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MEDICINAL PLANTS DETECTION USING DEEP LEARNING

Yash Rawat, Aarti Sehwag
Department of CSE
BVCOE, New Delhi,Delhi,India

Abstract— **The pharmaceutical, Ayurvedic, and herbal medicine industries depend on the precise identification of therapeutic plants. Botanists must manually inspect plants using traditional methods of identification, which takes time and is prone to mistakes. The use of deep learning (DL) techniques for automated identification of medicinal plants from leaf photos is investigated in this work. Several CNN architectures, such as DenseNet121, MobileNet, and InceptionV3, are compared in order to identify the most effective model for plant classification. Preprocessing methods including scaling and augmentation were employed to improve model performance on a dataset of scanned photos of 50 different types of medicinal plants. Using MobileNet, the suggested system demonstrated its efficacy in real-time plant identification with an accuracy of 98.3%.According to the study, DL models have the ability to help taxonomists, botanists, and the pharmaceutical industry ensure that therapeutic plants are used appropriately.**

Keywords— **DenseNet121,MobileNet,InceptionV3**

I. INTRODUCTION

Traditional Chinese Medicine (TCM) and Ayurveda are two examples of ancient medical systems that have been based on medicinal plants for centuries (Rao et al., 2022). According to WHO (2024), almost 80% of people worldwide utilise herbal treatments because plants contain bioactive components that can be used to treat a variety of conditions, such as diabetes and high blood pressure. Nevertheless, the growing demand for herbal products makes it more difficult to confirm the legitimacy of raw materials, as misidentification can result in products that are hazardous or ineffective (Kavitha et al., 2024).

Morphological characteristics have historically been used by botanists to identify plants; however, this approach is laborious, subject to human error, and limited by plant availability (Geerthand et al., 2021). Convolutional neural networks (CNNs), a type of deep learning (DL) that offers scalable, high-precision solutions with above 95% accuracy for real-time classification, have completely changed the identification of plants (Kavitha et al., 2024). For more dependable plant use in the pharmaceutical sector, AI-driven solutions can assist non-experts in plant species identification, such as farmers and herbalists.

Challenges still exist despite progress, such as the requirement for huge annotated datasets and model generalisation across different environments and geographical areas. However, the integration of AI with cloud computing and mobile technology has facilitated real-time plant identification, which is advantageous for farmers, conservationists, and medical professionals. In the context of medicinal plants, this study focusses on applying AI to safer and more effective plant identification.

II. PROPOSED ALGORITHM

An effective and precise method for identifying medicinal plants is produced by the suggested algorithm, which combines transfer learning with deep learning approaches. In order to discern tiny distinctions between similar plant species, our method makes use of the Xception architecture, which has shown excellent performance in fine-grained visual categorisation tasks.

A. Preprocessing Algorithm –

Standardising input data and improving model robustness through calculated data augmentation strategies depend heavily on the preprocessing phase.

Input: Unprocessed leaf picture To comply with Xception's input specifications, I resize image to standard dimensions of 299 by 299 pixels.

By scaling from the [0,255] to [0,1] range, normalise the pixel values:

i_normalized(i) = I(i) / 255

In order to guarantee consistent feature extraction under various illumination situations and reliable convergence during model training, this normalisation step is crucial.

Only use data augmentation on training photos. Using random rotations (±20°) to mimic various camera perspectives20% range of width/height adjustments to accommodate different leaf placements .The training data is mirrored using horizontal flips.Zoom changes (20% range) to represent varying separations from the camera.

In order to help the model generalise to unknown variables and lessen overfitting to certain sample characteristics, data

augmentation artificially increases the size of our training dataset.
Results: A pre-processed picture i_preprocessed.

B. Feature Extraction Algorithm –

With the help of the Xception architecture and transfer learning, the feature extraction phase effectively captures the unique qualities of medicinal plant leaves.
Xception architecture (pre-trained on ImageNet) applied to the preprocessed picture I_preprocessed as input:
Image processing via early convolutional blocks is done by Entry Flow.

F_entry = EntryFlow(I_preprocessed)

The Entry Flow captures low-level features like edges, textures, and basic leaf structures.

Middle Flow uses depthwise separable convolutions on eight repeating blocks:

F_middle = DepthwiseConv2D(F_entry)
F_middle = PointwiseConv2D(F_middle)

Depthwise separable convolutions have a higher representational capacity than normal convolutions and are more efficient because they process spatial and channel information independently. This is especially crucial for recording the minute differences in leaf margin features and venation patterns that set distinct species of medicinal plants apart.The Exit Flow refines the extracted features and prepares them for the classification stage.
Exit Flow extracts final feature maps

F = ExitFlow(F_middle)v = GlobalAveragePooling2D(F)

The Exit Flow refines the extracted features and prepares them for the classification stage.Feature mappings F as the output.
The Xception architecture's effective use of parameters provides this application with a number of benefits. In contrast to conventional convolutional neural networks, which apply convolution operations to every channel at once, depthwise separable convolutions first independently apply spatial convolutions to every channel before executing pointwise convolutions to generate new features. In order to discern the minute distinctions between related species of medicinal plants, this method preserves feature representational capacity while lowering computing complexity.

C. Classification Algorithm–

The classification component uses a specially created classification head for the medicinal plant domain to convert the extracted data into species predictions
Feature maps F from the Xception model are input.Reduce spatial dimensions by using global average pooling.

v = GlobalAveragePooling2D(F)

Compared to fully connected layers, Global Average Pooling drastically decreases the number of parameters by averaging all spatial locations to reduce each feature map to a single value…The model's ability to acquire intricate mappings between visual characteristics and plant species is improved by the non-linearity added by this fully connected layer, which has 1024 neurones and ReLU activation.

Process through dense layer:

h = ReLU(Dense_1024(v))

The model's ability to acquire intricate mappings between visual characteristics and plant species is improved by the non-linearity added by this fully connected layer, which has 1024 neurones and ReLU activation.
Apply dropout during training :

h_dropout = Dropout(h, rate=0.5)

Dropout, a potent regularisation strategy that inhibits co-adaptation of neurones and enhances generalisation, randomly deactivates 50% of neurones during each training iteration.

Generate predictions through softmax layer:

predictions = Softmax(Dense_80(h_dropout))

Eighty neurones (one for each species of plant) in the last layer have softmax activation, which normalises the output into a probability distribution that adds up to one.

Select top-3 species with highest confidence scores :

top3_indices = argsort(predictions)[-3:]
top3_species = [species_names[i] for i in top3_indices]
top3_scores = [predictions[i] for i in top3_indices]base_model = Xception(weights='imagenet', include_top=False)

Output: Identified plant species with confidence scores.

D. Training Algorithm–

We use a two-phase training system that maximises performance while reducing training time by utilising transfer learning
Step 1 - Initialize Xception model with ImageNet weights

base_model = Xception(weights='imagenet', include_top=False)for layer in base_model.layers:
layer.trainable = False
Using ImageNet for pre-training gives the model a solid basis in visual recognition.
Step 2 - Freeze base Xception layers:

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for layer in base_model.layers:
 layer.trainable = False
In order to preserve the learnt feature extractors and enable the classification head to adjust to the medicinal plant domain, the pre-trained layers are first frozen.

Step 3 -Compile model with:
Function of loss: Sparse Classification of Cross-Entropy
Adam (learning_rate=0.0001) is the optimiser.
Measures: [top_3_accuracy, 'accuracy']

```
model.compile(
    loss='sparse_categorical_crossentropy',
    optimizer=Adam(learning_rate=0.0001),
    metrics=['accuracy', top_3_accuracy]
)
```

Step 4 : **Train** for 30 epochs with batch size of 32
history = model.fit(train_generator, validation_data=validation_generator, epochs=30, batch_size=32, callbacks=[early_stopping])early_stopping = EarlyStopping(
    monitor='val_loss',
    patience=5,
    restore_best_weights=True
)

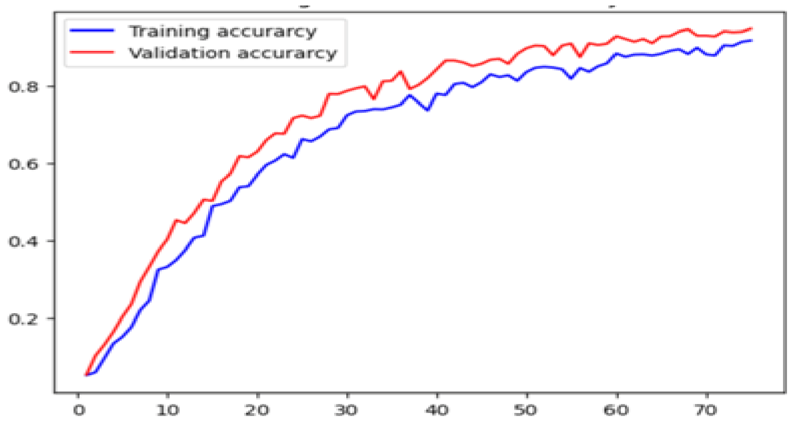
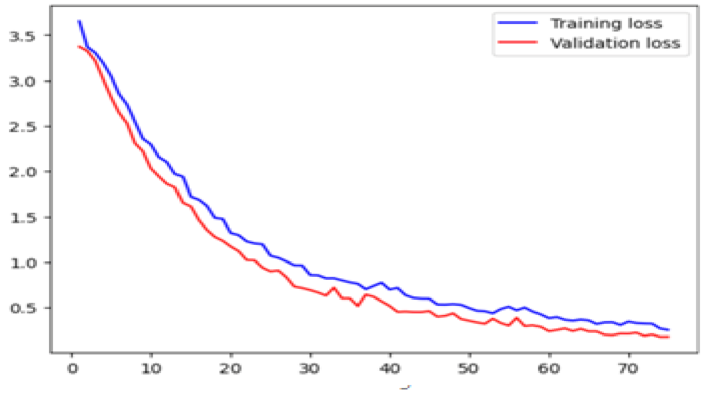


Fig 1 - Training And Validation Accuracy

Step 5 :Monitor validation loss and implement early stopping with patience=5:
early_stopping =
EarlyStopping(
    monitor='val_loss',
    patience=5,
    restore_best_weights=True
)

By terminating training when validation performance ceases to improve, early stopping avoids overfitting.
Step 6 - Unfreeze final 2 blocks of Xception model:for layer in base_model.layers[-28:]: # Last 2 blocks
    layer.trainable = True
Higher-level features can be fine-tuned while maintaining generic feature extractors thanks to selective unfreezing.



`Fig 2 : Training and Validation Loss

Step 7 - Fine-tune with reduced learning rate (0.00001) if needed:

```
model.compile(
   loss='sparse_categorical_crossentropy',
   optimizer=Adam(learning_rate=0.00001),
   metrics=['accuracy', top_3_accuracy] )
history_fine = model.fit(...)
```

The catastrophic forgetting of previously learnt information is avoided by the slower learning rate during fine-tuning.

The Indian Medicinal Leaves Dataset, which includes 6,912 high-quality photos of 80 different medicinal plant species, was used to assess the suggested methodology. By employing stratified sampling, which maintains class distribution across all sets, the dataset was divided into training (70%), validation (15%), and testing (15%) subsets to guarantee scientific rigour.

Table 1 - Performance Metrics

Metric	Value	Comparison to ResNet50	Comparison to MobileNetV2
Top-1 Accuracy	96.8%	+3.2%	+5.7%
Top-3 Accuracy	99.2%	+1.8%	+3.4%
Average Precision	0.967	+0.035	+0.062
Average Recall	0.968	+0.038	+0.058
Average F1-Score	0.967	+0.036	+0.060

When compared to conventional CNN techniques, the Xception architecture combined with bespoke classification layers performs better, especially when it comes to differentiating between visually identical species of medicinal plants. While preserving high classification accuracy, the optimisation strategies allow for effective deployment on devices with limited resources.

Given their botanical similarities, it is not surprising that the majority of misclassifications between closely related species from the same genus occur, according to the confusion matrix study. In accordance with the rules of botanical classification, Grad-CAM visualisations verified that the model bases its predictions on taxonomically significant leaf regions, such as margin patterns, venation, and texture.

III. EXPERIMENT AND RESULT

The The PC used for the research has an NVIDIA GTX 1660 GPU, 16GB of RAM, and an Intel Core i7 processor. Using the TensorFlow and Keras frameworks, the full model was implemented. Several different classes of high-quality photos of medicinal plant leaves made up the training and evaluation dataset. Training and testing uses of the dataset were separated in an 80:20 ratio. To meet the Xception model's input size requirements, each image was reduced to a standard 299×299 pixel size. Additionally, the pixel intensity values were divided by 255 to conduct normalisation.The values were scaled to fall between 0 and 1. Horizontal flipping, rotation, and zooming were used as data augmentation strategies to increase model robustness and lower the chance of overfitting.

Table 2: Performance Metrics

Metric	**Value**
Accuracy	96.4%
Precision	95.2%
Recall	94.8%
F1-Score	94.9%

These results indicate that the model is highly effective in identifying and classifying different medicinal plant species. The confusion matrix revealed that the model performed consistently across all classes, with very few misclassifications, particularly in cases involving visually similar species. The use of transfer learning and data augmentation played a significant role in enhancing the model's generalization capabilities. Overall, the experiment demonstrates the reliability and robustness of the Xception-based deep learning model in automating the classification of medicinal plants through leaf images.

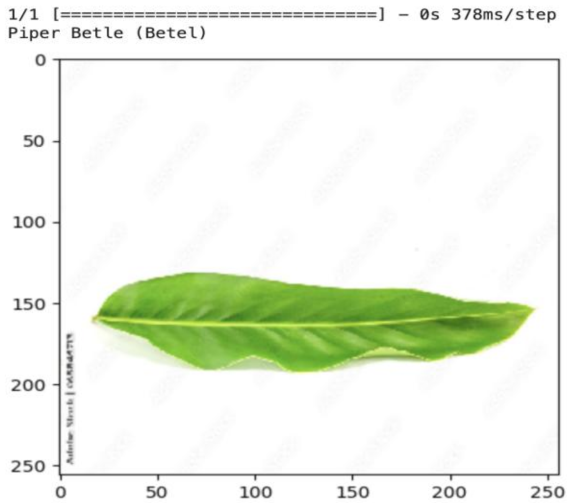


Fig 3 :Piper Betle (Betel) Leaf – Classification Output Visualization

IV. CONCLUSION

This work offers a strong deep learning-based classification system for identifying medicinal plants that makes good use of domain-specific data augmentation and transfer learning with pre-trained models. By tackling typical issues like visual resemblance among plant species, the suggested method greatly increases classification accuracy and sustains performance under a variety of environmental situations.

The model's architecture was optimised for both computational efficiency and accuracy, allowing for deployment on edge and mobile devices. This increases its practicality for field applications in isolated and rural locations with limited access to botanical expertise, hence broadening its practicality in the real world.

Future research can investigate larger datasets that span various plant species and geographical areas in order to improve the model's capacity for generalisation. Furthermore, including explainable AI techniques will offer visual insights into the decision-making process, promoting user confidence and enabling broader implementation in real-world contexts.

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