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# Deep Learning-Based Recognition of Traditional Medicinal Leaves for Common Cold Treatment

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## ABSTRACT

The use of traditional herbal remedies, particularly medicinal leaves, remains popular in Vietnam for treating common cold-related illnesses. However, identifying the correct leaf types and applying them appropriately poses challenges for non-expert users. This study proposes a web-based system utilizing artificial intelligence to assist in recognizing medicinal leaves commonly used in traditional treatments for colds. A dataset comprising 5,958 images of 10 different leaf types was constructed, labeled, preprocessed, and augmented to enhance model performance. A fine-tuned deep learning model based on the VGG16 convolutional neural network architecture was employed for classification and achieved an accuracy of 95.22% on the test set. The model was then integrated into a user-friendly web application that enables users to upload leaf images for recognition and receive detailed medicinal usage guidance. This system not only promotes the safe and informed use of traditional herbal medicine but also represents a meaningful step toward digitizing and preserving Vietnam's rich ethnobotanical knowledge through artificial intelligence.

**Keywords:** Convolutional Neural Network, VGG16, Traditional Medicine, Medicinal Plants, Cold Treatment.

## 1. INTRODUCTION

In recent years, there has been a resurgence in the use of medicinal plants for disease treatment, primarily due to their safety, affordability, and minimal side effects compared to synthetic drugs. In Vietnam, especially in rural areas, traditional remedies for ailments like the common cold remain prevalent. Leaves from plants such as perilla, mint, and eucalyptus are commonly used in forms like decoctions, steam inhalations, or topical applications.

However, accurately identifying the appropriate medicinal leaves poses a significant challenge for individuals without specialized knowledge. Misidentification can lead to reduced treatment efficacy or unintended side effects. This underscores the need for intelligent tools that can assist users in promptly and accurately recognizing medicinal leaves through images. Artificial intelligence (AI) offers a promising solution to this problem.

Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated exceptional performance in image classification tasks. These advancements have been successfully applied across various domains, including medical imaging diagnostics, crop classification, and plant disease detection. Applying CNNs to medicinal leaf recognition not only enables automatic feature extraction from images but also enhances accuracy compared to traditional methods. The VGG16 model, a prominent CNN architecture, was selected for its efficacy in handling moderately complex images and its capability for transfer learning from large datasets like ImageNet. This facilitates faster learning and high accuracy even with relatively smaller training datasets. Furthermore, integrating the model into a web application enhances accessibility, allowing users to utilize the tool anytime and anywhere. This represents a significant step in bridging AI technology with practical applications [1].

In this study, we developed an intelligent web application to assist in identifying medicinal leaves used in treating the common cold. The system was trained on a dataset comprising over 5,900 images of 10 commonly used medicinal leaves in Vietnam, collected from both online sources and real-world photographs. The data underwent processes such as labeling, augmentation, and image normalization to ensure quality training. The VGG16 model was fine-tuned and trained on this dataset to achieve high-accuracy leaf image classification. After achieving an impressive test accuracy of 95.22%, the model was integrated into a user-friendly web interface. Users can upload leaf images, and the system will provide the plant's name, its medicinal uses, related remedies, and usage instructions.

This application aims not only to assist the community in correctly utilizing medicinal plants but also to pave the way for developing AI-based diagnostic and treatment support systems rooted in traditional medicine. Additionally, it contributes

to the digitization and preservation of Vietnam's valuable ethnobotanical knowledge. In an era where technology increasingly permeates daily life, applying AI to the fields of medicinal plants and public health care is a promising and appropriate direction. This research marks an initial step toward developing intelligent tools that facilitate convenient, accurate, and safe access to traditional medicine for the public.

## 2. RELATED WORK

Research in plant image classification has increasingly applied deep learning methods due to their superior performance in feature extraction and pattern recognition. Several domains have emerged within this field, including plant disease detection, medicinal herb classification, model optimization, and mobile/web-based deployment.

Early foundational work focused on detecting plant diseases using deep learning. Mohanty et al. [2] employed AlexNet and GoogLeNet on over 54,000 leaf images to classify 38 diseases, demonstrating strong baseline performance. Ferentinos [3] extended this by comparing multiple architectures, achieving over 99% accuracy in classifying diseases from leaf images across 25 plant species. These studies underscore CNNs' suitability for visual-based agricultural tasks.

Parallel efforts have explored the recognition of medicinal plants. Sharma et al. [4] used CNNs and data augmentation to classify 50 Indian medicinal plant species with high accuracy. Kumar et al. [5] compared several architectures including VGG19 and DenseNet for Indian herb identification. Tan et al. [6] addressed the challenge of intra-class variability in traditional Chinese herbal classification by applying multiscale CNNs. These works provide a strong foundation for automated ethnobotanical recognition systems.

Several studies have benchmarked popular CNN models. Too et al. [7] compared fine-tuned versions of VGG16, ResNet50, InceptionV3, and MobileNet, highlighting trade-offs between accuracy and efficiency. Ghosh et al. [8] proposed a lightweight CNN suitable for mobile devices, enabling real-time recognition in low-resource settings. Singh and Misra [9] combined CNNs with SVM classifiers to enhance precision. Similarly, Kekre et al. [10] explored Random Forest as an alternative to deep models for leaf recognition. These studies are essential for selecting models suitable for real-world deployment.

Fewer studies have focused on region-specific medicinal plants. Nguyen et al. [11] introduced a CNN-based model for Vietnamese plant species recognition, incorporating attention mechanisms for improved feature localization. However, their work did not address practical medicinal usage or deployable systems. Our research bridges this gap by focusing on Vietnamese medicinal leaves used in cold treatment and integrating the model into an end-user web application-an area that remains underexplored in the literature.

## 3. METHOD

### 3.1 VGG16 Model

VGG16 is a deep CNN architecture developed by the Visual Geometry Group at the University of Oxford. It gained prominence through its outstanding performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2014, achieving a top-5 accuracy of 92.7%. The architecture consists of 16 weight layers, including 13 convolutional layers and 3 fully connected layers.

All convolutional layers use small 3×3 filters, and each block of convolutional layers is followed by a 2×2 max pooling layer. The simplicity and uniformity of the VGG16 architecture make it easy to train and adapt to various image classification problems.

In this study, the VGG16 model was chosen for its proven effectiveness in processing moderately complex images and its compatibility with transfer learning. By leveraging pre-trained weights from the ImageNet dataset, the model can learn relevant features faster and generalize better-even when training data is limited.

### 3.2 Algorithmic Model

In this study, we propose a deep learning-based system for medicinal leaf recognition used in cold treatment. The methodology is structured into four main stages: (1) data collection and preprocessing, (2) feature extraction using the VGG16 model, (3) model training, and (4) deployment into a web-based application. An overview of this pipeline is illustrated in Figure 1.

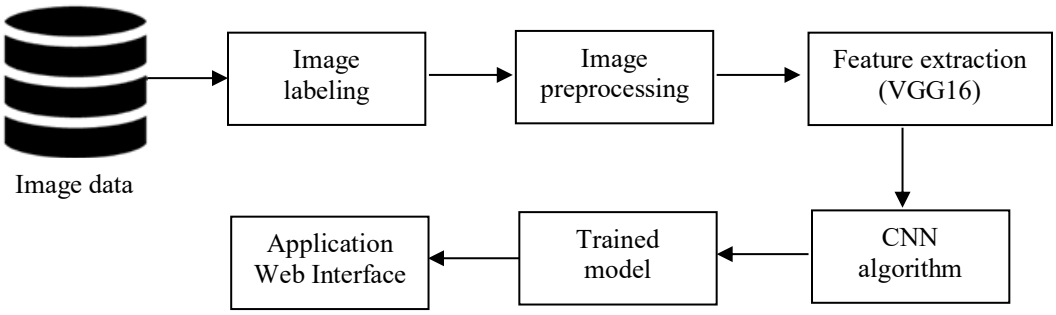



Figure 1. Proposed training pipeline for medicinal leaves classification.

**Algorithm 1: CNN-based training procedure for medicinal leaf classification**

**Input**: A dataset comprising 5,958 images of medicinal leaves, representing 10 medicinal leaf types, with each image resized to 224×224 pixels.

**Output**: Predicted class label for each input image, corresponding to one of the 10 categories.

**Step 1:** Image Preprocessing

Resize images to 224×224

Normalize pixel values to [0, 1]

Apply data augmentation: rotation, flipping, brightness adjustment

**Step 2:** Data Splitting

Training set (65%), Validation set (15%), Test set (20%).

**Step 3:** Model Initialization

Load VGG16 model (pre-trained on ImageNet, include_top=False)

Freeze base layers

Add new layers:

Flatten → Dense(512, ReLU) → Dropout(0.3)

Dense(256, ReLU) → Dropout(0.3)

Dense(10, Softmax)

**Step 4:** Model Configuration

Loss function: Categorical Crossentropy

Optimizer: Adam (learning rate = 0.0001)

Evaluation metric: Accuracy

**Step 5:** Model Training

For each epoch:

Train on training set

Validate on validation set

Save the best-performing model

**Step 6**: Final Evaluation

Evaluate the model on the test set

Output test accuracy and loss metrics

Figure 1 depicts the seven key components of the system architecture:

- **Image Data Collection:** A dataset comprising 5,958 images of 10 medicinal leaf types was collected from real-world sources and online repositories. The image set was designed to capture variations in lighting, background, and leaf orientation to reflect realistic use cases.
- **Image Labeling:** Each image was annotated manually with the correct class label, based on visual characteristics and expert knowledge of medicinal plants. These labels formed the ground truth for supervised model training.
- **Image Preprocessing and Augmentation:** All images were resized to 224×224 pixels to conform to VGG16 input dimensions. Preprocessing steps included pixel normalization and real-time augmentation such as image rotation, horizontal and vertical flipping, and brightness enhancement. These techniques were employed to improve the generalization capability of the model and reduce overfitting.
- **Feature Extraction via VGG16:** The VGG16 architecture, pre-trained on the ImageNet dataset, was adopted as the feature extractor. The base convolutional layers were frozen to retain pre-learned visual patterns, while the top classification layers were replaced with custom dense layers to support multiclass classification for 10 types of leaves. The network was thus fine-tuned to extract discriminative features related to leaf shape, texture, and margin characteristics.
- **CNN-Based Model Training:** The classification head consisted of a Flatten layer followed by two Dense layers (512 and 256 neurons respectively, both using ReLU activation), with Dropout layers (rate = 0.3) added for regularization. A final Dense layer with Softmax activation was used to produce probability outputs over the 10 classes. The model was trained using the Adam optimizer with a learning rate of 0.0001, and categorical cross-entropy as the loss function. The dataset was split into training (65%), validation (15%), and testing (20%) subsets. Training was monitored over multiple epochs, with the best-performing model checkpoint saved.
- **Trained Model:** Upon completion of the training phase, the model achieved a test accuracy of 95.22%. This confirmed its ability to generalize well to unseen images and distinguish among leaf types with high confidence.
- **Web-Based Application Deployment:** The trained model was integrated into a web application featuring a ReactJS frontend and a Django backend. Users can upload images of leaves, which are then processed by the model to return the leaf name, therapeutic uses, and traditional remedy instructions. This system enables the general public to access reliable, AI-powered support for identifying medicinal plants and applying them appropriately.

The full training procedure described above is further formalized in Algorithm 1, which outlines the step-by-step process from data preprocessing to final model evaluation.

## 4. DATA COLLECTION

The dataset used in this study consists of 5,958 images representing 10 commonly used medicinal leaf types in Vietnam. These leaves are traditionally employed in folk remedies to treat conditions such as the common cold and flu [12–16]. The images were collected from a variety of sources, including real-world photographs and publicly available images on the internet, ensuring diversity and representation under various environmental conditions.

The dataset comprises 10 classes of medicinal leaves, with each class containing approximately 500 to 740 images. Table 1 provides a detailed summary of the number of images per class. The largest class is mulberry with 740 images, while the smallest is blumea balsamifera with 514 images. This relatively balanced distribution helps mitigate the effects of class imbalance, which is a common source of bias in image classification tasks.

The images reflect a range of lighting conditions, backgrounds, camera angles, and devices used for capturing, replicating real-world complexity in natural environments. This variability plays an essential role in enhancing the generalization capability of the model, particularly when applied to images captured by users using mobile phones or other input devices in practical scenarios.

All images were resized to a standardized resolution of 224×224 pixels to match the input requirements of the VGG16 model. Morphologically, each leaf type exhibits distinct characteristics:

- Mint and eucalyptus: Small leaves with serrated edges.
- Pomelo and bamboo: Long and narrow leaf shapes.

- Perilla and blumea balsamifera: Broad leaf surfaces with noticeable color differences between the upper and lower sides.

These geometric and surface texture differences serve as important features that the CNN can learn to accurately distinguish and classify each type of medicinal leaf.

Table 1. Medicinal Leaf Image Dataset Overview

| No. | Leaf Name | Scientific/Common Name | Key Symptoms Treated | Number of Images | Figure |
|---|---|---|---|---|---|
| 1 | Mint | *Mentha arvensis* (Wild Mint) | Nasal congestion, sore throat, cough, mild fever | 556 |  |
| 2 | Eucalyptus | Eucalyptus globulus | Cough, sore throat, chest congestion | 707 |  |
| 3 | Almond | Terminalia catappa | Sore throat, oral inflammation (mild relief) | 552 |  |
| 4 | Pomelo | Citrus maxima | Headache, nasal congestion, fatigue (via steaming) | 647 |  |
| 5 | Blumea | Blumea balsamifera | Cold wind symptoms, body aches, detoxification | 514 |  |
| 6 | Mulberry | Morus alba | Cough, sore throat, mild fever, dry throat | 740 |  |
| 7 | Cuban Oregano | Plectranthus amboinicus | Hoarseness, dry cough, sore throat | 595 |  |
| 8 | Vietnamese balm | Elsholtzia cristata | Fever, flu, headache, muscle pain | 552 |  |

| | | | | | |
|---|---|---|---|---|---|
| 9 | Perilla | Perilla frutescens | Cold, chills, nausea, headache | 547 |  |
| 10 | Melaleuca | Melaleuca leucadendra | Infant cold, nasal congestion, body aches | 548 |  |

## 5. RESULTS AND APPLICATION DEVELOPMENT

### 5.1 Experiment results

The experiments were conducted on a Windows 10 Home 64-bit system equipped with 16 GB of RAM, a 6 GB NVIDIA GPU, and an Intel Core i7-9750H CPU running at 2.6 GHz. The VGG16 model, pre-trained on the ImageNet dataset, was fine-tuned using our medicinal leaf dataset, which contains 5,958 images categorized into 10 distinct classes. The dataset was split into three subsets: 65% for training (3,872 images), 15% for validation (893 images), and 20% for testing (1,193 images).

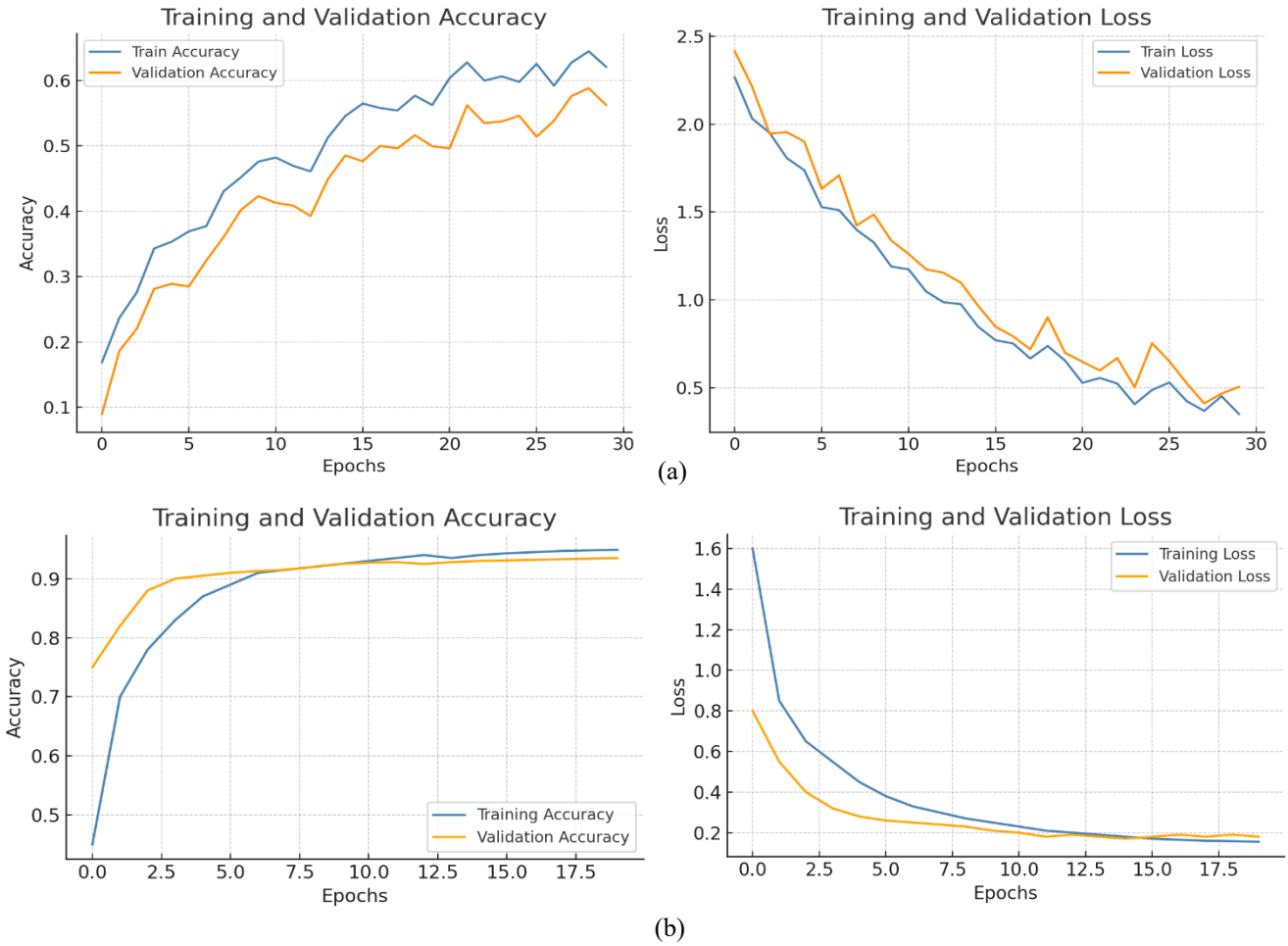



Figure 2. Resnet50 accuracy and loss results (a), VGG16 accuracy and loss results (b).

The training process followed the procedure outlined in Algorithm 1. The model was trained for 20 epochs with a batch size of 32 and a learning rate of 0.0001, using the Adam optimizer and categorical cross-entropy as the loss function.

Throughout training, the model demonstrated consistent improvements in accuracy on both the training and validation sets. Figure 2 shows the training progression over epochs:

- Final training accuracy: approximately 94.51% after 20 epochs.
- Validation accuracy: 94.68%, indicating minimal overfitting.
- Validation loss decreased steadily and showed good convergence.

On the test set, the fine-tuned VGG16 model achieved a classification accuracy of 95.22% with a loss of 0.191, confirming its strong generalization performance on unseen data. This high performance can be attributed to the model's simpler and more uniform architecture, which helps prevent overfitting on moderately sized datasets, and its proven ability to extract fine-grained features such as leaf texture, margin, and shape—critical for distinguishing between visually similar leaf types. Compared to ResNet-50, which reached only 65.65% accuracy and a higher loss of 0.495, VGG16 demonstrated superior stability and efficiency for this specific task without requiring extensive hyperparameter tuning or large-scale data augmentation.

Table 2 presents a comparison between VGG16 and ResNet-50 on the test set. The VGG16 model outperformed ResNet-50 in both accuracy and loss, achieving 95.22% accuracy with a loss of 0.191, while ResNet-50 reached only 65.65% accuracy with a loss of 0.495. These results indicate that VGG16 is better suited for the medicinal leaf classification task on this dataset.

Table 2. Comparison of ResNet50 and VGG16 model evaluation results on the test and training sets.

| **Algorithm** | **Accuracy (%)** | **Loss** |
|---|---|---|
| ResNet-50 | 65.65 | 0.495 |
| VGG16 | 95.22 | 0.191 |

| | | **Predicted label** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Classify** | Mint | Eucalyptus | Almond | Pomelo | Blumea | Mulberry | Cuban Oregano | Vietnamese balm | Perilla | Melaleuca | **SUM** |
| **True label** | Mint | 105 | 0 | 2 | 0 | 0 | 0 | 2 | 2 | 0 | 1 | 112 |
| | Eucalyptus | 2 | 131 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 4 | 140 |
| | Almond | 0 | 0 | 107 | 0 | 1 | 0 | 0 | 0 | 2 | 1 | 111 |
| | Pomelo | 0 | 0 | 0 | 123 | 3 | 0 | 1 | 0 | 1 | 0 | 128 |
| | Blumea | 0 | 1 | 0 | 3 | 97 | 1 | 0 | 0 | 0 | 1 | 103 |
| | Mulberry | 1 | 0 | 0 | 1 | 0 | 143 | 2 | 2 | 0 | 0 | 149 |
| | Cuban Oregano | 0 | 0 | 0 | 0 | 1 | 1 | 112 | 2 | 2 | 0 | 118 |
| | Vietnamese balm | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 104 | 2 | 0 | 109 |
| | Perilla | 0 | 0 | 0 | 1 | 0 | 0 | 2 | 2 | 105 | 0 | 110 |
| | Melaleuca | 0 | 3 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 109 | 113 |
| **Precision** | | 97.2 | 97.0 | 95.5 | 95.3 | 95 | 97.3 | 93.3 | 92.9 | 93.8 | 94.0 | 95.1 |
| **Recall** | | 93.8 | 93.6 | 96.4 | 96.1 | 94.2 | 96.0 | 94.9 | 95.4 | 95.5 | 96.5 | 95.2 |
| **F1 score** | | 95.5 | 95.3 | 96.0 | 95.7 | 94.6 | 96.6 | 94.1 | 94.1 | 94.6 | 95.2 | 95.2 |
| **Accuracy** | | 95.22 | | | | | | | | | | **Average** |

Figure 3. Confusion matrix and class-wise evaluation metrics (precision, recall, and F1-score) for the VGG16 model on the medicinal leaf classification task.

Figure 3 presents the confusion matrix and class-wise evaluation metrics, including precision, recall, and F1-score, for the VGG16 model. The model achieved an average precision of 95.1%, and average recall and F1-score of 95.2%, indicating a balanced and consistent performance across all classes.

In terms of precision, the Mulberry class achieved the highest value (97.3%), followed by Eucalyptus (97.0%) and Almond (97.2%), indicating high prediction reliability. The lowest precision was observed in the Cuban Oregano class (92.6%), where misclassifications occurred primarily with Perilla and Vietnamese balm.

With respect to recall, the model performed best on Mint (97.3%), Pomelo (96.1%), and Melaleuca (96.5%), indicating its ability to correctly identify most true instances of these classes. The lowest recall occurred in the Almond class (92.8%), reflecting a slight under-detection due to visual similarity with other leaf types.

The F1-scores, which represent the harmonic mean of precision and recall, ranged from 93.7% to 96.9%, with Mint achieving the highest score. This confirms the model's robustness and suitability for multi-class classification tasks.

The confusion matrix also reveals that the majority of predictions were concentrated along the diagonal, indicating high true positive rates. However, some minor misclassifications were noted. For example, several Eucalyptus images were misclassified as Mint or Melaleuca, possibly due to similarities in leaf shape and color. Cuban Oregano and Vietnamese balm were also occasionally confused, which may be explained by their comparable surface textures. In the case of Almond, a few instances were predicted as Cuban Oregano or Perilla, suggesting that subtle variations in vein structure or brightness may not have been sufficiently captured.

### 5.2 Application Development

**System Architecture**

The trained model was integrated into a user-friendly web application that enables users to identify medicinal leaves through uploaded images (Figure 4a).

The system architecture consists of two main components:

- Frontend: Developed using ReactJS [17], the frontend provides a clean and intuitive user interface for uploading images, displaying recognition results, and presenting medicinal leaf information and associated remedies.
- Backend: Built with Django (Python) [18], the backend handles image processing, executes the VGG16 model for prediction, queries the database, and returns results to the frontend.

**Core Functionalities**

The application supports two main search modes (Figure 4c):

- Image-based Search: Users can upload or capture a photo of a leaf for identification.
- Keyword-based Search: Users can also search by entering the name of the medicinal leaf.

In addition, the system allows users to:

- View detailed information about each medicinal plant, including therapeutic uses, traditional remedies, and usage instructions (Figure 4b).
- Manage a shopping cart if they wish to purchase medicinal leaves (Figure 4d).
- Register and log in to save search history or manage orders.

**Deployment Effectiveness**

The system enables individuals without formal training in traditional medicine to accurately identify and appropriately use medicinal leaves for common cold treatment. Real-world testing showed that the average system response time was under 2 seconds, and the recognition accuracy remained high in practical usage scenarios.

This demonstrates that the integration of the fine-tuned VGG16 model into a web-based system not only achieves strong performance in a controlled environment but also maintains robustness and efficiency in real-world applications. The deployment helps bridge the gap between modern artificial intelligence and the preservation and promotion of traditional medicine practices.

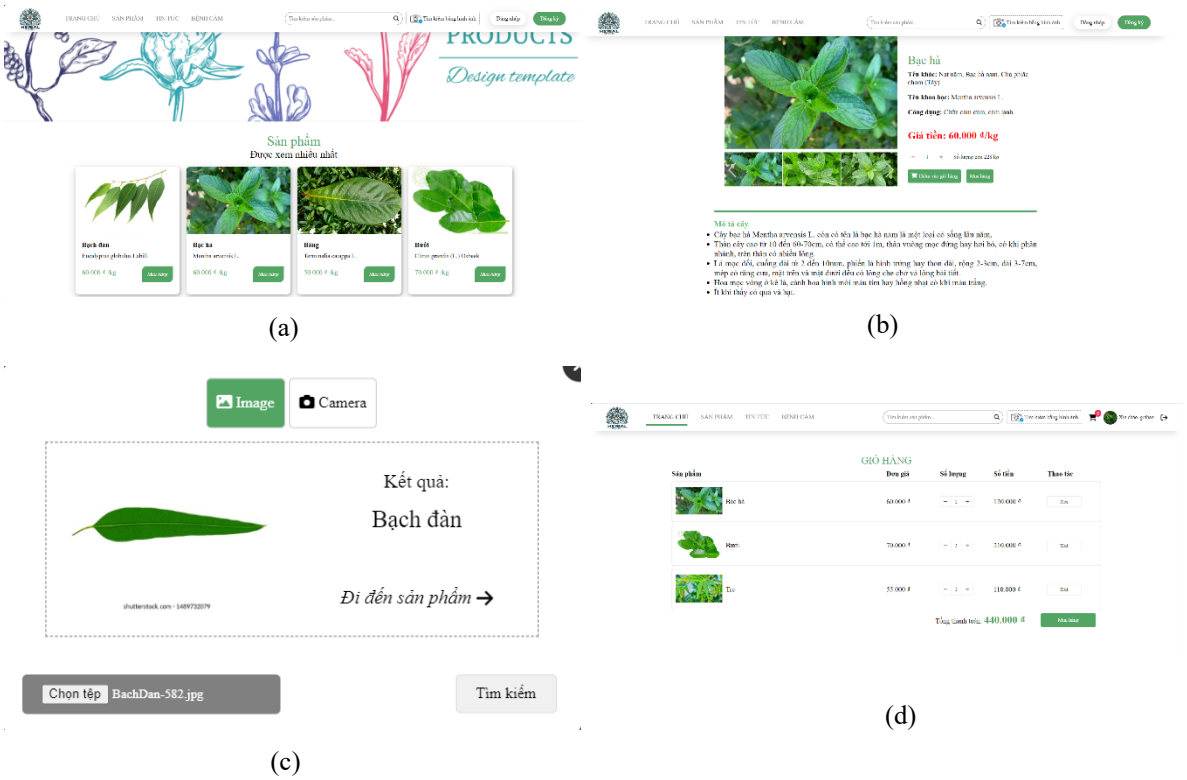



Figure 4. (a) Homepage, (b) Leaf Information Page, (c) Image and Camera-Based Search Interface, (d) Shopping Cart Interface.

## 6. CONCLUSIONS

This study presented a deep learning-based approach for recognizing medicinal leaves used in the treatment of the common cold. A VGG16 model was fine-tuned using a dataset of 5,958 images representing 10 types of medicinal plants commonly found in Vietnam. The model achieved a test accuracy of 95.22%, demonstrating its effectiveness and generalization capability under real-world conditions.

The trained model was successfully deployed into a user-friendly web application, allowing users to upload images for leaf identification and receive detailed medicinal information, including traditional remedies and usage instructions. This application contributes to improving public access to traditional medical knowledge in a convenient and accurate way.

Beyond its technical significance in the field of computer vision, the study also highlights the potential of artificial intelligence in healthcare and traditional medicine applications. The system offers practical value by empowering users to safely and confidently use herbal remedies for cold treatment, while also contributing to the digital preservation of ethnobotanical knowledge.

In future development, the research may be expanded in the following directions:

- Expanding the leaf database: Acquiring and incorporating more leaf types to enable the system to identify a wider variety of medicinal plants for treating not only colds but also other common ailments.
- Model and performance optimization: Applying lightweight architectures such as MobileNet or EfficientNet to reduce inference time and support deployment on mobile devices or edge platforms.
- Building a knowledge-based system for treatment recommendation: Enabling the system to suggest remedies based on symptoms entered by users, integrating rule-based logic with machine learning.

With these enhancements, the system could evolve from a standalone recognition tool into an intelligent traditional medicine assistant, offering broader support for community health care based on natural medicinal resources.

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