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HERBAL GARDEN

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ABSTRACT

Medicinal plant identification has traditionally been a challenging task, requiring expertise and significant time investment. Many users, including researchers, students, and herbal enthusiasts, often struggle to accurately identify plants and access reliable information about their characteristics and uses. The goal is to make plant identification more accessible and efficient by leveraging technology. One effective approach is the use of machine learning. Images of plants uploaded by users serve as input to a machine learning model, which processes the data to identify the plant species and provide detailed information about its properties and applications. This solution bridges traditional knowledge with modern advancements, making plant identification accurate and accessible for everyone.

Keyword: Image Recognition, Plant Classification, Healthcare, Plant Identification, Interactive Learning

INTRODUCTION:

The exploration and utilization of medicinal plants have been integral to healthcare systems worldwide, particularly in traditional medicine. Despite the long history of herbal medicine, one of the key challenges remains the accurate identification of plant species and the understanding of their potential therapeutics applications. Traditional methods of plant identification often rely on expert knowledge and can be time-consuming, making them inaccessible to many users, including researchers, students, and herbal enthusiasts. With the growing interest in herbal remedies and the need for accessible, reliable information, there is a pressing demand for solutions that combine modern technology with traditional knowledge.

The rapid development of digital technologies, including machine learning and image recognition, offers a promising solution to this problem. Machine learning, in particular, has revolutionized various fields by enabling systems to analyze and interpret vast amounts of data in real-time. In the context of medicinal plant identification, machine learning can process plant images to provide accurate identification and detailed information about the plant's properties, benefits, and uses. This project seeks to create an advanced platform that allows users to upload images of plants for automated identification, providing valuable insights into their medicinal applications and promoting the preservation of traditional knowledge.

By harnessing the power of machine learning algorithms, the system will not only improve the accuracy and efficiency of plant identification but also enable users to explore and learn about the diverse range of medicinal plants in an interactive and educational environment. With continuous advancements in machine learning techniques, this platform will evolve, adapting to new plant species and improving its capabilities over time. As the use of herbal medicine continues to grow, this project aims to bridge the gap between ancient wisdom and modern technology, making medicinal plant knowledge more accessible, reliable, and impactful for a global audience.

LITERATURE REVIEW

The concept of integrating technology with botany has gained traction in recent years, with numerous projects exploring plant recognition using ML algorithms. Researchers have employed convolutional neural networks (CNNs) and transfer learning methods for image-based plant identification, yielding remarkable results. Studies also highlight the need for combining botanical features with regional and cultural contexts to ensure holistic information dissemination. However, gaps persist in creating a unified platform that not only identifies plants but also educates users about their applications.

PROPOSED METHODOLOGY

The Herbal Garden project adopts a waterfall model for structured development. It comprises the following phases:

1. Data Collection

Data collection is a critical phase in developing the herbal garden project. A curated dataset of 15,000 images representing 30 medicinal plant species was used.

These images were sourced from trusted online botanical repositories and local fieldwork, ensuring high-quality data for training. Each class corresponds to a unique medicinal plant species, and images were captured in diverse environments to incorporate natural variability.

This phase focused on capturing leaves, whole plants at different stages of growth to ensure the robustness of the dataset. High-resolution images were organized into a directory structure where each folder represented a class. Metadata such as plant names and descriptions were also documented. This structured approach allowed for easy indexing and streamlined the later stages of preprocessing and model training.

2. Data Preprocessing

Preprocessing involved preparing the raw dataset to ensure it was suitable for training the machine learning model. Images were normalized to scale pixel values between 0 and 1, enabling the model to converge faster during training. Data augmentation techniques were employed, such as random rotation, flipping, zooming, and shearing, to artificially increase the dataset size and improve generalization.

The dataset was divided into training and validation sets using an 80:20 split ratio. Each subset retained a balanced representation of all classes to prevent biases.

File directories were reorganized, and corrupted images were excluded to maintain data integrity. Pre-processed images were resized to

224x224 pixels to meet the input requirements of the MobileNetV2 model.

This phase ensured that the model was exposed to varied and clean data, improving performance on unseen inputs.

3. Model Training

The training process involved using MobileNetV2, a lightweight convolutional neural network, as the base model. Pre-trained weights from ImageNet were utilized for transfer learning, which enabled the model to leverage generic features like edges and textures learned from millions of images.

A custom classification head was added, comprising a global average pooling layer, a dense layer with 512 neurons, a dropout layer to reduce overfitting, and a final SoftMax output layer for multiclass classification. The base layers of MobileNetV2 were frozen during initial training to retain their pre-trained feature extraction capabilities.

The model was compiled with the Adam optimizer and categorical Cross entropy loss, suitable for multiclass problems. It was trained over 50 epochs with a batch size of 32. Accuracy and loss metrics were tracked for both training and validation sets, enabling monitoring of the model's performance.

4. Web Application Development

A user-friendly web application was developed to make the herbal garden accessible to end users. This interactive platform allowed users to upload images of plants for identification. The web interface displayed the predicted class, confidence score, and additional details such as medicinal uses and preparation methods.

The application leveraged Flask as the backend framework, connecting the trained model to the frontend interface. Images uploaded via the web app were pre-processed in real-time, and predictions were displayed within seconds. Additional features included a quiz module for studies. The web app was designed to handle simultaneous user requests efficiently, ensuring scalability.

TYPES

The Herbal Garden project employs a comprehensive classification framework, categorized into the following types to ensure accurate and efficient medicinal plant identification:

1.Leaf-Based Identification:

Utilizes distinct features such as shape, venation patterns, colour, and texture. Parameters like serrated margins or reticulate venation play a critical role in differentiating plant species.

2.Flower-Based Identification:

Focuses on the morphological characteristics of flowers, including petal arrangement, colour variations, and structural size. This approach is particularly effective for species with similar foliage but distinct floral traits.

3.Fruit-Based Identification:

Analyses unique fruit features such as size, shape, surface texture, and colour transitions across growth stages. This method is ideal for identifying plants with characteristic fruits like jackfruit or pomegranate.

4.Whole-Plant Identification:

Integrates data from all plant components, including leaves, flowers, fruits, and stems

5.Texture and Environmental Context:

Examines additional factors like bark texture, surrounding environmental elements, and seasonal variations. These cues complement other features to enhance the model's robustness.

MACHINE LEARNING MODELS

1. Convolutional Neural Networks (CNN)

CNNs are deep learning models that excel at image classification tasks, including plant recognition, as seen in your project. They work by applying filters to images to detect patterns such as edges, textures, and shapes. CNNs are highly effective in processing spatial data and automatically learn important features from raw input images, reducing the need for manual feature extraction. In your plant identification model, CNNs are used to extract spatial hierarchies from the images of medicinal plants.

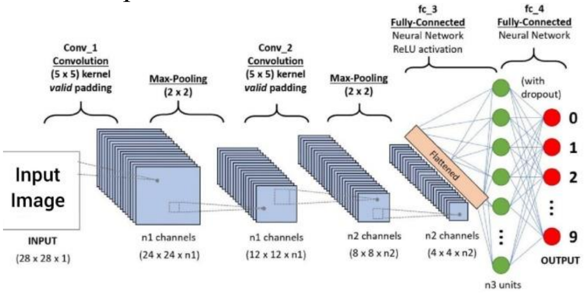

Fig 1 – CNN architecture

2.Transfer Learning with MobileNetV2

Transfer learning involves taking a pre-trained model on a large dataset and fine-tuning it for a specific task. In your case, MobileNetV2, a lightweight CNN model pre-trained on ImageNet, was used as the base model for your plant classification task. By freezing the layers of MobileNetV2 and adding a custom classifier, your model benefits from the knowledge learned from a vast image dataset, making it more efficient and accurate for plant recognition with less data.

3. Image Augmentation

In the context of plant classification, data augmentation techniques such as rotation, zooming, shifting, and flipping were applied to the training data. These techniques increase the variety of images and prevent overfitting by artificially expanding the training set. This helps the model generalize better, especially when working with a limited dataset. Your notebook includes data augmentation with Image Data Generator to improve model robustness.

4. Adam Optimizer

The Adam optimizer, used in your model, is an adaptive learning rate optimization algorithm that computes individual adaptive learning rates for different parameters from estimates of first and second moments of the gradients. It combines the advantages of two other popular optimizers (AdaGrad and RMSProp), making it efficient for training deep learning models like the one you used for plant classification.

5. Multiclass Classification

Your plant classification model is a multiclass classification problem where the goal is to assign each input image to one of 30 different plant species. The model uses SoftMax activation in the final layer to output probabilities for each class, and the class with the highest probability is chosen as the predicted label. The categorical cross-entropy loss function is used to optimize the model, which is suitable for handling multiple classes.

6. Global Average Pooling

Instead of using fully connected layers, your model applies Global Average Pooling (GAP) after the convolutional base (MobileNetV2). GAP reduces the dimensionality of the feature maps by taking the average of all the values in each feature map, allowing the model to produce a more compact representation of the image.

This method reduces the risk of overfitting and makes the model more efficient by eliminating the need for a large number of parameters.

7. Dropout Regularization

To prevent overfitting, dropout regularization is applied in your model. During training, dropout randomly sets a fraction of the input units to 0 at each update step, which helps in reducing overfitting by forcing the model to generalize better.

In plant classification model, a dropout rate of 50% was used after the dense layer to improve generalization.

8.Model Evaluation and Visualization

After training the model, it's important to evaluate its performance using metrics like accuracy and loss. In your case, both training and validation accuracy/loss were plotted over epochs to observe the model's performance and detect any signs of overfitting. Visualizing these metrics helps in understanding whether the model is improving or if any adjustments are needed in the training process.

9. Model Prediction

Once the model is trained, it can be used to predict the class of a new image. For example, you used a function to load and preprocess an image, then predict the plant species with the highest probability. The output is the predicted class label along with the model's confidence level in that prediction, which helps in determining the accuracy of individual predictions.

10. Saving the Model

Once the model has been trained, saving it in the correct format is essential for later use. In your case, the model was saved as an .h5 file. However, TensorFlow now recommends saving the model in the. keras format, as the .h5 format is considered legacy. The model file can later be loaded for inference or further fine-tuning.

WORKFLOW

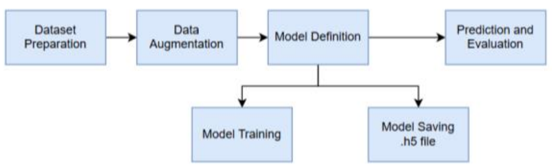

Fig 2 – Workflow

1. Dataset Preparation:

This step involves gathering raw data and preparing it for analysis. It includes cleaning the data, removing noise, normalizing values, and splitting the dataset into training, validation, and test sets.

Examples: resizing images, labeling datasets, and addressing missing data issues.

2. Data Augmentation:

To improve the robustness of the model and reduce overfitting, data augmentation is applied. It artificially expands the dataset by applying transformations like rotation, flipping, cropping, and scaling.

Examples: flipping images horizontally, adjusting brightness, or random cropping.

3. Model Definition:

This involves designing the architecture of the deep learning model. Layers such as convolutional layers, pooling layers, fully connected layers, and activation functions are defined here.

Tools commonly used: TensorFlow, PyTorch, or Keras.

4. Model Training:

During this phase, the model learns from the training data. The parameters of the model (weights and biases) are adjusted through optimization algorithms like Stochastic Gradient Descent (SGD) or Adam.

This step involves defining hyperparameters like learning rate, batch size, and number of epochs.

5. Model Saving (.h5 file):

Once the training is complete, the trained model is saved in a format like .h5 for Keras models. This allows the model to be reused later without retraining.

Benefits: saving computation time and enabling deployment.

6. Prediction and Evaluation:

The final step evaluates the model's performance on unseen test data. Metrics such as accuracy, precision, recall, and F1-score are used to assess the model.

Based on the results, further fine-tuning or re-training may be performed.

OUTPUT

Fig 3 - Output Screenshot 1

Fig 4 – Output Screenshot 2

Fig 5 – Output Screenshot 3

CONCLUSION

This project utilized a combination of advanced machine learning techniques to build a plant identification system capable of recognizing 30 distinct plant species. The process incorporated pre-trained models like MobileNetV2, along with methods such as data augmentation and transfer learning. Throughout the training process, metrics like accuracy, loss, and validation performance were carefully monitored to ensure reliable results.

The implementation showcased the potential of integrating feature extraction and classification into a single streamlined workflow. Additionally, the use of techniques like recall, precision, and overall accuracy helped evaluate the model's performance effectively. Future directions could include exploring additional architectures or integrating the system into real-world applications for enhanced usability.

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