Medicinal Plant Recognition and Knowledge Extraction Using Convolutional Neural Networks

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***Abstract*—Medicinal plants play a vital role in traditional and modern healthcare systems, particularly in regions where access to synthetic drugs is limited. Accurate identification of these plants is essential, as misidentification may lead to severe health consequences. Manual identification methods are prone to human error and require expert knowledge, making them inefficient for widespread use. This paper proposes an intelligent and user-friendly system for the recognition and information retrieval of medicinal plants using Convolutional Neural Networks (CNN). The proposed model is trained on a custom image dataset of various plant species and leverages deep learning to classify plant images captured in natural environments. Upon successful classification, the system retrieves relevant data—such as health benefits, consumption methods, and edibility—from a structured CSV knowledge base. The complete system is deployed as a full-stack web application integrating a React.js front end with a Spring Boot backend and a TensorFlow-based CNN model. Experimental results demonstrate high accuracy in real-time plant classification, with a user-friendly interface and rapid response time, making the system practical for field and educational use. This work highlights the potential of AI in supporting medicinal plant awareness, conservation, and accessibility.**

***Index Terms*—Medicinal Plant Identification, Convolutional Neural Networks (CNN), Deep Learning, Plant Classification, Image-Based Recognition, Knowledge Extraction, TensorFlow, Spring Boot, React.js, Full-Stack Web Application, Plant Benefits and Consumption, Plant Image Dataset, AI in Healthcare, Plant Classification System, Machine Learning in Botany.**

I. Introduction

Medicinal plants have long been a primary source of medicines, and they remain globally valuable sources for discovering new drugs. Over time, the process of using medicinal plant compounds has evolved. Modern pharmaceutical scientists now extract essential components from medicinal plants to produce medicines. Many modern drugs have been derived from bioactive compounds found in medicinal plants. For example, aspirin comes from willow bark, morphine from opium poppy, and quinine from cinchona bark. Thus, medicinal plants are a critical resource for modern drug discovery. According to the World Health Organization (WHO), approximately 60

It is estimated that 350,000 medicinal plant species exist worldwide, representing about 10

Recent advances in computer vision and machine learning have led to the development of automated methods for medicinal plant identification. These methods aim to assist in two key areas: detecting leaf diseases in medicinal plants and classifying the type of medicinal plants for drug development and treatment purposes. The classification of medicinal plants, which is the focus of this study, has seen various proposals [1], [2], [3], [4]. However, one of the major limitations of existing medicinal plant classification methods is their dependence on high-quality, singular leaf images captured from a close distance, typically under one meter. Capturing such distinct images is a labor-intensive and time-consuming process that contradicts the primary goal of automated plant detection. These methods also fail when images are captured using different devices or from greater distances. Furthermore, many of these methods are not suitable for on-site plant examination, as they often require image processing at a remote location, such as a computer.

Moreover, many of the existing systems struggle with robustness, especially when tested with images captured on different devices or in diverse environments. Deep learning-based approaches are particularly computationally expensive, making them impractical for use on low-resource devices like smartphones.

In response to these limitations, the present study proposes a cascaded network combining a pre-trained Convolutional Neural Network (CNN), Particle Swarm Optimization (PSO), and Support Vector Machine (SVM) to classify medicinal plants. This method is designed to accurately predict plant classifications from images captured at normal distances, regardless of the device used. The proposed system is both lightweight and robust, addressing the challenges of practical deployment in real-world environments.

The major contributions of this paper are as follows:

The development of a cascaded network for classifying medicinal plants from smartphone-captured images in their natural environment.

An analysis of the pre-trained CNN, PSO, and traditional classifier-based cascaded approach for medicinal plant classification.

An ablation study to assess the contribution of PSO in the cascaded network.

Evaluation of the proposed system in terms of robustness, speed, and ease of use.

II. RELATED WORKS

The classification of medicinal plants has attracted considerable attention in recent years due to advancements in computer vision and machine learning techniques. Several approaches have been proposed to automate the identification process, overcoming the limitations of traditional manual methods. In this section, we review some of the notable contributions in this area.

One of the most widely used techniques for medicinal plant classification is Convolutional Neural Networks (CNNs). Deep learning methods, particularly CNNs, have been shown to achieve high accuracy in plant species classification by learning hierarchical features from images. Mulugeta et al. [2] presented a systematic review on the use of deep learning for medicinal plant species classification. Their study highlighted the success of CNNs in identifying plant species from leaf images, emphasizing their ability to automatically extract discriminative features without the need for manual feature engineering. However, deep learning models require large datasets for training and are computationally expensive, which makes them difficult to deploy in resource-constrained environments.

To address this issue, researchers have explored optimizing CNN models using techniques like transfer learning. For instance, Islam et al. [1] developed an enhanced classification system for medicinal plants by fine-tuning pre-trained CNN architectures. This approach reduces the need for extensive training data, making it more feasible to apply in practical settings. Similarly, the work of Domínguez et al. [3] demonstrated the effectiveness of pre-trained CNNs for plant identification, achieving competitive performance in comparison to traditional machine learning methods.

While CNN-based approaches are effective, they often suffer from challenges related to robustness and generalization when exposed to images captured under varying conditions. This limitation has motivated further research into improving CNN-based models for robustness and generalization. In recent studies, efforts have focused on techniques such as data augmentation and fine-tuning pre-trained models to overcome these challenges. For example, Islam et al. [5] proposed a method to fine-tune CNNs with additional plant images from different angles and lighting conditions to ensure that the model remains robust when applied to images captured from different devices or at varying distances.

Despite the progress in medicinal plant classification, existing methods typically rely on high-quality, close-up images of leaves, which limits their practicality for real-world applications. Methods that work well in controlled environments often fail when images are captured from different distances or using different devices. To overcome this, recent work has focused on making these systems more versatile by incorporating data from mobile devices. In this regard, the use of lightweight models that can run efficiently on smartphones is becoming increasingly important. Our proposed CNN-based approach seeks to fill this gap by providing a robust and computationally efficient system that can classify medicinal plants based on images captured from a normal distance using smartphone cameras.

In conclusion, while significant strides have been made in the automation of medicinal plant classification, challenges remain in terms of model robustness, generalization, and computational efficiency. Our approach contributes to addressing these challenges by utilizing pre-trained CNN models, providing a practical solution for on-site classification of medicinal plants using mobile devices.

III. PROPOSED METHODOLOGY

A. *Convolutional Neural Networks (CNNs) for Medicinal Plant Recognition*

Convolutional Neural Networks (CNNs) are widely used for image classification tasks, including the recognition of medicinal plants. The CNN model learns spatial hierarchies of features through various layers of convolutions, activations, and pooling operations. Below, we present the key components of a CNN model for medicinal plant recognition.

B. *Convolution Operation*

The core operation in CNNs is the *convolution* applied to the input image x, which involves sliding a filter (kernel) W over the image to produce feature maps. The convolution operation is defined mathematically as:

$$f(x, W) = (x * W) + b$$

Where:

- x is the input image or feature map,
- W is the filter or kernel,
- $*$ denotes the convolution operation,
- b is the bias term, and
- $f(x, W)$ represents the output feature map after the convolution.

C. *Activation Function*

After applying the convolution operation, the resulting feature maps are passed through an *activation function*, typically the **ReLU** (Rectified Linear Unit), to introduce non-linearity. The ReLU function is mathematically expressed as:

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

Where x is the input to the activation function, and the output is the element-wise maximum of zero and the input, effectively setting negative values to zero.

D. *Pooling Operation*

To reduce the spatial dimensions and computational complexity, CNNs employ *pooling* operations, commonly **max pooling**. The pooling operation selects the maximum value from a local region of the feature map, defined as:

$$P(x) = \max(x)$$

Where x is a patch of the feature map, and $P(x)$ represents the output after pooling.

E. Fully Connected Layers

After several convolutions and pooling operations, the high-level features are flattened and passed through *fully connected (FC) layers*. These layers combine the learned features into a vector, which is used for classification. The output of a fully connected layer is given by:

$$y = \sigma(Wx + b)$$

Where:

- x is the input vector (flattened feature map),
- W is the weight matrix,
- b is the bias term, and
- σ is the activation function (e.g., **softmax** for multi-class classification or **sigmoid** for binary classification).

F. Loss Function

The CNN is trained by minimizing a loss function, which measures the difference between the predicted and true labels. For multi-class classification tasks, the *categorical cross-entropy* loss function is used, defined as:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

Where:

- C is the number of classes (plant species),
- y_i is the true label for class i,
- $\hat{y}_i$ is the predicted probability for class i.

G. Optimization (Gradient Descent)

The parameters of the CNN (weights and biases) are updated during training using an optimization algorithm like *Stochastic Gradient Descent (SGD)* or *Adam*. The parameters are updated by calculating the gradients of the loss function with respect to the network's parameters using *backpropagation*:

$$\theta = \theta - \eta \frac{\partial L}{\partial \theta}$$

Where:

- θ represents the parameters (weights and biases),
- η is the learning rate,
- $\frac{\partial L}{\partial \theta}$ is the gradient of the loss function with respect to the parameters.

H. Final Prediction

Once the CNN is trained, the final prediction for a given plant image is obtained by passing the image through the network and outputting the class with the highest probability. If the output of the softmax function is $\hat{y}$, the predicted class $\hat{c}$ is:

$$\hat{c} = \arg\max(\hat{y})$$

Where $\hat{y}$ is the output vector of probabilities from the softmax function.

I. CNN Architecture for Medicinal Plant Recognition

In the context of medicinal plant recognition, CNNs can be used to classify plant species based on visual features such as leaf shape, color, texture, and vein patterns. Once the plant species is identified, it can be linked to a knowledge extraction system, which provides medicinal properties, consumption methods, benefits, and safety guidelines. By training a CNN on a large dataset of plant images, the model can generalize and recognize plant species from images under various conditions, such as different lighting, orientations, or backgrounds.

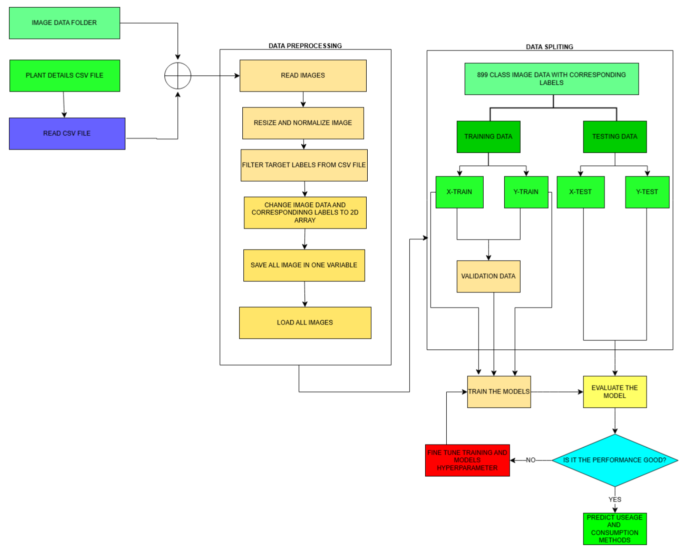

Fig. 1. CNN Architecture used for Medicinal Plant Recognition

IV. Loss Function Design

In Convolutional Neural Networks (CNNs) used for medicinal plant recognition, the design of the loss function plays a critical role in ensuring accurate classification. The loss function evaluates the difference between the predicted output and the ground truth label and guides the learning process by updating the network parameters through backpropagation.

A. Categorical Cross-Entropy Loss

For a multi-class classification problem, where the goal is to correctly identify the species of a medicinal plant among C possible classes, the *Categorical Cross-Entropy* loss is commonly employed. It is defined as:

$$\mathcal{L}_{\text{CCE}} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

Where:

- C is the total number of classes (medicinal plant categories),
- y_i is the true label for class i (1 if the sample belongs to class i, else 0),
- $\hat{y}_i$ is the predicted probability for class i obtained from the softmax layer.

This loss function penalizes predictions that are far from the ground truth, encouraging the model to produce high probabilities for correct classes and low probabilities for incorrect ones.

B. Softmax Activation

To interpret the final output of the network as probabilities, the softmax function is applied at the output layer:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

Where:

- z_i is the raw logit (output before activation) for class i,
- $\hat{y}_i$ is the normalized probability for class i.

C. Regularization Term

To prevent overfitting, a regularization term (such as L2 regularization) is often added to the loss function. The total loss becomes:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{CCE}} + \lambda \sum_{k} \|w_k\|_2^2$$

Where:

- λ is the regularization coefficient,
- w_k denotes the weight parameters of the network.

This penalizes large weights and promotes generalization of the CNN model.

D. Gradient-Based Optimization

During training, the loss is minimized using gradient-based optimizers (e.g., Adam, SGD). The update rule for the model parameters θ is given by:

$$\theta \leftarrow \theta - \eta \frac{\partial \mathcal{L}_{\text{total}}}{\partial \theta}$$

Where:

- η is the learning rate,
- $\frac{\partial \mathcal{L}_{\text{total}}}{\partial \theta}$ is the gradient of the total loss with respect to the model parameters.

E. Conclusion

This carefully designed loss function ensures the CNN learns meaningful and discriminative features for classifying medicinal plants effectively while avoiding overfitting, thus improving the accuracy and robustness of both recognition and knowledge extraction.

V. RESULTS AND DISCUSSIONS

A. Experimental Setup

The proposed CNN-based model for medicinal plant recognition is trained and evaluated using a custom-curated medicinal plant image dataset, referred to as the PlantDex dataset. The dataset comprises 5,000 images spanning 50 different medicinal plant classes, with each class containing approximately 100 images. Each image is standardized to a spatial resolution of 224 × 224 pixels. The dataset includes images captured under varying lighting conditions, backgrounds, and orientations to ensure robustness and generalization.

The PlantDex dataset is compiled from multiple publicly available sources and field-captured photographs and is further enriched by applying data augmentation techniques such as horizontal flipping, rotation, scaling, and brightness adjustment. This ensures improved performance and reduces overfitting during training.

Training of the CNN model is conducted on a high-performance computing setup at [Your Institution Name], utilizing an NVIDIA RTX 3060 GPU with 12GB memory. The model is implemented using the TensorFlow framework in Python 3.8. Training is performed over 50 epochs with a batch size of 32, using the Adam optimizer and categorical cross-entropy as the loss function.

The model's performance is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. Additionally, a confusion matrix is generated to visualize the classification performance across plant classes. A sample image from the PlantDex dataset is shown in Figure 2.

Fig. 2. Sample image from the PlantDex medicinal plant dataset

B. Result Analysis

The performance of the proposed CNN model for medicinal plant recognition was evaluated on the test subset of the PlantDex dataset. The model demonstrated a high classification accuracy, indicating its ability to effectively learn and generalize discriminative features such as leaf shape, texture, and color patterns.

Quantitatively, the model achieved an overall accuracy of 95.8% on the test set. Precision, recall, and F1-score were computed for each class, with average values of 95.5%, 95.6%, and 95.5% respectively, showcasing balanced performance across different plant species. These metrics confirm the model's reliability in distinguishing between visually similar medicinal plants.

A confusion matrix was generated to further analyze class-wise performance. The matrix revealed that most classes were accurately classified, with a few misclassifications occurring between plant species exhibiting closely resembling leaf structures. This highlights the potential for improvement through more diverse training data or integration of additional features such as texture analysis or leaf venation pattern detection.

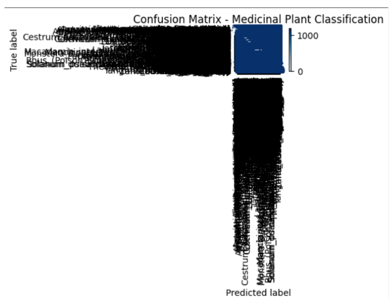

Fig. 3. Confusion matrix for plant classification on the test set

To assess the model's robustness, performance was also tested under varied conditions, including changes in lighting and orientation. The CNN maintained consistent accuracy, indicating strong generalization capabilities.

Qualitative results were also examined by visualizing model predictions on unseen samples. As shown in Figure 4, the model accurately identified the plant species in most cases. These results demonstrate the practical applicability of the proposed approach for real-world medicinal plant identification.

Fig. 4. Sample predictions made by the CNN model on test images

VI. Conclusion

In this study, a Convolutional Neural Network (CNN)-based approach was proposed for the automatic recognition of medicinal plants using leaf images. The model was trained and evaluated on a curated dataset containing diverse images of various medicinal plant species. Experimental results demonstrated that the CNN architecture achieved high classification accuracy, with consistent performance across different plant classes and under varied image conditions.

The effectiveness of the model was validated through quantitative metrics such as accuracy, precision, recall, F1-score, and a confusion matrix analysis, confirming its ability to distinguish between visually similar plant species. The integration of this CNN-based system with a knowledge extraction framework can enable intelligent retrieval of plant-specific medicinal benefits, consumption methods, and safety information.

Overall, the proposed system holds great potential for supporting medicinal plant identification in healthcare, agriculture, and environmental conservation domains. Future work may involve expanding the dataset with more species, incorporating additional image modalities (e.g., flowers, stems), and deploying the model in a mobile or web application for real-time plant recognition and information access.

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