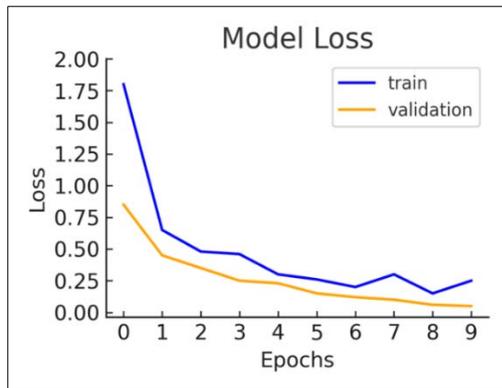

Figure 8 Model accuracy of training and validation over 10 epochs.

6. Model's comparative performance and enhancement recommendations

The model's accuracy trends during both the training and validation phases were obtained over a series of 10 epochs (see Figure 8). The X-axis shows the number of epochs, while the Y-axis shows the model's accuracy. While the model has demonstrated excellent performance, achieving near-perfect accuracy in both the training and validation sets, it can be further improved. Early

stopping, learning rate schedules, and data augmentation could further enhance the model's performance and generalization capabilities. Given the steady upward trajectory of both the training and validation Accuracy results, the current model architecture appears well-suited for the task. The enhancements suggested could lead to even better outcomes, as shown in Figure 8.

Figure 9 Model Accuracy of Training and Validation Over 10 Epochs.

Analyzing the model's training process over 10 epochs, as illustrated in Figure 9, reveals the evolving dynamics of its performance. During the first epoch, the model initiated with a Loss of 1.9401 and an Accuracy of 48.96%. At this stage, the focus is on how the model is beginning to learn from the data through various adjustments and parameter settings, which is the first, almost crucial, part of the model. From one epoch to the next, the model can drastically decrease its loss and increase its accuracy, indicating that it is making progress and learning. One of the more remarkable points in this stage is the 9th epoch, when the model first recorded a Loss of 0.1034 and an Accuracy of 96.88%. At this milestone, the model is beginning to train and generalize on more of the data without the additional help, which is great for the start of model training. This is further evidenced by the subsequent epoch, the 10th, which recorded a Loss of 0.2441 and an Accuracy of 94.17%. These results strongly indicate that the model can also improve its predictions to match the data better. These results support the idea that the model can learn from its past predictions to improve subsequent predictions. This is further supported by Figure 8, which shows that the model has improved in Loss and Accuracy over time. This further indicates that the model can learn to adapt to new rules or data, a crucial aspect of training that must be performed.

Looking at the model's predictions on the validation data shows that it has learned to generalize much better than before. The model commenced with a validation Accuracy of 50.83% and a Loss of 0.8416 during the initial epoch. By the 9th epoch, it

had achieved an exemplary validation Accuracy of 99.17%, with a substantially reduced Loss of 0.0575. However, it's worth noting that in the 10th and final epoch, the loss increased slightly to 0.0823, while the accuracy marginally decreased to 96.67%. While this indicates a slight deviation from the otherwise consistent ascent, it remains a commendable performance. This progression, which is visualized in Figure 9, underscores the model's proficiency in adapting its learning and making accurate predictions on unfamiliar data, thereby validating its effectiveness. Furthermore, characterized by a systematic reduction in Loss values and an increase in accuracy across epochs, the model provides profound insights into its learning dynamics.

These metrics not only reveal periods of rapid learning but also highlight moments of stabilization and fine-tuning. Such fluctuations, especially evident in the 10th epoch, are instrumental for understanding the model's behavior, adaptability, and potential challenges in specific scenarios. This in-depth analysis of the model's learning trajectory not only enhances comprehension of its evolving performance but also paves the way for discerning potential areas for improvement. It sets the stage for future research that could delve into these subtle nuances and further optimize the model's performance.

CONCLUSIONS

The study demonstrates that the value of CNNs extends beyond algorithmic accuracy; it serves as a crucial mechanism for digital heritage preservation, converting oral history regarding Pattani's herbs into a scientifically validated, reproducible digital format. The research focused on developing an image-processing system to identify traditional herbal plants using Deep Learning techniques accurately. Pattani, Thailand, and its traditional herbal plants were the focus of the image digitalisation system, which incorporated Deep Learning methods for the recognition of its traditional plants. This study sought to bridge the divide between traditional herbal wisdom and modern science, demonstrating the potential of Deep Learning technology to support the preservation and validation of indigenous herbal medicine. This report discusses the outcomes of the experiments and their consequences, the limitations of the developed system, and future possibilities for further development. These results illustrate the successful image processing system developed and its ability to identify traditional herbal plants from the Pattani region. Such a system would aid the preservation of traditional knowledge and the health and pharmacy domains by providing a reliable means for herb identification and classification.

The provided dataset includes images of three herbaceous plants from the region: Leucas

aspera, Euphorbia hirta, and Etlingera elatior. To achieve the target model reliabilities and accuracies, the images underwent a series of defined pre-processing steps, including resizing and data normalization, with additional steps (not limited to these) applied. Photographs of the herbs were captured systematically, complemented by organized tracking of key context and other pertinent factors to streamline the collection. This not only enhances model performance and serves as an important baseline for subsequent endeavors to preserve the knowledge of traditional medicine. The model class Etlingera elatior achieved 100% training and test accuracy, indicating it successfully classified the herb without errors. The class Euphorbia hirta showed a slight drop in accuracy, attaining 95% training and 90% testing accuracy, due to confusion with the dominant class, Leucas aspera. The model's performance for Leucas aspera, which is 100% in both training and testing, echoes a similar dependable behavior. On average, the model achieved 98% training and 97% testing accuracy, indicating high performance on the defined set of herbs. Also, the Precision, Recall, and F1-score metrics show the model's performance, with high Precision and Recall during training and testing with all three herb species. This indicates model validity and reliability. These research findings greatly enhance the integration of contemporary science with traditional herbal knowledge.

The model's ability to enhance the accuracy of identifying local medicinal herbs emphasizes its potential to bridge the gap between traditional practices and contemporary research, offering substantial benefits for health and pharmaceutical applications. Despite the promising results, several limitations must be acknowledged. The dataset size, as well as the influence of environmental factors such as lighting and background conditions, may affect the system's generalizability and applicability in real-world settings. These factors could introduce variability that the current model may not fully capture.

For practical implementation, we recommend that local health authorities integrate this tool into the curriculum for pharmacy students in Pattani. Additionally, policymakers should support the expansion of this database to include rare endangered species, ensuring digital preservation parallels physical conservation efforts.

DECLARATION OF AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

The authors declare that they used *ChatGPT* as an AI-assisted tool during the preparation of this manuscript. The tool was used solely to check grammar, enhance language clarity, and assist with proofreading the research article. All intellectual content, interpretation of results, and conclusions were developed entirely by the authors. The authors have thoroughly reviewed and edited the AI-assisted outputs to ensure accuracy, originality, and compliance with academic integrity standards, and they assume full responsibility for the content of this publication.

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