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Plant Species Identification Using a Custom CNN Model and Geometric Morphometrics – A Comparative Analysis

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Abstract: The purpose of this study is to assess how well CNNs and different classifiers perform when it comes to identifying plant leaves based on their morphometric characteristics. Two methods have been used for this. 1) Using our custom named PLI-CNN(Plant Leaf Identifier-CNN) model 2) utilizing conventional classifiers to extract features from leaf images for classification. To identify distinct patterns, a dataset of leaf images from 10 different plant types is used to train our PLI-CNN model. Multiple classifiers are utilized to extract and classify morphometric features simultaneously. According to the results, classical classifiers can also achieve high accuracy using quality data, despite CNNs' superiority at feature learning. This suggests that both approaches can benefit from continued study into plant species identification and automated botanical studies.

Keywords: *Plant leaf identification, Convolutional Neural Networks, Morphometric Features, Deep Learning, Image Classification, Agricultural Automation*

1. Introduction

In many different fields, such as agriculture, environmental monitoring, and biodiversity conservation, plant identification is essential. Traditionally, the main technique used by traditional taxonomic procedures to distinguish between distinct plant species is leaf shape. On the other hand, new developments in computational methods have potential to transform the identification of plant leaves, and, improving the precision and effectiveness of classification of plant species. This work aims to improve plant leaf identification by utilizing the capabilities of contemporary computational techniques. We can either choose Geometric Morphometric methods (GMM) or classic Traditional Morphometrics (TM). Although TM uses statistical methods to measure a wide range of parameters, GMM makes use of landmark and outline data to provide better capabilities in breaking down complicated taxa by differentiating between shape and non-form components.

Using a deep learning Convolutional Neural Network (CNN) model and conventional morphometrics model combined with machine learning classifiers, we investigate two different methods for leaf class identification in this study. Creating a custom CNN model, named PLI-CNN (Plant Leaf Identifier-CNN), specifically for leaf categorization is the first approach. This method uses CNNs' deep learning ability to identify features from leaf images and categorize them into appropriate classes. To identify unique characteristics of various plant species, a dataset of leaf images is used to train the PLI-CNN model. The second approach uses conventional morphometric measures to extract features. The five different classifiers—Support Vector Machines (SVM), Artificial Neural Networks (ANN), k-Nearest Neighbors (k-NN), Naive Bayes (NB), and Random Forest are then fed these measurements, which include leaf form, size, and other morphological properties.

The purpose of this comparative study is to assess how well our PLI-CNN model performs in leaf categorization in contrast to conventional morphometrics. We hope to determine the advantages and disadvantages of each strategy for leaf class identification by contrasting these two approaches. This work advances automated plant classification systems and sheds light on the best practices for precise and effective leaf categorization. Furthermore, creating reliable leaf classification algorithms may have a wide range of useful uses. For example, precise plant species identification can help with yield optimization, pest control, and crop management in agriculture. These systems can also be very useful instructional tools, allowing enthusiasts and students to quickly identify different plant species when out in the field.

2. Literature Study

JING WEI TAN et al [1]: To improve plant classification and conservation, this research investigates the use of deep learning in plant leaf recognition. It walks through the method step-by-step, from extracting texture and shape data to segmenting plant leaf photos. Using techniques like K-nearest neighbors, Kohonen network, and Support Vector Machines to compare 50 plant leaf databases, it reveals notable variances, most notably in ginkgo leaf

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identification. The study highlights how accurate recognition can be achieved with minimal recognition times using this strategy, even in complex backdrops. All things considered, it shows how deep learning can improve our understanding of and ability to preserve plant species, providing information for future study and use.

SUE HAN LEE et al [2] : This paper proposes the use of leaf databases for plant predictive modelling, which results in different leaf characteristics depending on the type of data and how it is extracted. Convolutional Neural Networks (CNN) are introduced in this study in response, together with Deconvolutional Networks (DN) for feature interpretation, for the purpose of directly extracting leaf features from raw input data. The results show a hierarchical representation in the leaf data, with venation orders outperforming outline shape as representative features. Hybrid feature extraction models are designed with these discoveries in mind, as they are consistent with botanical definitions of leaf features. As a result, the study provides insights into how to innovate to increase the discriminative capacity of plant classification systems.

JIANG HUIXIAN et al [3] : This paper investigated the use techniques of deep learning, mainly Convolutional Neural Networks (CNN), for accurate and efficient plant image recognition. It highlights the importance of plant identification in fields like agriculture and environmental science and details the methodology, including dataset preparation and model architecture. Through extensive experiments, the study demonstrates that deep learning models significantly outperform traditional methods in terms of accuracy and robustness. Despite challenges like varying lighting conditions and species similarities, the paper concludes that deep learning and ANN offer substantial improvements and hold promise for future advancements in plant recognition technology.

VINCENZO VISCOSI et al [4]: Despite their usefulness in quantitative form analysis, computerized geometric morphometric approaches have not been widely used in botanical investigations, as the literature review highlights. Botanists have not yet completely realized the potential of these techniques, in contrast to zoologists who make extensive use of them. For landmark-based geometric morphometrics, plant leaves—which are frequently used in taxonomic analyses—are a good fit. This work illustrates size and shape variable calculation, hierarchical design for error testing and variation analysis, and size-effect control (allometry) for discrimination accuracy assessment using free software and sessile oak leaf datasets. The findings show a low measurement error, significant individual variation, and effective discrimination accuracy. In order to improve scientific precision in the characterization of biodiversity, the study promotes a wider integration of geometric morphometrics in botanical taxonomy and biology.

3. Proposed Method

This research consists of two methodologies:

1. Creating a custom CNN model (PLI-CNN) specifically for leaf categorization is the first approach. This method uses CNNs' deep learning ability to identify features in leaf photos and categorize them into the appropriate classes. To identify the unique characteristics of various plant species, a dataset of leaf images is used to train the PLI-CNN model.

2. The second approach uses conventional Geometric Morphometric measures to extract features. These measurements that comprise of size, shape, and other morphological characteristics of leaves are subsequently given as inputs to various classifiers. We use five machine learning approaches - Support Vector Machines (SVM), Artificial Neural Networks (ANN), k-Nearest-Neighbors (k-NN), Naïve-Bayes (NB) and Random Forest to classify these attributes.

3.1 *Conventional Neural Networks (CNNs)*

1. Dataset Collection: We used a dataset of 1500 images which was heavily sourced from PlantVillage Dataset. There are ten classes that have been considered in our dataset, which are, Apple, Blueberry, Cherry, Grape, Peach, Pepper Bell, Potato, Raspberry, Strawberry, and Soybean.

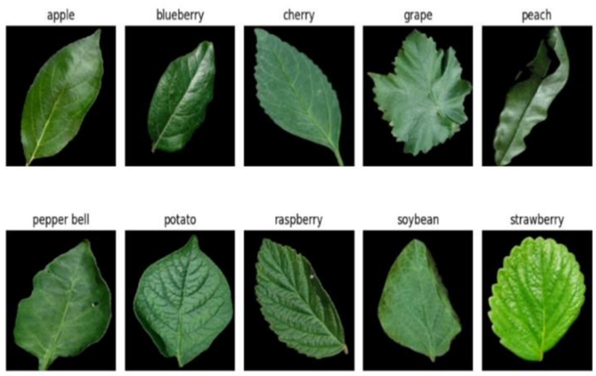

Fig. 3.1.1 Data Set

2. Image Pre-processing: To improve the quality of input data for machine learning models, image preprocessing is essential. OpenCV is used to transform images from the original BGR format to RGB format. To focus on structural elements and lessen computational complexity, images are transformed to grayscale. Then, Gaussian blur has been used to blur away features and noise which improves edge recognition. To highlight edges in the image, the gradient magnitude is calculated using the Sobel operator. To create binary pictures, absolute edges are thresholded and morphological skeletonization is carried out to extract the crucial leaf shape characteristics.

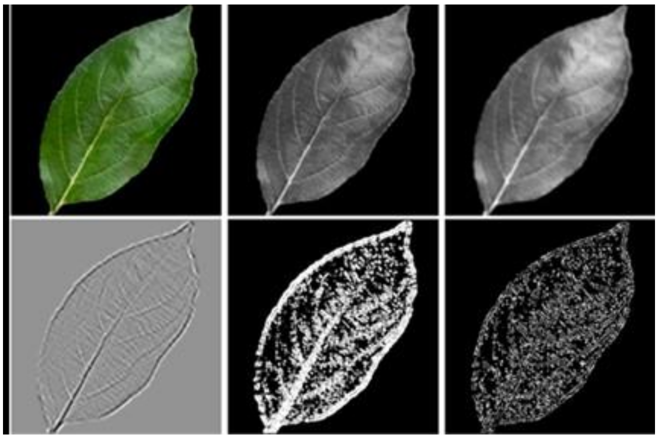

Fig 3.1.2 Single Image Pre-Processing

3. Model Architecture - PLI-CNN: Our Plant Leaf Identifier – CNN (PLI-CNN) model comprises of multiple layers arranged in a sequential fashion. It is intended to classify grayscale images with a pixel size of 256x256 into 10 groups. To process the input images, the input layer is a Conv2D layer comprising of 16 filters, a 3x3 sized kernel, and the ReLU activation function. A MaxPooling2D layer that decreases the spatial dimensions by a factor of two comes after this.

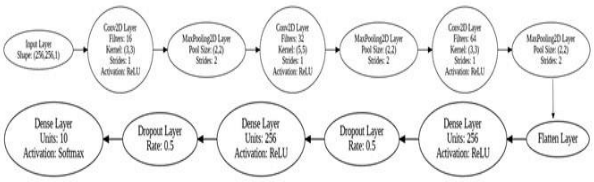

Fig 3.1.4 PLI-CNN Model Architecture -1

The design then consists of a MaxPooling2D layer for additional dimensionality reduction after a second Conv2D layer with 32 filters and a 5x5 kernel size. With a 3x3 sized kernel and 64 filters, the third Conv2D layer is followed by a MaxPooling2D layer that further reduces spatial disparity. The convolutional layers' output is then flattened into a 1D vector and fed through two fully connected (Dense) layers, each of which has ReLU activation and 256 units. Each thick layer is followed by 0.5 dropout layers to avoid overfitting. To produce a probability distribution across the ten classes considered, the last layer taken is a Dense layer that has 10 neurons and the activation function being Softmax.

The optimizer, loss function and evaluation metrics are the three main components that are configured during the compilation of the model.

```
model = Sequential()

model.add(Conv2D(16, (3,3), 1, activation='relu', input_shape=(256,256,1)))
model.add(MaxPooling2D())

model.add(Conv2D(32, (5,5), 1, activation='relu'))
model.add(MaxPooling2D())

model.add(Conv2D(64, (3,3), 1, activation='relu'))
model.add(MaxPooling2D())

model.add(Flatten())

model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))

model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))

model.add(Dense(10, activation='softmax'))
```

Fig. 3.1.3 PLI-CNN Model Architecture Code

Optimizer (Adam): Adam optimizer is selected due to its efficacy and efficiency in managing huge datasets and intricate models. In contrast to conventional gradient descent techniques, it helps to converge more quickly and consistently by adjusting the learning rate in accordance with the moving averages of the gradients and their squared values. This makes it especially suitable for applications involving variable data properties and high-dimensional parameter spaces.

Loss Function (Sparse categorical cross-entropy): Because it works best in multi-class classification problems when labels are given as integers (each class is represented by a single integer), sparse categorical cross-entropy is chosen. By enabling the model to operate directly with integer labels, sparse categorical cross-entropy streamlines the data preprocessing and makes it more efficient and straightforward than categorical cross-entropy, for which one-hot encoded labels are necessary.

We evaluated and optimized the model performance in this study using accuracy and loss functions. To provide for a thorough review, the dataset was divided into three parts: 1) To enable the model to understand patterns and characteristics from the data, it is trained using the Training Set (70%). 2) Checkpoint for adjusting hyperparameters is provided by the Validation Set (20%), which is used to fine-tune model parameters and prevent overfitting, and, 3) the Testing Set (10%), applied to examine the accuracy and generalization capacity of the final model performance in an objective manner.

3.2 Morphometrics

1. Dataset Creation: Our initial step was defining the features and labels we wished to extract from the photos of plant leaves in order to build our dataset. "apple," "blueberry," "cherry," "grape," "peach," "pepper bell," "potato," "raspberry," "soybean," and "strawberry" were the definitions of the labels used in this technique. Area, perimeter, physiological length, physiological width, aspect ratio, rectangularity, circularity and seven Hu Moments ('hu1' through 'hu7') are among the attributes or features

calculated.

2. Image Processing: We went through the relevant image folder for every label (apple, blueberry, etc.). To improve quality and prepare each image for feature extraction, a number of pre-processing procedures were performed on them:

- Reading and Converting Images: We used OpenCV to read the image and convert it from BGR to RGB format.
- Grayscale Conversion: Next, a grayscale conversion was applied to the RGB image.
- Gaussian Blur: A 25x25 kernel size Gaussian blur was added to lower noise and enhance edge detection.
- Thresholding: The blurry image was transformed into a binary image by applying Otsu's approach, which allowed the leaf in the foreground to be distinguished from the background.
- Inversion: To make sure the leaf was white on a black background, the binary picture was inverted.

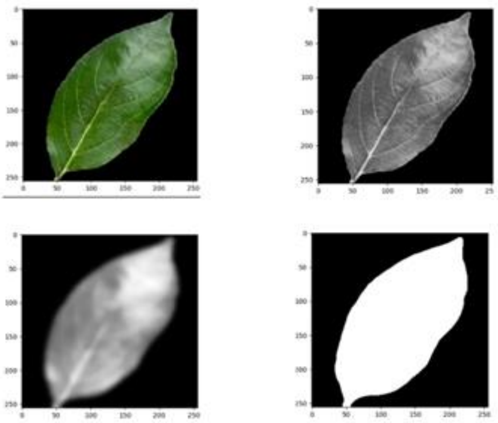

Fig 3.2.1 Image Pre-Processing

3. Feature Extraction: We identified many features for every contour in the image by using the binary image that had been previously processed:

- Area: The contour's area.
- Perimeter: The elongation of the contour's periphery.
- Bounding Rectangle: It denotes the physiological length and width of the contour. Its width (w) and height (h) are measured.
- Aspect Ratio: The ratio of width to height.
- Rectangularity: The ratio of the contour area to the bounding rectangle's area.
- Circularity: The area to perimeter squared ratio.
- Hu Moments: In order to represent the contour's form features, seven invariant, moments, or Hu Moments, were computed.

After each characteristic was computed, it was added to a list and saved in a dictionary. To determine each leaf's class, the labels were also added to this lexicon. The gathered data was transformed into a Pandas DataFrame with columns corresponding to the specified features and labels after all photos had been processed.

4. Model Training and Evaluation: First, we extracted the labels and features from the above .csv file. Each of the other columns indicated a feature (X), and the 'label' column was designated as the target variable (y). 80% of the dataset was then used for testing, while the remaining 20% was used for training.

For the purpose of classifying the leaf images using the collected features, we tested five classifiers. Naive Bayes, Random Forest, Artificial Neural Networks (ANN), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) were among the classifiers used. Using scaled training and testing data, each classifier was put through its paces.

4. Results

Our comparative research of our CNN model and different classifiers yielded important insights into how well they performed depending on the features that were extracted.

Table 1 : RESULTS

CLASSIFIER	ACCURACY
CNN	91% - 94%
SVM	83%
KNN	82%
RANDOM FOREST	94%
NAÏVE BAYES	51%
ANN	92%
TUNED ANN	97%

4.1 CNN

Although it has a larger computational complexity than other neural networks, the Convolutional Neural Network (CNN) demonstrated varied accuracy ranging from 91% to 94%, confirming its efficacy in capturing complex patterns and spatial hierarchies in leaf images.

```
4/4 [==============================] -
Training Accuracy: 0.9744318127632141
Validation Accuracy: 0.921875
Test Accuracy: 0.932692289352417
```

4.1.1. CNN Results

CNNs are exceptionally good in learning spatial hierarchies of features automatically and adaptively, which is their main advantage when it comes to image-related tasks.

4.2 SVM

With an accuracy of 83%, the Support Vector Machine (SVM) classifier demonstrated a good capacity for generalization across several leaf classes. SVM's memory efficiency and efficacy in high-dimensional domains are advantages. SVMs are sensitive to the selection of the kernel and regularization parameters, and they can be computationally demanding for large datasets.

Classification Report for SVM:

	precision	recall	f1-score	support
apple	0.83	0.89	0.86	27
blueberry	0.96	0.82	0.88	28
cherry	0.96	0.96	0.96	23
grape	0.95	0.95	0.95	20
peach	0.90	0.67	0.77	27
pepper bell	0.65	0.93	0.76	40
potato	0.81	0.63	0.71	27
raspberry	0.70	0.79	0.74	29
soybean	0.95	0.69	0.80	26
strawberry	0.91	0.94	0.92	32
accuracy			0.83	279
macro avg	0.86	0.83	0.84	279
weighted avg	0.85	0.83	0.83	279

SVM Accuracy: 0.83

Fig 4.2.1 SVM Classification Report

4.3 KNN

Comparably, the K-Nearest Neighbors (KNN) classifier performed admirably, exhibiting an accuracy of 82%, proving its usefulness in spite of its ease of use. The simplicity of KNN's implementation and its intuitive nature are its main advantages. KNN can be sensitive to the number of neighbors and distance metric selected, which might cause it to run slowly for large datasets since it needs to calculate the distance to each training sample during prediction.

Classification Report for KNN:

	precision	recall	f1-score	support
apple	0.77	0.89	0.83	27
blueberry	0.95	0.75	0.84	28
cherry	1.00	1.00	1.00	23
grape	0.95	1.00	0.98	20
peach	0.93	0.93	0.93	27
pepper bell	0.74	0.80	0.77	40
potato	0.79	0.70	0.75	27
raspberry	0.71	0.69	0.70	29
soybean	0.60	0.69	0.64	26
strawberry	0.87	0.81	0.84	32
accuracy			0.82	279
macro avg	0.83	0.83	0.83	279
weighted avg	0.82	0.82	0.82	279

KNN Accuracy: 0.82

Fig 4.3.1 KNN Classification Report

4.4 RANDOM FOREST

With an accuracy of 91%, the Random Forest classifier demonstrated exceptional performance as well, showing capacity to manage data fluctuation through the use of numerous decision trees. Random Forest has several advantages, including as its ability to handle both numerical and categorical data, ease of implementation, and resistance to overfitting. However, for larger forests, it may consume significant computer resources and be less interpretable than single decision trees.

Classification Report for Random Forest:

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	27
blueberry	1.00	1.00	1.00	28
cherry	1.00	1.00	1.00	23
grape	0.95	0.95	0.95	20
peach	0.89	0.93	0.91	27
pepper bell	0.90	0.95	0.93	40
potato	0.89	0.89	0.89	27
raspberry	0.88	0.76	0.81	29
soybean	0.88	0.88	0.88	26
strawberry	0.97	1.00	0.98	32
accuracy			0.94	279
macro avg	0.94	0.94	0.94	279
weighted avg	0.93	0.94	0.93	279

Random Forest Accuracy: 0.94

Fig 4.4.1 Random Forest Classification Report

4.5 NAÏVE BAYES

The Naive Bayes classifier, on the other hand, has a much lower accuracy of 51%. The Naive Bayes model's strong independence assumptions, which might not apply to the complex and connected morphometric characteristics of plant leaves, are the cause of this disparity. Naive Bayes' simplicity and efficiency are its advantages, especially when dealing with big datasets. The assumption of feature independence, which is frequently incorrect, is its drawback.

Classification Report for Naive Bayes:

	precision	recall	f1-score	support
apple	1.00	0.56	0.71	27
blueberry	0.61	0.71	0.66	28
cherry	0.91	0.87	0.89	23
grape	0.48	1.00	0.65	20
peach	0.67	0.15	0.24	27
pepper bell	0.48	0.72	0.58	40
potato	0.00	0.00	0.00	27
raspberry	0.22	0.14	0.17	29
soybean	0.32	0.92	0.48	26
strawberry	0.83	0.16	0.26	32
accuracy			0.51	279
macro avg	0.55	0.52	0.46	279
weighted avg	0.55	0.51	0.45	279

Naive Bayes Accuracy: 0.51

Fig 4.5.1 Naïve Bayes Classification Report

4.6 ANN

With a high accuracy of 92%, the Artificial Neural Network (ANN) classifier demonstrated exceptional performance. This finding highlights the ANN's capacity to deduce intricate patterns from the morphometric parameters, which makes it an effective tool for classifying leaves. The flexibility and capacity to simulate non-linear interactions are two of ANN's primary features. The drawbacks of ANNs are that they are computationally expensive, need a lot of data for training, and can overfit if improperly regularized.

Classification Report for ANN:

	precision	recall	f1-score	support
apple	0.93	0.93	0.93	27
blueberry	0.93	0.93	0.93	28
cherry	0.96	0.96	0.96	23
grape	0.95	0.95	0.95	20
peach	0.87	1.00	0.93	27
pepper bell	0.97	0.90	0.94	40
potato	0.92	0.85	0.88	27
raspberry	0.83	0.83	0.83	29
soybean	0.88	0.88	0.88	26
strawberry	0.97	1.00	0.98	32
accuracy			0.92	279
macro avg	0.92	0.92	0.92	279
weighted avg	0.92	0.92	0.92	279

ANN Accuracy: 0.92

Fig 4.6.1 ANN Classification Report

4.7 TUNED ANN

The Tuned ANN produced an exceptional outcome, achieving a high accuracy of 97% following hyperparameter modification. This indicates that fine-tuning model parameters is crucial for improving performance and obtaining almost flawless categorization outcomes. Following settings were found to be the best fit: {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (100, 100), 'learning_rate': 'constant','solver': 'adam'}. The greatest cross-validation accuracy that could be achieved during the tuning process was 96.40%, demonstrating how well parameter adjustment can enhance model performance.

Classification Report for tuned ANN:

	precision	recall	f1-score	support
apple	0.93	1.00	0.96	27
blueberry	1.00	0.96	0.98	28
cherry	1.00	1.00	1.00	23
grape	1.00	1.00	1.00	20
peach	0.96	1.00	0.98	27
pepper bell	1.00	0.97	0.99	40
potato	0.89	0.93	0.91	27
raspberry	0.90	0.90	0.90	29
soybean	1.00	0.92	0.96	26
strawberry	1.00	1.00	1.00	32
accuracy			0.97	279
macro avg	0.97	0.97	0.97	279
weighted avg	0.97	0.97	0.97	279

Tuned ANN Accuracy: 0.97

Fig 4.7.1 Tuned ANN Classification Report

5. Conclusion and Future Scope

To sum up, by utilizing both morphometric feature extraction approaches and Convolutional Neural Networks (CNN), our study contributes significantly to the field of plant leaf identification. We have shown in our report how well these methods work for correctly categorizing plant leaves according to their outward appearance. The CNN model demonstrated remarkable accuracy in the range of 91 - 94% in categorizing plant leaves into their respective species, owing to its capacity to learn hierarchical characteristics straight from photos. This demonstrates how deep learning approaches can effectively capture complex patterns and changes in leaf images, opening the door to the development of effective automated identification systems.

Furthermore, we used standard machine learning classifiers in with morphometric parameters including perimeter, length, width, circularity, rectangularity, and Hu moments to achieve promising results. Specifically, the Tuned ANN classifier achieved an impressive 97% accuracy rate, demonstrating the effectiveness of morphometric feature extraction in capturing crucial attributes for leaf classification.

We have created a thorough framework for plant leaf identification that can reliably differentiate between various species by merging these approaches. This framework has enormous potential for use in a variety of fields, including agriculture, biodiversity protection, and environmental monitoring, where it is crucial to identify species quickly and accurately. In order to increase classification accuracy, future research can look into improving both the CNN model and the morphometric feature extraction procedure.

In the future, we hope to expand our research by improving our framework for plant leaf identification by utilizing the FLAVIA dataset. The FLAVIA dataset is a significant resource for fine-tuning our classification models because of its large collection of high-quality leaf images that represent various plant species. By adding the FLAVIA dataset to our framework, we can improve the quality of our training data and create more reliable convolutional neural network (CNN) and classic morphometric models, which will increase efficiency. Through the integration of a wide variety of leaf images from FLAVIA, we can improve our CNN model's capacity for generalization, which will increase its accuracy and enable it to categorize a wider range of plant species.

Additionally, the FLAVIA dataset offers a chance to investigate cutting-edge methods for feature extraction and representation. We may generate more complete feature sets that capture a larger range of leaf attributes by merging our existing dataset with morphometric features.

6. References and Footnotes

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References

[1] Deep Learning for Plant Species Classification Using LeafVein Morphometric Jing Wei Tan, Siow-Wee Chang, Sameem Abdul-Kareem, HwaJen Yap, and Kien-Thai Yong

[2] How deep learning extracts and learns leaf features for plant classification Sue Han Lee, Chee Seng Chan, Simon Joseph Mayo, Paolo Remagnin

[3] The Analysis of Plants Image Recognition Based on Deep Learning and Artificial Neural Network Jiang Huixian

[4] Leaf Morphology, Taxonomy and Geometric Morphometrics: A Simplified Protocol for Beginners Vincenzo Viscosi1*, Andrea Cardini2,3,4

[5] D. Wang, A. Khosla, R. Gargeya, H. Irshad, and A. H. Beck, "Deep learning for identifying metastatic breast cancer," *Int. Symp. Bio. Imaging's Grand Challenge*, arXiv:1606.05718, 2016.

[6] G. Hinton, L. Deng, D. Yu, G. E. Dahl, A. R. Mohamed, N. Jaitly, A. Senior, V. Vanhoucke, P. Nguyen, T.N. Sainath and B. Kingsbury, "Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups," *IEEE Signal Process. Mag.*, vol. 29, no. 6, pp. 82— 97, Nov. 2012.

[7] R. Malladi, and J. A Sethian, "A unified approach to noise removal, image enhancement, and shape recovery," *IEEE Trans. Image Process.*, vol. 5, no. 11, pp. 1554–1568, Nov. 1996.

[8] V. Metre and J. Ghorpade, "An overview of the research on texture based plant leaf classification," *Int. J. Comput. Sci. Net.*, vol. 2, 2013.

[9] C. Arun, W. S. Emmanuel, and D. C Durairaj, "Texture feature extraction for identification of medicinal plants and comparison of different classifiers," *Int. J. Comput. Appl.*, vol. 62, no. 12, 2013.

[10] J. S. Cope, P. Remagnino, S. Barman, and P Wilkin, "The extrac- tion of venation from leaf images by evolved vein classifiers and ant colony algorithms," in *Int. Conf. Adv. Concepts Intell. Vis. Syst.*,Dec. 2010, pp. 135–144.

[11] B. S. Anami, S. N. Suvarna, and A Govardhan, "A combined color, texture and edge features based approach for identification and classification of indian medicinal plants," *Int. J. Comput. Appl.*, vol. 6, no. 12, pp.45–51, 2010.

[12] M. Larese, R. Craviotto, M. Arango, C. Gallo, and P. Granitto, "Legume identification by leaf vein images classification," in *Proc. 17th Iberoamerican Congr. Progress Pattern Recognit. Image Anal. Comput. Vis. Appl.*, 2012, pp. 447–454.

[13] A. Kadir, L. E. Nugroho, A. Susanto, and P. I. Santosa, "Neural network application on foliage plant identification," *Int. J. Comput. Appl.*, vol. 29, no. 9, pp. 15– 22, 2013.

[14] M. Sulc, and J. Matas, "Texture-based leaf identification,"

Proc. Eur. Conf. Comput. Vis., 2014, pp. 185–200.

[15] S. H. Lee, C. S. Chan, P. Wilkin, and P. Remagnino, "Deep- plant: Plant identification with convolutional neural networks," in *Proc. IEEE Int. Conf. Image Process.*, Sep. 2015, pp. 452–456.

[16] Deep Learning for Plant Species Classification Using Leaf Vein Morphometric Jing Wei Tan , Siow-Wee Chang , Sameem Abdul-Kareem, Hwa Jen Yap , and Kien-Thai Yong

[17] K. J. Willis, et al., "State of the World's plants 2017,"*Report*, RoyalBotanic Gardens, Kew 2017.

[18] A. Krizhevsky, I. Sutskever, and G. E Hinton, "Imagenet classifica-tion with deep convolutional neural networks," in *Proc. 25th Int. Conf. Neural Inf. Process. Syst.*, 2012, pp.1097–1105.

[19] I. Goodfellow, Y. Bengio, and A. Courville, "Introduction," *Deep Learning*. Cambridge, MA: MIT Press, vol. 1, pp. 1– 12, 2015.

[20] D. Wang, A. Khosla, R. Gargeya, H. Irshad, and A. H. Beck, “Deep learning for identifying metastatic breast cancer,” *Int. Symp. Bio. Imaging’s Grand Challenge*, arXiv:1606.05718, 2016.

[21] R. Malladi, and J. A Sethian, “A unified approach to noise removal, image enhancement, and shape recovery,” *IEEE Trans. Image Process.*, vol. 5, no. 11, pp. 1554–1568, Nov. 1996.

[22] V. Metre and J. Ghorpade, “An overview of the research on texture based plant leaf classification,” *Int. J. Comput. Sci. Net.*, vol. 2, 2013.

[23] C. Arun, W. S. Emmanuel, and D. C Durairaj, “Texture feature extraction for identification of medicinal plants and comparison of different classifiers,” *Int. J. Comput. Appl.*, vol. 62, no. 12, 2013.

[24] J. S. Cope, P. Remagnino, S. Barman, and P Wilkin, “The extrac- tion of venation from leaf images by evolved vein classifiers and ant colony algorithms,” in *Int. Conf. Adv. Concepts Intell. Vis. Syst.*,Dec. 2010, pp. 135–144.

[25] B. S. Anami, S. N. Suvarna, and A Govardhan, “A combined color, texture and edge features based approach for identification and classification of indian medicinal plants,” *Int. J. Comput. Appl.*, vol. 6, no. 12, pp.45–51, 2010.

[26] M. Larese, R. Craviotto, M. Arango, C. Gallo, and P. Granitto, “Legume identification by leaf vein images classification,” in *Proc. 17th Iberoamerican Congr. Progress Pattern Recognit. Image Anal. Comput. Vis. Appl.*, 2012, pp. 447–454.

[27] A. Kadir, L. E. Nugroho, A. Susanto, and P. I. Santosa, “Neural network application on foliage plant identification,” *Int. J. Comput. Appl.*, vol. 29, no. 9, pp. 15– 22, 2013.

[28] M. Sulc, and J. Matas, “Texture-based leaf identification,” *Proc. Eur. Conf. Comput. Vis.*, 2014, pp. 185–200.

[29] S. H. Lee, C. S. Chan, P. Wilkin, and P. Remagnino, “Deep- plant: Plant identification with convolutional neural networks,” in *Proc. IEEE Int. Conf. Image Process.*, Sep. 2015, pp. 452–456.