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IDENTIFICATION OF PLANTS USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT: We use deep convolutional neural networks to identify the plant species captured in a photograph and evaluate different factors affecting the performance of these networks. We use powerful deep learning architecture, namely MOBILENETV2, are used for this purpose. Transfer learning is used to fine-tune the pre-trained models, using the plant task datasets of MEDICINAL PALNT. To decrease the chance of overfitting, data augmentation techniques are applied based on image transforms such as rotation, translation, reflection, and scaling. Furthermore, the networks parameters are adjusted and different classifiers are fused to improve overall performance. Our best combined system has achieved an overall accuracy of 90%.

Key words: Image Identification, Deep Learning, CNN Variants, Medicinal Leaf Dataset.

1.INTRODUCTION:

A key component of protecting natural resources is plants. Identification of plant species yields important information regarding plant classification and its attributes. Since manual interpretation depends on each person's unique visual perception, it is not exact. Digital leaf photos with textural qualities that aid in identifying a particular pattern are convenient to sample and take. The venation and leaf form are the primary characteristics that help differentiate between different plant species.

The identification of plants is based on the description of leaf shape and venation, which is the main idea in the identification process. Image processing, pattern recognition, and other approaches are used because information technology is developing quickly. It is challenging to document changes in leaf properties throughout time.
For this reason, a dataset must be created as a reference for a similar investigation. The majority of plant identification techniques use leaves because of their appealing qualities and year-round availability.

More precisely, we outline the fundamental ideas, provide a summary of the CNN VARIANTS that are currently in use, present the most recent studies using CNN VARIANTS to identify species, and talk about potential future study areas.

2.ASSOCIATED WORK:

Numerous scholars worldwide have suggested image-based processing methods for plant identification. Here, we provide a brief overview of a few of the methods that have been raised in the literature.

A technique for plant identification through images [1] uses the centroid of the leaf shape is determined by fitting the leaf boundary points in a continuous contour with Radial Basis Function Neural Networks (RBFNN). Next, the centroid's distance from the predefined spots was calculated and normalized. Furthermore, the algorithm for extracting features was computed with respect to its temporal complexity. While introducing readers to pertinent botanical ideas along the way, we discuss [2] the primary computational, morphometric, and image processing techniques that have been employed in recent years to evaluate plant photographs. We present a broad range of analytical techniques in use and talk about measuring leaf outlines, flower morphology, vein architecture, and leaf textures. We also talk about other systems that make use of this research, such as various robotic systems utilized in agriculture and hand-held digital field guide prototypes. We wrap up by talking about the ongoing projects and unresolved issues in the area. The rapid expansion of the Internet and the rise in user numbers in recent decades have made network security crucial. In an effort to maintain the greatest level of security, intrusion detection systems (IDSs) have been one of the most popular research subjects in network security recently. In this [3] a 2-layered feed-forward neural network is used to address an IDS. In order to prevent neural networks from "over-fitting," the "early stopping" technique is applied during the training phase. The DARPA dataset is used to assess the suggested system. The DARPA connections that were chosen are pre-processed, and the feature range is changed to [-1, 1]. These changes have a significant impact on the final detection findings. According to experimental data, the system performs suitably and precisely, and it is simpler than in similar circumstances. And retrieving images of flowers is a crucial step in computer-aided identification of plant species. In order to extract flower regions from flower photos, we propose in this study [4]an efficient segmentation method based on colour clustering and domain knowledge. We employ two shape-based feature sets, Centroid-Contour Distance (CCD) and Angle Code Histogram (ACH), to characterize the form features of a floral contour and the colour histogram of a flower region to characterize the colour features of the flower for flower retrieval. The outcomes of our experiments demonstrated the accuracy with which flower areas could be produced using our colour clustering and domain knowledgebased flower region extraction method. Our Region-of-Interest (ROI) based retrieval approach using both colour and shape features can outperform a method based on the global colour histogram proposed by Swain and Ballard and a method based on domain knowledge-driven segmentation and colour names proposed by Daset al. Flower retrieval results on a database of 885 flower images collected from 14 plant species showed this .The research suggests a content-based picture retrieval method based on color and texture cues in place of the high computational complexity and poor retrieval accuracy of the existing method. Users give each feature a weight, and then use the normalized Euclidean distance to compute the similarity between the combined color and texture data. Although the suggested approach's feature vector dimension results in a lower rate than the standard way, experiment findings demonstrate that it has higher retrieval accuracy than conventional methods using color and texture data.When it comes to either human or computerized plant identification, shape is the most often utilized characteristic.[6] Three low-level traits are investigated in this work in order to determine which one contributes the most to the identification of plant leaves. 455 leaves of herbal medicinal plants are used for intra- and inter-class identification; 70% of the dataset is used for training, while the remaining 30% is used for testing. Scale Invariant Feature Transform (SIFT) is used to extract shape features, color moments are used to represent color, and SegmentationBased Fractal Texture Analysis (SFTA) is used to characterize texture features. Fusion of texture and shape outperformed fusion of texture, shape, and color, according to an intraclass analysis. When compared to the identification rate using color or shape, the identification rate utilizing a single texture feature was also the highest.The idea that texture is the low-level feature that discriminates is further supported by inter-class analysis. Findings show that a single texture characteristic worked better than a color or shape feature, with a 92% identification rate.But for those who are not professionals and know very little or nothing about common botanical terms,[7] this becomes a laborious and difficult task. Still, this effort can be made somewhat easy by the advances in the disciplines of computer vision and machine learning. Though significant progress has been achieved, there is still no system that is so developed that it can recognize every species of plant. We have attempted to do the same in this investigation. Four processes are often involved in plant identification: acquiring images, pre-processing, feature extraction, and classification.Lastly, Multiclass-support vector machine was used to perform the classification; this method produced an accuracy of approximately 93.26%, which we want to improve even further. Numerous studies have been conducted to identify plant leaves. It does not, however, meet user expectations. In this work,[8] we provide a novel method for identifying plant leaves using kernel descriptors (KDES). Bo et al. have recently proposed KDES. It has been demonstrated that this is resilient to various object recognition issues. Once again, this strategy outperforms the state of the art, as demonstrated by the experimental findings obtained on two plant leaf datasets in this work.The experimental results demonstrate that compared to the previous methods, the suggested method has a greater recognition rate, is more robust, and requires less time to complete the training process.

3.DATASET COVERAGE : [Medical Leaf Dataset from Kaggle]

Kaggle is a website that provides a variety of datasets for practice and competition for those who are interested in data science and machine learning. Kaggle offers a number of medical leaf datasets, each with unique features and a focus. We have used the medical leaf dataset for identification of plant through images. The dataset consists of various images of plant leaves with various labels indicating their type and including multiple classes such as healthy, rust, and multiple types of leaf blight. The dataset is suitable for tasks like disease detection and classification in plant leaves, which can have applications in agriculture and plant health monitoring. Research projects that use CNN Variants to predict the plants to found great use in this dataset.

4.PROPOSED METHOD:

In proposed method, we are performing the identification of plants using Deep Convolution Neural Network of deep learning based on images. Deep learning approaches that have already shown to be quite successful in various image-based object classification scenarios are applied to the challenge of plant identification. To improve identification accuracy on the test set, multiple models are trained and prediction results are then bagged. When it comes to late fusion, ensembles typically perform better when there is a substantial degree of variation between the models. To produce a diversified collection of models, the following elements are change among them:

- Training dataset
- Random dataset partitioning for training and validation
- Network architecture
- Batch size
- Type of Solver
- learning rate schedule (base learning rate and decay factor)
- Training Picture (for weight initialization and model training)
- picture size
- Aspect ratio of Picture
- Augmentation of data (methods and degrees of influence)

A. Model Architecture:

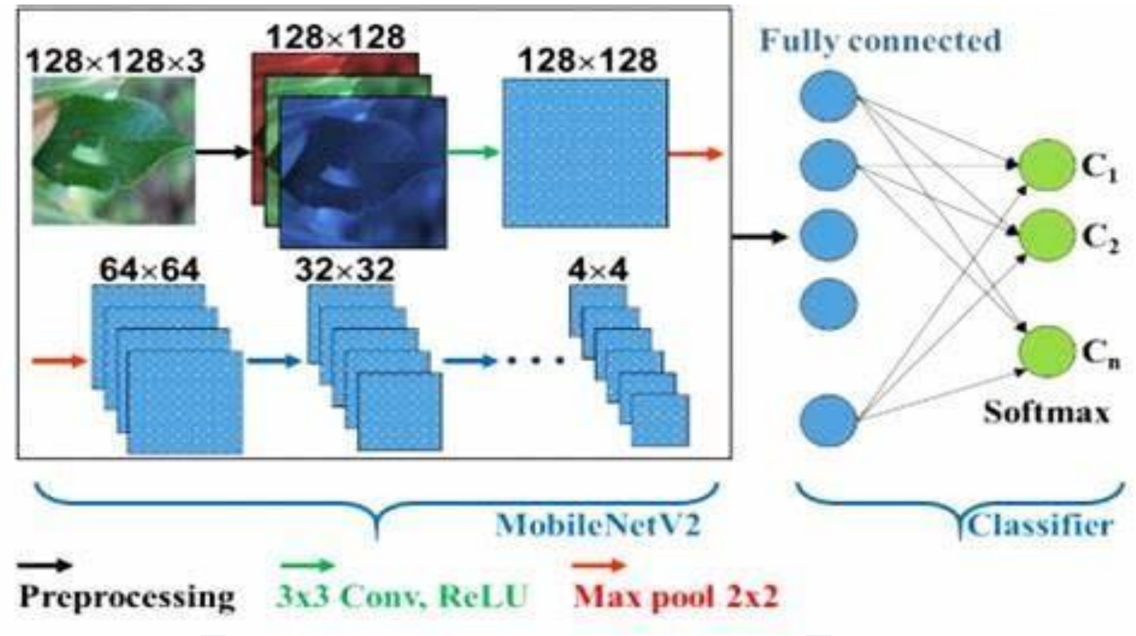

Fig: Architecture of mobilenetV2

B. Data Preprocessing:

To evaluate to what extent DCNNs can learn from noisy data compared to trusted data, some models are trained using only images of the Encyclopedia of Life dataset (plus in some cases images of the Medical Leaf dataset) while others are trained with all available images. It was also tried to form a mixture of both main datasets (see section Results).

The initial images used for testing and training have random aspect ratios and sizes. The networks utilized in this work only take square photos of a specific size, therefore images must be preprocessed by cropping or rescaling. Training images are rescaled to different dimensions and occasionally aspect ratios are also adjusted in order to increase variation within models.

Results in earlier Datasets projects were previously improved by assembling models using various image scales. Enhancing generalization involves scaling images to various dimensions and then randomly cropping them such that the network may see patches of marginally different resolutions and sections of the original image.

In addition, the datasets are divided into random partitions, or stratified folds, allowing each model to use a separate fold for training and the remaining folds for validation. the packing of models that have been trained on various folds. To guarantee compatibility with the model, the dataset should be loaded and pre-processed before being used to train a MobileNet model with an input size of 224x224 pixels. Each image must be resized to 224 by 224 pixels, the pixel values must be normalized to fall between 0 and 1, and if necessary, the class labels must be encoded into a numerical format. This is carried out for every image in the test set as well.

Fig: Santalum Album (Sandalwood)

Fig: Trigonella Foenumgraecum(Fenugreek)

Fig : Alpinia Galanga (Rasna)

Fig : Artocarpus Heterophyllus (Jackfruit)

C. Data Augmentation:

Diversifying the dataset is essential when augmenting data for a MobileNet model with 224x224 pixel input size in order to improve the model's capacity for generalization. A number of methods can be used to do this, including zooming in on the images, flipping them horizontally, shifting them vertically and horizontally, applying shear transformations, rotating them by a specific degree range, and choosing a fill mode for newly produced pixels.

To apply these augmentation approaches, for example, you can utilize the Image Data Generator class from TensorFlow and Keras. You can improve the performance and generalization of your MobileNet model by using data augmentation to produce a more robust and diversified training dataset. You also can use data augmentation methods like rotation, flipping, and shifting to make the training dataset more diverse.

After that, the dataset is usually divided into training, validation, and test sets. The training set is used to train the model, the validation set is used to adjust hyperparameters, and the test set is used to assess the performance of the finished model. At last, the pre-processed data is grouped together to enable effective training of the model.

Packages Used:

Packages	Language Interface	Platform
Tensorflow	Python (Keras), c/c++, java, go, r	Linux, macOS, Windows
Keras	Python,R	Linux, macOS, Windows
Numpy	Python, R, and Julia	Linux, macOS, Windows
matplotlib	Python, R, and Julia	Linux, macOS, Windows
tkinter	Python, R, perl and Tcl/Tk(native language of tkinter library)	Linux, macOS, Windows

Activation Functions:

a) RELU:

The Rectified Linear Unit activation function across its network, including in the last layer of classification and its depth wise separable convolutions. The definition of the activation function is: f(x) = max(0,x).

This activation function is added to MobileNetV2 after every convolutional layer to add non-linearity and aid in the network's ability to recognize intricate patterns in the input. ReLU is used in MobileNetV2 to improve speed while preserving efficiency, which is important for embedded and mobile applications.

b) SOFTMAX:

The probability distribution over the classes is usually computed in the final classification layer using the softmax activation function. The definition of the softmax function is:

$$softmax(xi)=e^{x}{}_{i}/\sum_{j}e^{x}{}_{j}$$

In MobileNetV2, the raw scores (logits) are converted into class probabilities a measure of each class's chance of being the right classification for a given input after the last fully connected layer using the softmax algorithm.

5. RESULTS :

The specific plant species being categorized, the amount and quality of the dataset, and the training parameters are some of the variables that can affect the effectiveness of a MobileNet-based plant identification model. MobileNetV2 is generally effective at achieving high accuracy at a low model size, which makes it appropriate for deployment on smartphones with limited resources.

With MobileNetV2, you would need to train the model on a collection of plant photos and assess its performance on a test set in order to obtain precise answers for a plant identification task. Accuracy, precision, recall, and F1 score are a few examples of evaluation metrics that might be used to gauge how well the model can identify different plant species.

In general, MobileNetV2 is a well-liked option for plant identification because of how well it handles image classification jobs and how efficient it is, especially on devices with low processing power.

6.CONCLUSION:

Deep convolutional neural networks were used to identify plant species by the application of transfer learning. The networks that are used are pre-trained deep learning models from MOBILENETV2. For plant identification, MobileNetV2 provides a strong and effective solution. Due to its focus on depth-wise separable convolutions and effective model design, MobileNetV2's architecture is ideal for deployment on devices with limited resources.

Through the use of transfer learning, optimization, and suitable data preprocessing methods, MobileNetV2 can be efficiently trained to identify plant species from photos with a high degree of accuracy. By adding to the training dataset, adjusting the model's architecture, and optimizing its hyperparameters, the model can be made even better. All things considered, MobileNetV2 is a useful tool for environmental and agricultural applications since it offers a scalable and effective solution for plant identification chores.

And we tested these networks using various network parameters and data augmentation on the Medicinal plant task datasets. To enhance system performance, we then combined the predictions of the top classifiers.

7.FUTURE WORK:

Future developments in MobileNetV2-based plant identification could concentrate on a number of areas. First, in order to increase the diversity of the training dataset and enhance the model's capacity to generalize to previously undiscovered plant species, scientists should investigate more advanced data augmentation methods.

Second, in order to make the MobileNetV2 model more efficient for deployment on edge devices and allow for real-time plant identification in field situations, efforts could be made to compress the model. Furthermore, examining the transferability of features acquired by MobileNetV2 among various plant species or domains may result in more resilient and versatile models.

Additionally, investigating fine-grained classification methods and ensemble learning strategies may improve the model's accuracy and capacity to distinguish between closely related plant species.

And last, adding other modalities to MobileNetV2, including text or environmental data, may result in more complete and precise plant identification systems. In general, future efforts to identify plants using MobileNetV2 show promise for enhancing environmental and agricultural monitoring methods.

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