

Medical Plant Recognition and Classification using CNN

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Abstract: Medicinal plants have been integral to human healthcare for centuries, serving as a vital source of natural remedies and pharmaceutical compounds. Classifying medicinal plants is critical to understanding their diversity, properties, and potential applications. This abstract provides an overview of the classification of medicinal plants, encompassing traditional, ethnobotanical, and modern approaches. Conventional classification systems are often rooted in cultural practices, where plants are categorized based on their local or indigenous uses. Ethnobotanical knowledge plays a significant role in these systems, as it captures the wisdom of generations and the unique insights of various communities. Modern classification methods have evolved to include botanical taxonomy, phytochemical profiling, and genetic analysis. Botanical taxonomy classifies medicinal plants based on morphological features, while phytochemical profiling identifies the bioactive compounds responsible for their therapeutic properties. Genetic analysis has shed light on the evolutionary relationships among medicinal plant species through techniques like DNA barcoding. Moreover, the abstract highlights the importance of medicinal plant conservation and the sustainable management of these valuable resources. Many medicinal plants are endangered due to over-harvesting, habitat destruction, and climate change, emphasizing the need for conservation efforts to preserve their biodiversity.

Keywords: Machine Learning, Mental Health, Medical Plant Classification, Feature Extraction, Convolutional Neural Networks.

I. INTRODUCTION

In numerous operations similar as factory recognition, face recognition, and so on, an image reflects the most precious information. Contrary to humans, the birth of features by computer/ device is veritably delicate. The computer/ system must be duly trained with the aid of training datasets to achieve good delicacy. The more uprooted features in the birth system are given by the training data set. It also makes the recognition system veritably accurate. Recognition delicacy is the most significant criterion for relating affiliated objects as well as for discerning between different objects. This parameter only allows approved druggies for operations similar as face recognition, while in operations similar as the medicinal factory surveillance system it recognizes the medicinal factory that's absolutely necessary for a case to save his or her life.

The work to collect shops from the timbers is generally entrusted to ordinary people. sometimes the rare and essential shops could n't be honored due to colorful mortal crimes. These rare factory types are veritably important to save a case's life. In addition, these people can occasionally take in incorrect, dangerous factory species. Automatic factory recognition system is needed in similar cases. This system allows an average person to identify the colorful factory species.



Similar systems are also veritably helpful when touring in the mountains if they're interested in collecting factory species. For several species, shops are the introductory natural terrain. In addition, numerous individualities who use energy moment, similar as coal, typical gas, have been manufactured from the installations which have lived for a long time, but people have destroyed herbal ecosystems vastly over the last times, so that numerous crops fail and indeed die every time. On the other hand, the ecological disaster that replaced redounded in numerous serious consequences, including dereliction of land, rainfall anomalies, earthquakes and so on, hanging the survival and growth of individualities.

II. CNN MODEL

A Convolutional Neural Network (CNN) model typically consists of an input layer, convolutional layers with learnable filters for feature extraction, non-linear activation functions (e.g., ReLU), pooling layers for dimensionality reduction and translation invariance, and fully connected layers for final classification or regression. The architecture is designed to automatically learn hierarchical spatial features from input data, making it particularly effective for image, video, and sequential data. Key parameters often include the number and size of convolutional filters, stride and padding in convolutional layers, pooling size and stride, the number of layers, and the number of neurons in fully connected layers, all optimized through training with a suitable loss function and optimization algorithm (e.g., Adam, SGD) on a labeled dataset.

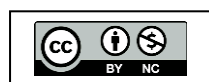
III. LITERATURE REVIEW

Medicinal plants have been an essential source of therapeutic compounds and alternative medicines for people worldwide. Recent advances in computer vision have made plant identification from images a rapidly evolving research area, showing promising results in terms of accuracy and real-world applications.

Valdez, Aliac, and Feliscuzo (2020) presented a new medicinal plant dataset with ten plant species and one class of mixed weeds and vines, proposing a MobileNetV3-based model with transfer learning, achieving 97.43% accuracy. This study highlights the feasibility of an efficient and reliable classifier for medicinal plants.

Similarly, Thella and Ulagamuthalvi (2021) discussed the significance of plant identification for environmental conservation, plant resource management, and medicine preparation, focusing on automated systems that classify plants using leaf features. The lack of experts in plant taxonomy necessitates such automated systems.

In another study, Pushpa et al. (2020) proposed a system for classifying Indian medicinal plants using texture features of leaves, emphasizing the challenges of manual identification. Their approach uses digital image processing for feature extraction and employs K-nearest neighbour (KNN) classifiers for automatic plant classification. These studies collectively showcase the importance of automating medicinal plant classification, particularly in biodiversity conservation, medicine preparation, and research.



IV. IMPLEMENTATION

The proposed system aims to accurately classify medicinal plants using a Convolutional Neural Network (CNN). The system is implemented using Python and Keras libraries with TensorFlow backend. The primary objective is to extract important spatial features from plant images, enabling precise classification even with visually similar species.

A] Dataset Preparation:

Images of various medicinal plants were collected and organized into two main directories: `training_set` and `testing_set`, each containing subfolders named after plant classes. The dataset includes seven classes of medicinal plants. All images were resized to 64×64 pixels for uniformity.

B] CNN Architecture:

The CNN was constructed using a sequential model comprising multiple convolutional, pooling, and fully connected layers:

- Input Layer: Accepts RGB images of size 64×64×3.
- Convolution Layers: Three sets of convolution operations were applied with filter sizes of 1×1, extracting fine-grained local features.
- Pooling Layers: MaxPooling layers with pool size 2×2 reduce spatial dimensions and control overfitting.
- Flatten Layer: Converts the 2D feature maps into a 1D vector.
- Fully Connected Layers:
 - A dense layer with 256 neurons and ReLU activation.
 - Dropout layer (80%) to prevent overfitting.
 - Output layer with 7 neurons using softmax activation for multi-class classification.

C] Training Configuration:

The model was compiled using the Stochastic Gradient Descent (SGD) optimizer with a learning rate of 0.01 and categorical_crossentropy as the loss function. The model was trained over 50 epochs using data generators with the following augmentation for the training set:

- Rescaling: 1. /255
- Shear range: 0.2
- Zoom range: 0.2
- Horizontal flip: Enabled

The ImageDataGenerator class from Keras was used for both training and testing sets. The batch size was set to 32.

D] Evaluation and Results:

The model achieved high classification accuracy:

- Training Accuracy: ~99.71%
- Testing Accuracy: ~99.40%

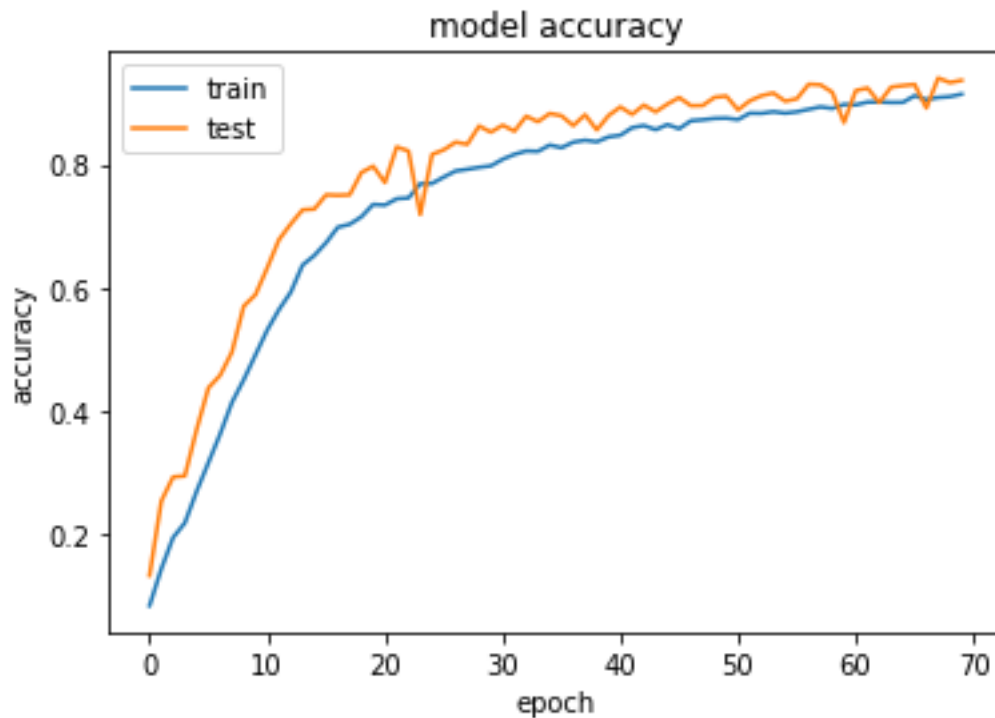


Figure 1: Accuracy Graph

V. RESULTS AND DISCUSSION

The CNN model was trained for 50 epochs using a dataset consisting of seven classes of medicinal plants. The training process utilized real-time data augmentation and validation against a separate test set. The system achieved the following:

- Training Accuracy: 99.71%
- Testing Accuracy: 99.40%

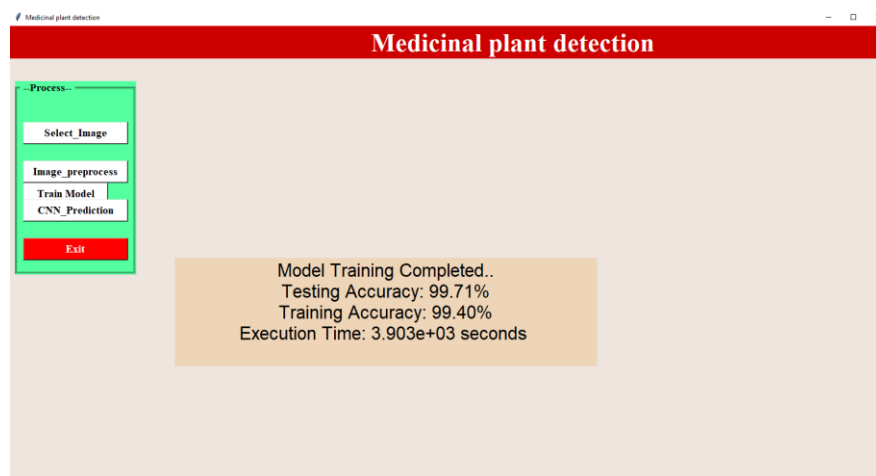


Figure 2: Model Training and Accuracy



The accuracy and loss graphs generated during training clearly demonstrate convergence and minimal overfitting, indicating effective generalization on unseen data. The use of dropout layers and image augmentation techniques contributed significantly to the model's robustness. Moreover, class-wise predictions confirmed the model's capability to distinguish between visually similar plant types. The results showcase the viability of CNN-based architectures for high-accuracy plant species recognition.

VI. CONCLUSION

This study presents an efficient and accurate system for medicinal plant classification using deep learning techniques. By implementing a CNN-based architecture and augmenting the dataset with image preprocessing, the model achieved high performance in identifying medicinal plants. The system has the potential to support researchers, herbalists, and the public in identifying plant species quickly and accurately. Future work may explore the integration of this model into a mobile application and expanding the dataset to include a larger variety of plant species for broader applicability.

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