Identification Of Tree Species From Images Using Convolutional Neural Networks(CNN)

Nirmale bhupinder kour S. Singh[1],Khansole B.A[2]
[2]Professor
[1, 2] Matoshri Pratishtha Group of Institutions, Nanded.

Abstract- *The abstract outlines a methodology for automatically identifying tree species through analyzing leaf images using machine learning techniques, specifically convolutional neural networks (CNNs). It highlights the challenge of obtaining root samples for identification and emphasizes the importance of feature extraction in distinguishing between species. By leveraging multi-dimensional features such as color, shape, and leaf vein signatures, the proposed CNN-based approach aims to provide a robust solution for tree species identification.*

The abstract introduces the significance of tree species identification in forest management, highlighting the challenges in obtaining root samples for identification. It proposes a method wherein leaf images are uploaded to a PC, and essential features are extracted using image processing techniques. Emphasis is placed on the critical role of feature extraction in ensuring the robustness of the identification system. The abstract then discusses the utilization of machine learning techniques, specifically convolutional neural networks (CNNs), to automatically identify tree species. It underscores the multi-dimensional nature of leaf features such as color, shape, and vein signatures, and the difficulty in finding a single feature for accurate identification. The CNN approach is presented as a solution to integrate these features effectively. Finally, the abstract lists keywords related to the topic, including tree species identification, machine learning techniques, classification, and feature extraction.

Keywords- Tree species identification; machine learning techniques;classification; Neural Network (CNN)

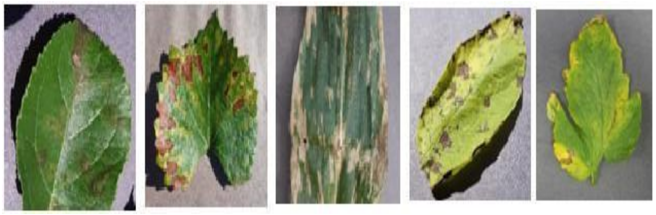
I. INTRODUCTION

Tree species identification is crucial for forest management. From the perspective of plant taxonomy, leaves, flowers, roots, and fruits all carry important information to distinguish different species. Roots, however, are buried in the ground and not easy to obtain. When the leaf image is uploaded to PC and then its essential features are identified and recorded using image processing methods. Feature extraction is a critical stage because the ability of a system to discriminate various types of leaves depends on the features extracted. The features have to be stable in order to make the identification system robust. Subsequently the plant leaf is recognized using techniques of machine learning. We will provide an effective approach to automatically identify tree species convolutional neural network(CNN). The convolutional neural network is a widely-used classifier, and provides an alternative for the traditional image recognition approach.

The work will identify tree species by analyzing tree leaves, which have multi-dimensional features such as color, shape, and leaf vein signatures. Since it is difficult to find a single leaf feature to accurately identify tree species, convolutional neural networks are employed to integrate multi-dimensional leaf features. The most important sector of our Economy is Agriculture. Various types of disease damages the plant leaves and effects the production of crop there for Leaf disease detection is important. Regular maintenance of plant leaves is the profit in agricultural products. Farmers do not expertise in leaf disease so they producing lack of production. Leaf disease detection is important because profit and loss depend on production. So that here use deep learning techniques to detect apple, grape, corn [11], potato, and tomato plant leaves diseases. That contains twenty-four types of leaf diseases and twenty-four thousand leaves images are used [13].

Apple, grape, corn, potato, and tomato plant leaves which are categorized total 24 types of labels apple label namely: Apple scab, Black rot, apple rust, and healthy. Grape label namely: Black rot, Esca, healthy, and Leaf blight. Corn label namely: Corn Cercosporin spot Gray spot, Corn rust, Corn healthy, Corn Northern Blight[11][13]. Potato label namely: Early blight, healthy, and Late blight. Tomato label namely: bacterial spot, early blight, healthy, late blight, leaf mold, septoria leaf spot, spider mite, target sport, mosaic virus[11][13].

The dataset consist of 31,119 images of apple, grape, potato and tomato, all Images are resized into 256 x 256,that images divided into two parts training and testing dataset[11][13].



1. Apple scab 2. Grape Esca 3.Corn leaf spot 4.potato Early 5.Tomato BactBlightSpot

Fig.1.1.Leaves with Disease part.

In fig.1 we can see vegetable and fruit leaves like potato, tomato, corn, apple, grape with diseased part this disease can be easily detected using deep learning techniques [13].

This disease detected using convolutional neural network (CNN), and also this model is compared with VGG16. Images are resized into 224 x 224[13].

1.1Overview of Existing Work

Existing work related to leaf disease detection using CNNshow to detect and classify leaf disease using image processing techniques that follow steps like

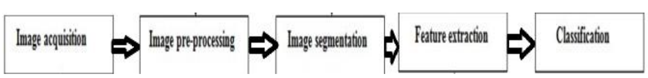


fig 1.1 general block dig of feature based approach

Image Acquisition involves capturing images via a digital camera, storing them digitally for MATLAB processing.

Image Preprocessing aims to enhance image information by removing distortions and reinforcing features. Techniques include adjusting image size dynamically, filtering noise, converting images, enhancing features, and applying morphological operations.

In Image Segmentation, the K-means clustering technique partitions pictures into clusters, with at least one cluster containing the major area of unhealthy parts. The algorithm classifies objects into K categories based on features. Feature extraction involves extracting texture features using GLCM (Gray-Level Co-occurrence Matrix) after forming clusters. For disease testing, Classification utilizes the Random Forest classifier, which is effective in categorizing leaf diseases.

1.2IMPLEMENTATION WORK:

The dataset comprises 24 types of plant leaves, including Apple, Corn, Grape, Potato, and Tomato, with various disease labels. Among 31,119 images, 24,000 are selected, resized to 256 x 256, and divided into training and testing datasets using an 80-20 split. A CNN model is then trained on this data for disease classification.

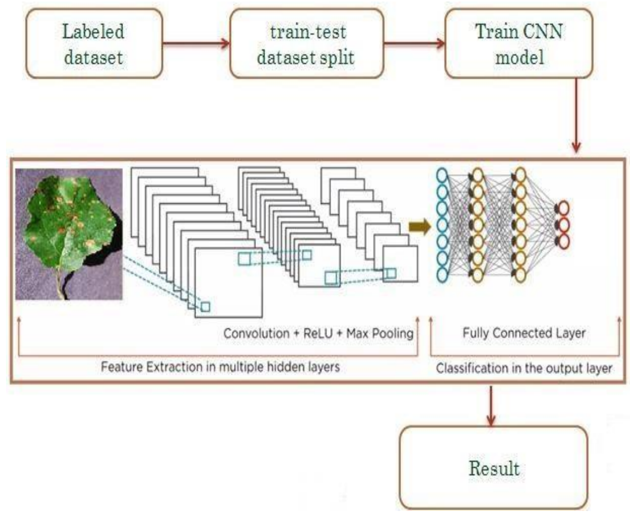


Fig1. 2: Proposed workflow [12].

CNNs are adept at classifying unstructured image inputs into output labels. They require minimal preprocessing, automatically extract features, and excel in leaf disease detection. The LeNet architecture, a simple CNN model, is often employed for this purpose. It comprises convolution, activation, max-pooling, and fully connected layers. The model expands upon LeNet with additional convolution, activation, and pooling layers. Each block includes these layers for feature extraction and introduces non-linearity. Dropout regularization with a 0.5 keep probability mitigates overfitting. The classification block entails two fully connected layers followed by a softmax activation function for probability computation across ten classes.

III. METHODOLOGY

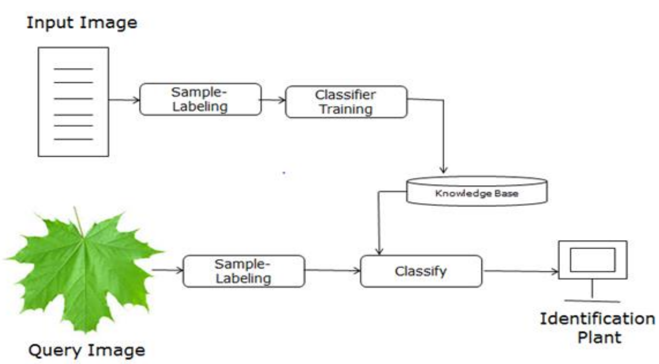
3.1 Design of the proposed solution

1. Convolutional neural networks model

CNNs, a class of deep neural networks, excel in analyzing visual data with minimal preprocessing. Also known as SIANNs, they exhibit shift invariant properties due to their shared-weights architecture. Inspired by the animal visual cortex, CNNs mimic the receptive field concept, where neurons respond to stimuli within specific regions. They require less preprocessing compared to traditional methods, learning filters autonomously instead of relying on hand-engineering. This self-learning capability reduces dependence on prior knowledge and human effort in feature design, making CNNs highly advantageous for image classification tasks.

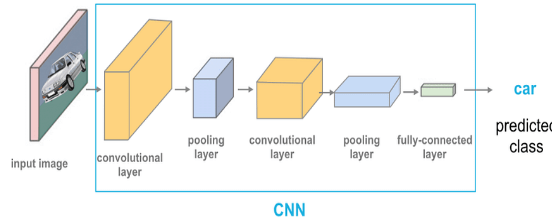
How to take a image

To standardize backgrounds in the Leafsnap database, a three-step preprocessing approach is implemented. First, images are converted from RGB to grayscale using Equation 2. Then, the OTSU algorithm segments foreground and background. Finally, background pixels are set to (255,255,255) in the original image for a clean background. Additionally, image size is reduced to 50x50 using bilinear interpolation to lower computational costs while maintaining classification accuracy. CNNs, a type of deep, feed-forward network, are commonly utilized in machine learning for visual imagery analysis.



CNNs, or ConvNets, minimize preprocessing needs with a shared-weights architecture, known as SIANNs for their shift invariance. Inspired by the animal visual cortex, they mimic its connectivity pattern, where neurons respond within localized receptive fields. Compared to other methods, CNNs require less preprocessing, autonomously learning filters instead of hand-engineering. This autonomy reduces dependence on prior knowledge, a significant advantage. CNNs comprise input and output layers with multiple hidden layers, including convolutional, pooling, fully connected, and normalization layers, enabling efficient feature extraction and classification in image tasks.

Different types of layers are userd:



1. Convolution
2. ReLU Layer
3. Pooling
4. Fully Connected

Convolutional layers execute convolution operations, mimicking neural responses to visual stimuli. Each neuron processes data within its receptive field, enabling CNNs to handle image translation, rotation, and distortion through tiling. Unlike fully connected networks, applying them to images requires an impractical number of neurons due to large input sizes. The convolution operation mitigates this issue by reducing free parameters, facilitating deeper networks with fewer parameters. This resolves challenges like vanishing or exploding gradients encountered in training traditional deep neural networks, enhancing training efficiency through backpropagation.

Pooling layers in convolutional networks combine outputs of neuron clusters, like max pooling selecting the maximum value from each neuron cluster, or average pooling calculating the average. Fully connected layers link all neurons between layers, akin to traditional MLPs. Pooling involves sliding a 2D filter over each channel of a feature map, summarizing features within its region. Output dimensions after pooling are $(nh - f + 1) / s \times (nw - f + 1) / s \times nc$, where nh, nw are feature map dimensions, nc is channel count, f is filter size, and s is stride length. Common CNN architecture involves stacking convolution and pooling layers.

The image above shows why we call these kinds of layers “fully connected” or sometimes “densely connected.” All possible connections layer-to-layer are present, meaning every input of the input vector influences every output of the output vector. However, not all weights affect all outputs. Look at the lines between each node above. The orange lines represent the first neuron (or perceptron) of the layer. The weights of this neuron only affect output A, and do not have an effect on outputs B, C or D.

IV. PERFORMANCE EVALUTION

4.1 CONFUSION MATRIX

Predicted class

Table 1 Confusion Matrix

	C_1	$\neg C_1$
C_1	**True Positives (TP)**	**False Negatives (FN)**
$\neg C_1$	**False Positives (FP)**	**True Negatives (TN)**

Actual class

true positives (TP): These are cases in which we predicted yes (they have the disease), and they do have the disease.
true negatives (TN): We predicted no, and they don't have the disease.
false positives (FP): We predicted yes, but they don't actually have the disease. (Also known as a "Type I error.")
false negatives (FN): We predicted no, but they actually do have the disease. (Also known

Example Confusion Matrix:

n=165	Predicted: NO	Predicted: YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

This is a list of rates that are often computed from a confusion matrix for a binary classifier:

1 **Accuracy:** Overall, how often is the classifier correct?
- (TP+TN)/total = (100+50)/165 = 0.91

2 **Misclassification Rate:** Overall, how often is it wrong?
- (FP+FN)/total = (10+5)/165 = 0.09
- equivalent to 1 minus Accuracy
- also known as "Error Rate"

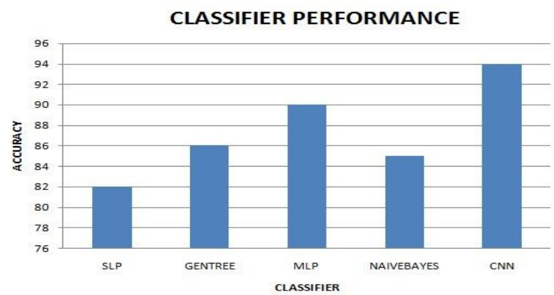
3 **True Positive Rate:** When it's actually yes, how often does it predict yes?
- TP/actual yes = 100/105 = 0.95
- also known as "Sensitivity" or "Recall"

4 **False Positive Rate:** When it's actually no, how often does it predict yes?
- FP/actual no = 10/60 = 0.17

5 **Specificity:** When it's actually no, how often does it predict no?
- TN/actual no = 50/60 = 0.83
- equivalent to 1 minus False Positive Rate

6 **Precision:** When it predicts yes, how often is it correct?
- TP/predicted yes = 100/110 = 0.91

7 **Prevalence:** How often does the yes condition actually occur in our sample?
- actual yes/total = 105/165 = 0.64



1. STUDIESAND FINDINGS

Now it is the time to articulate the research work with ideas gathered in above steps by adopting any of below suitable approaches:

A.Bits and Pieces together

In this approach combine all your researched information in form of a journal or research paper. In this researcher can take the reference of already accomplished work as a starting building block of its paper.

JumpStart

This approach works the best in guidance of fellow researchers. In this the authors continuously receives or asks inputs from their fellows. It enriches the information pool of your paper with expert comments or up gradations. And the researcher feels confident about their work and takes a jump to start the paper writing.

V. CONCLUSION

Using the image processing and machine learning we identify leaf species and classification using Convolutional neural networks(CNN). CNNs are designed to work with image data.CNN are mostly useful very large dataset, large number of feature and complex classification task.In our project we took a large dataset that's why we used Convolutional neural networks(CNN)and its give a better result than other machine learning and classification algorithm. The traditional system was only detect leaf and identify that tree.But in our system we identify that tree and give some information about that tree. In this project we got a 95.6% accuracy.

REFERENCES

[1] Hong Zhou, Huahong Huang," Tree Species Identification Based on Convolutional Neural Networks", 2016 IEEE.

[2] ZalikhaZulkifli, PutehSaad, ItazaAfianiMohtar," Plant Leaf Identification using Moment Invariants & General Regression Neural Network" 2011 IEEE

[3] IbtisamAbMajid, ZulkifleeAbdLatif, and Nor Aizam Adnan," Tree Species Classification Using Worldview-3 Data", 2016 IEEE.

[4] AkhtarJamil and BulentBayram," Tree Species Extraction and Land Use/Cover Classification From High-Resolution Digital Orthophoto Maps", 2017 IEEE.

[5] .Abdul Kadir, "Leaf Identification Using Fourier Descriptors and Other Shape Features," Gate to Computer Vision and Pattern Recognition-2015.

[6] Hong Fang, Huijie Li, "Plant Leaves Recognition and Classification Model Based on Image Features and Neural Network", IJCSI International Journal of Computer Science Issues, March 2014.

[7] Abdul Kadir, "A Model of Plant Identification System Using GLCM, Lacunarity and Shen Features", Research Journal of Pharmaceutical, Biological and Chemical Sciences, Volume 5, Issue 2, pp. 1-10, 2014.

[8] Zhaobin Wang, Xiaoguang Sun, Yide Ma, Hongjuan, Zhang ,YurunMa,WeiyingXie, Zhaobin Wang, Yaonan Zhang, "Plant Recognition Based on Intersecting Cortical Model", IEEE –2014.

[9] Bin Wang, Douglas Brown, YongshengGao, John La Salle, "MARCH: Multiscale-arch-height description for mobile retrieval of leaf images",Elsevier – 2014.

[10] B. Yanikoglu, E. Aptoula , C. T irkaz, "Automatic plant identification from photographs", achine Vision and Applications · August 2014.

[11] Hong Fang, Huijie Li, "Plant Leaves Recognition and Classification Model Based on Image Features and Neural Network", IJCSI International Journal of Computer Science Issues, March 2014.

[12] Abdul Kadir, Lukito Edi Nugroho, AdhiSusanto and Paulus InsapSantosa, "Performance Improvement of Leaf Identification System Using Principal Component Analysis", International Journal of Advanced Science and Technology, July, 2012.

[13] T .Vijayashree and A. Gopal, "Classification of T ulsi Leaves Based on T exture Analysis", Middle-East Journal of Scientific Research 23 (Sensing, Signal Processing and Security)-2015.

[14] Abdul Kadir, "Leaf Identification Using Fourier Descriptors and Other Shape Features," Gate to Computer Vision and Pattern Recognition-2015

[15] Heba F Eid," Leaf Plant Identification system based on hidden naïve bays classifier" , 4th International Conference on Advanced Information Technology and Sensor Application-2015

[16] AnantBhardwaj, ManpreetKaur, and Anupam Kumar, "Recognition of plants by Leaf Image using Moment Invariant and Texture Analysis", International Journal of Innovation andApplied Studies, Volume 3, Issue 1, 2013, pp. 237-248.

[17] AnantBhardwaj, ManpreetKaur, and Anupam Kumar, "Recognition of plants by Leaf Image using Moment Invariant and Texture Analysis", International Journal of Innovation and Applied Studies, Volume 3, Issue 1, 2013, pp. 237-248