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Medicinal Plant Recognition

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Project Introduction

For centuries, medicinal plants have played a vital role in treating various health conditions. However, identifying these plants correctly requires knowledge and experience, which not everyone has. This is where technology comes in.

In this presentation, we will show you how we can use Artificial Intelligence and computer vision to automatically recognize medicinal plants from images. This not only helps in preserving traditional knowledge but also makes plant identification faster, easier, and more accessible for everyone.

Project Introduction

Why CNN ? Convolutional Neural Networks (CNNs) are powerful tools for image classification, which makes them ideal for analyzing plant images effectively.

Project Objective : To develop an automated system capable of identifying medicinal plants from an image and providing information about their health benefits.

Problem Statement : CNN-based models require large, diverse, and well-labeled datasets to perform accurately and generalize well.
However, existing plant image datasets are often limited, imbalanced, or not suited to real world conditions.
This lack of quality data makes it difficult to train robust models and affects the reliability of automated plant recognition systems.

Proposed Methodology

We developed an automated system using CNNs to identify medicinal plants. Our approach:

Dataset : Used a preprocessed Kaggle dataset of labeled plant images.

Preprocessing : Normalized pixel values and applied augmentation

CNN Model : Convolutional layers for feature extraction ,Pooling layers for dimensionality reduction, Dropout and ReLU for regularization

Training : Trained with Adam optimizer, validated on separate test sets.

Results : Achieved high accuracy in species classification

Data Collection & Preprocessing

❖ Dataset :

Size : The dataset contains abou 16000 images, with varying numbers of images per class (some classes have over 500 images, others have fewer than 200).

The dataset is not perfectly balanced, which may impact model performance.

Objective : Classify plant images into 16 different medicinal plant species using deep learning.

Data Collection & Preprocessing

- **Preprocessing :**

  Resizing all images to a standard input size

  Normalizing pixel values

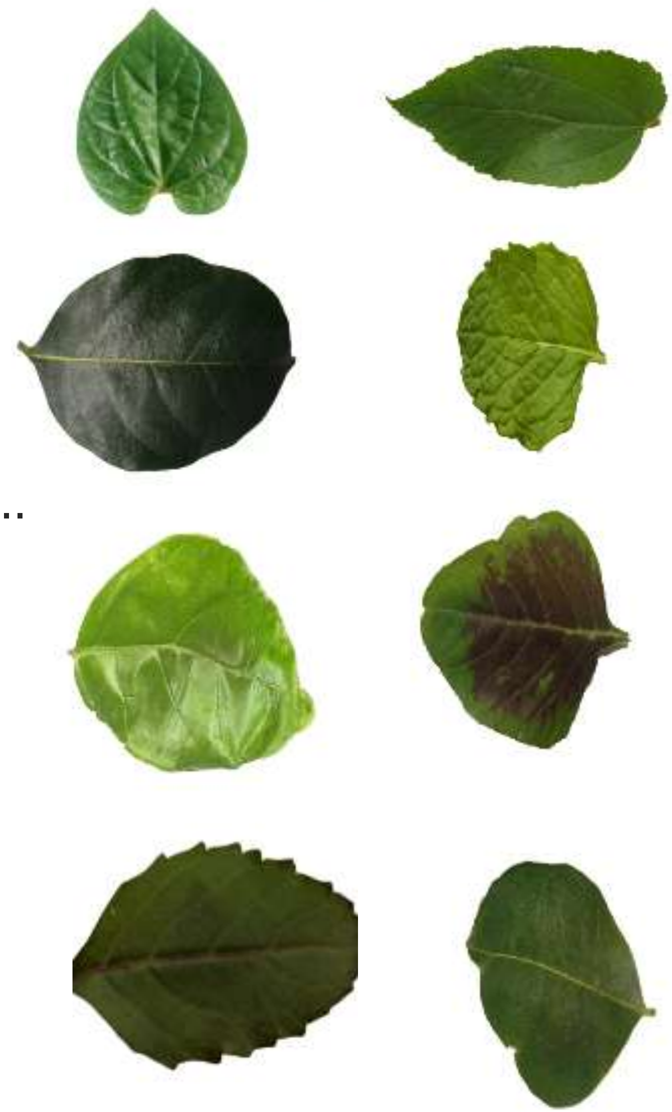
  Data augmentation to improve model generalization

- **Split:**

  80% training, 20% validation

Data Collection & Preprocessing

❖ **Sample Images of Medicinal Plants:**



The dataset contains images of medicinal plants taken in various conditions.
Each image is labeled according to the plant species, such as Aloe vera, Mint, Basil, and Neem...
These samples help the model learn to recognize different leaf shapes, colors, and textures associated with each plant

Model Architecture

We used a Convolutional Neural Network (CNN) based on MobileNetV2 to classify medicinal plant images.

Architecture Overview :

- **Input:**

  Images resized to 160x160 with 3 color channels (RGB).

- **Data Augmentation:**

  Applied random horizontal flip and rotation to improve model generalization.

- **Preprocessing:**

  Pixel values are rescaled from 0–255 to 0–1.

- **Feature Extractor – MobileNetV2:**

  We use MobileNetV2 pretrained on ImageNet.

  The top (classification head) is removed.

  It extracts high-level features from the input images.

  It's set to non-trainable to reduce training time and avoid overfitting.

Model Architecture

- **Pooling & Fully Connected Layers :**

  Global Average Pooling to reduce feature map dimensions.

  Dropout layers to prevent overfitting.

  Dense(128, relu) for learning final representations.

  BatchNormalization for training stability.

- **Output Layer :**

  Final Dense layer with softmax activation outputs the probabilities for each plant class.

- **Training Details:**

  Loss Function: Sparse Categorical Crossentropy

  Optimizer: Adam

  Metrics: Accuracy

  We also used callbacks like EarlyStopping and ReduceLROnPlateau.

- **Why MobileNetV2?**

  Lightweight and fast

  Efficient for real-time applications

  Performs well on small datasets

Model Architecture

❖ Model Summary :

Layer (type)	Output Shape	Param #
input_layer_8 (InputLayer)	(None, 160, 160, 3)	0
sequential_6 (Sequential)	(None, 160, 160, 3)	0
rescaling_2 (Rescaling)	(None, 160, 160, 3)	0
mobilenetv2_0.75_160 (Functional)	(None, 5, 5, 1280)	1,382,064
global_average_pooling2d_2 (GlobalAveragePooling2D)	(None, 1280)	0
dropout_4 (Dropout)	(None, 1280)	0
dense_4 (Dense)	(None, 128)	163,968
batch_normalization_2 (BatchNormalization)	(None, 128)	512
dropout_5 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 30)	3,870

```
Total params: 1,550,414 (5.91 MB)
Trainable params: 168,094 (656.62 KB)
Non-trainable params: 1,382,320 (5.27 MB)
```

Final Results

Evaluation Metrics Summary :

- Accuracy : Model achieved 99.00% overall accuracy .
- Precision : Precision: 99.03%,
- Recall:99.00% indicating strong reliability across classes.
- F1-Score: High harmonic ,confirms the model's balanced performance,

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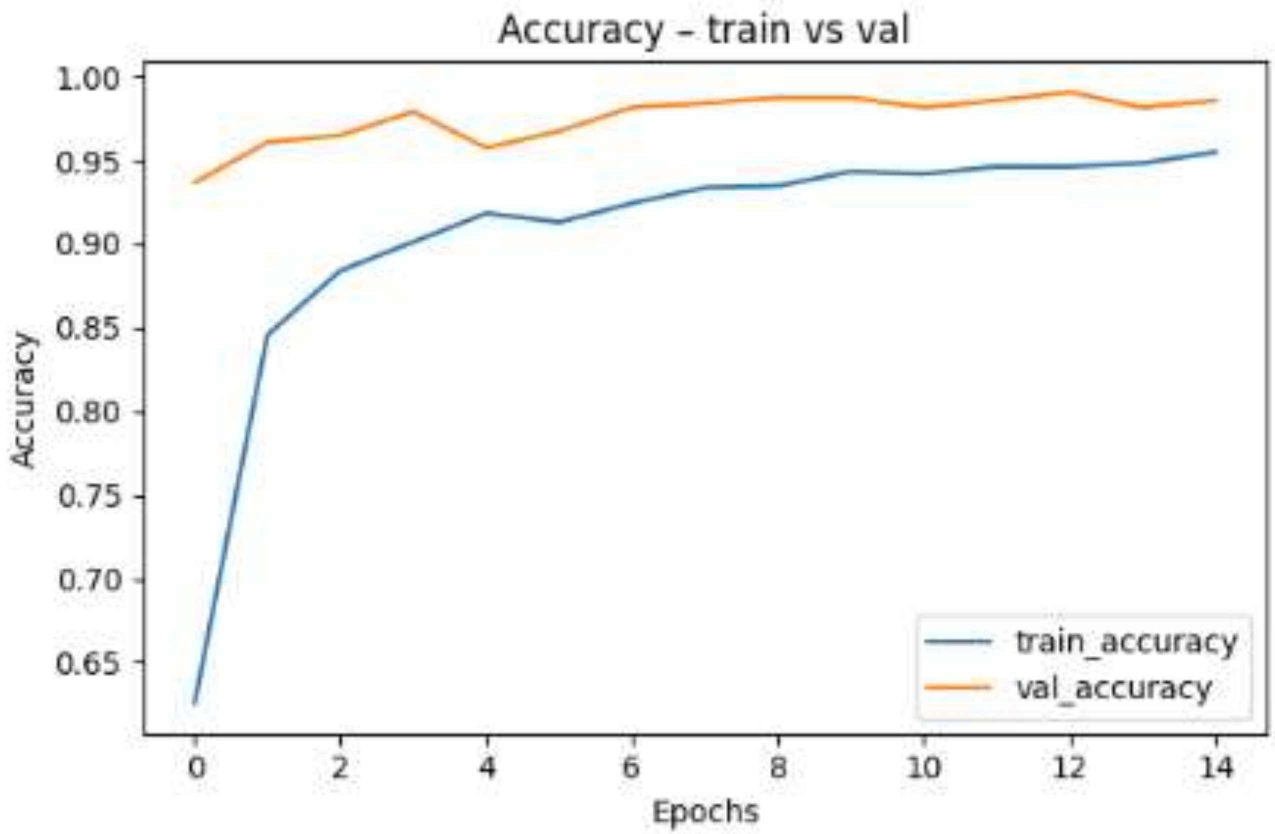
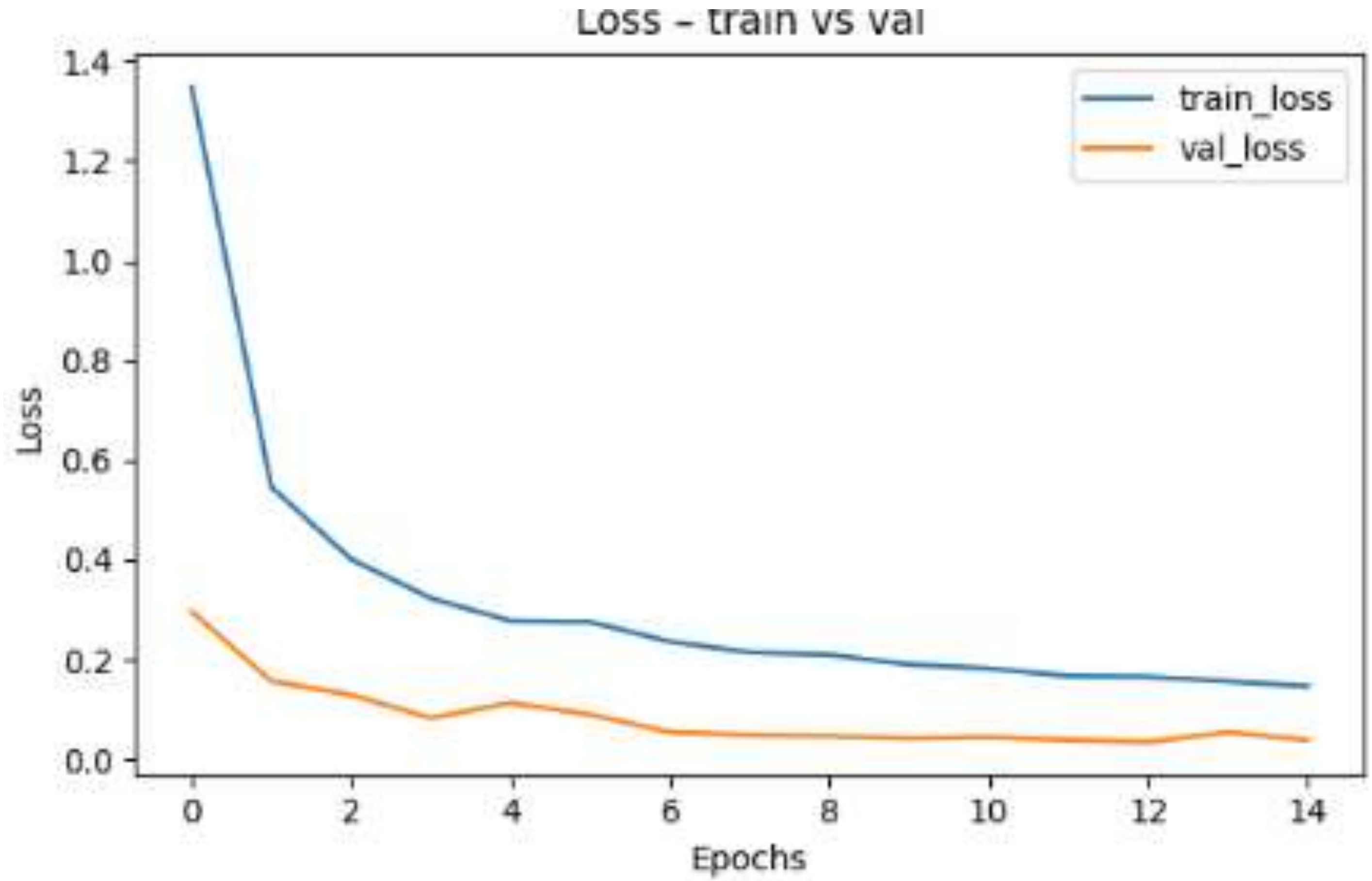
=== Résultats globaux ===
Accuracy  : 99.083%
Précision : 99.118%
Rappel    : 99.083%
F1-score  : 99.083%
```

Final Results



Final Results

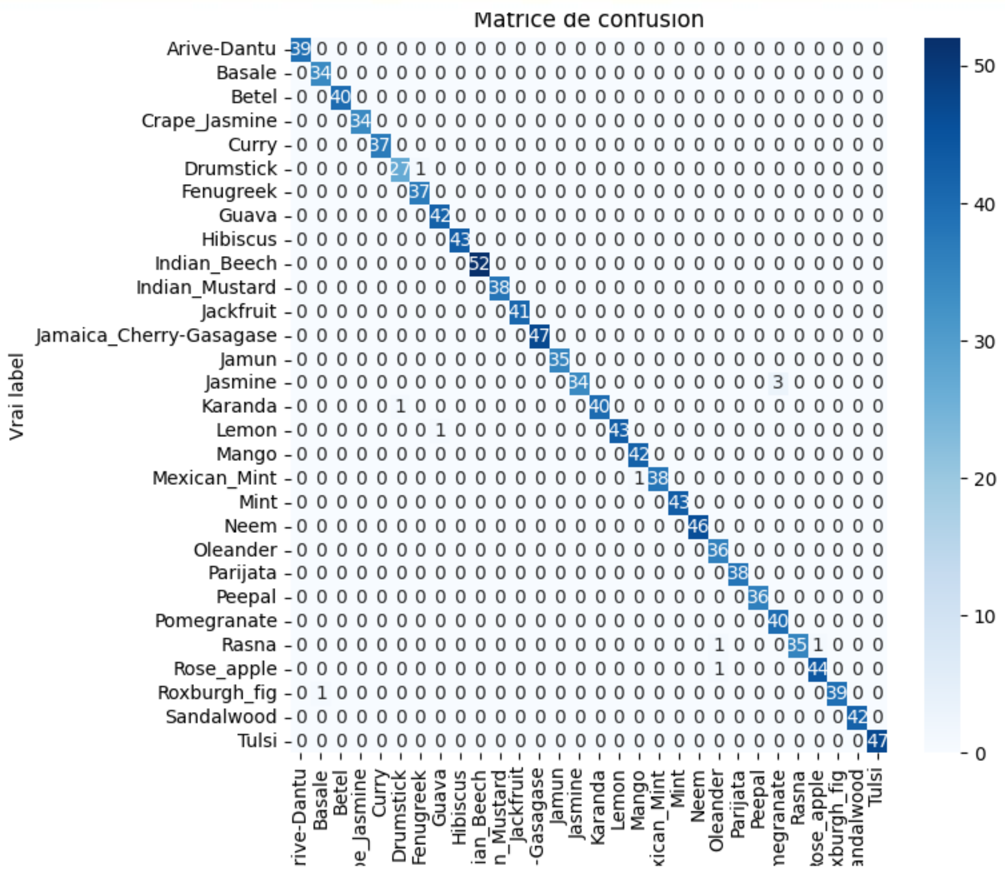


Final Results

The confusion matrix :

The confusion matrix provides a comprehensive evaluation of our CNN model's classification performance across all 30 medicinal plant class Key observations:

- High Accuracy Confirmation
- Improvement Opportunities



Final Results

Model Predictions :

Conclusion and Future work

- This project successfully implemented a CNN model for accurate medicinal plant identification using image data, achieving over 92% classification accuracy.
- The system demonstrates strong potential for real-world applications in botany, herbal medicine, and biodiversity conservation.
- **Next Steps for Enhancement :**

Dataset Expansion : Incorporate additional species, particularly rare and regional varieties.

Advanced Modeling : Implement transfer learning and multi-class classification .

Deployment Optimization : Develop lightweight versions for edge devices and offline use.

- By pursuing these improvements, this framework can evolve into a comprehensive global solution for plant identification, supporting both scientific research and public education

THANK YOU FOR LISTENING!

ANY QUESTIONS ?