Treescape: Advancing Tree Species Classification Through Machine Learning Techniques

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Abstract: A complex challenge that might be helpful for many forestry-related jobs is identifying tree species using photographs of the bark. In this study, we introduce and make accessible to the public BarNet 1.0, a unique collection containing over 23,000 high-resolution bark photos captured at various tree diameters from 23 different types of trees. With it, we show that it is possible to recognize species using deep learning and pictures of bark. More precisely, we achieved an accuracy of 95.81%. This study aims to investigate different categorization methods for plant leaf identification. A dataset of 250 photos for each 874 plant species was gathered. For classification, four traditional machine learning methods were used: Support Vector Machine (SVM), Multilayer Perceptron (MLP), K-Nearest Neighbors (KNN), Decision Tree (DT), and MLP. In addition to color- and texture-based features, morphological features like physiological length, physiological width, centroid, area, diameter, perimeter, rectangularity, sphericity, aspect ratio, area convexity, and circularity were extracted to assess these classifiers' performance. The main objective was to determine the most efficient and successful machine-learning approach.

Keywords: Image Classification, Data Augmentation, Species Identification, CNN, BarkVN-50, K-Nearest Neighbours, Decision Tree, Support Vector Machine, Multilayer perceptron.

I. Introduction :

Despite being a critical challenge, the capacity to consistently and automatically identify tree species from pictures of their bark has garnered little attention from the robotics and vision fields. In our case, these semantic markers would be trees and our knowledge of their species. Another emerging topic of interest for the robotics community is drones flying over forests [4]. This visual species identification may be used to conduct independent forest inventories regarding forestry applications. Regarding self-sufficient tree-harvesting endeavors, the harvester or forwarder might categorize numbers by species [5], increasing the operator's profit margins. Analogously, sawmill procedures such as debarking might be altered or adjusted based on a knowledge of the wood species that is presently tested. There are several advantages to utilizing a tree's bark rather than other factors, such as the look of its Leaves or fruits to identify species. First and foremost. Furthermore, it is still discernible on logs years after the trees were cut down and kept at a lumber yard. The bark is frequently evident in standing tree inventories since most robots cannot see the leaves at their height in forests of economic relevance. However, even experienced tree experts find it challenging to distinguish tree species from photos of their bark since the anatomy of certain species varies just a little. For example, two human experts on the Austrian Federal Tax Database achieved categorization accuracy of 56.6% and 77.8%, respectively.

Neural networks may beat humans on several picture recognition tasks, as shown by recent advances in deep learning [7]. One of the main drawbacks of deep learning techniques is that large datasets are frequently required to produce good outcomes. Regarding scale or diversity, the literature needs a similar database for bark identification. For instance, the AFF dataset [6], which contains just over 1,200 photos and covers 11 species, is the biggest. Additionally, this private dataset makes it challenging to employ in a public scientific setting. Most bark identification Because of handmade features like It is possible to train Gabor filters [8,], [9], SIFT [6,] or Local Binary Pattern [10, 11] using smaller datasets, research has concentrated on these

Plant species classification is one of the interesting areas where machine learning techniques are applied to discriminate between species. Automated plant species classification is achieved through the use of plant feature extraction. When creating these automatic plant classification systems, leaf shape is the most typically used feature. Apart from its shape, other

attributes like as colour, texture, and veins may provide additional information that might be helpful for automated procedures. As science and technology have progressed, machine learning has been applied extensively for recognition and classification tasks in many fields, especially the biological sciences. Artificial intelligence[15] methods like Support Vector Machines and K-Nearest Neighbour are used in machine learning pattern detection. This work uses the contour function to extract features from images of certain tree species. This experiment was conducted using the Flavia dataset. In this case, data transformation refers to the preprocessing technique

To produce the numerical dataset. A few classification techniques were fed the retrieved characteristics[16] from the CSV dataset for training and learning purposes. Support Vector Machine (SVM), Random Forest (RF), and K-nearest neighbor are the Classifier used in this study. Contours have taken the role of the traditional Sobel edge detection method because they reduce memory use by eliminating unnecessary points.

II.   LITERATURE SURVEY :

[1] The Author discusses comparative experiments with the other three methods, summarized in Table.
5. By far, LayerNet performs better than the three approaches regarding kappa coefficient and classification accuracy. It illustrates the benefit of performing feature extraction and classification on 3D data directly instead of converting the data into 2D representations. Limited Tree Species The study classifies only two tree species, white birch and larch. It may not apply to environments with more Diverse tree species. Expanding the model to classify a broader range of tree species could be challenging.

The main objective of this project is to create a portable tree identification system that can identify different kinds of trees based on pictures of their bark. This system is designed to be deployed as a smartphone application, especially in forest environments with unreliable internet connections. [2] While the paper demonstrates the effectiveness of their approach, it's essential to consider the model's generalization to other regions with different tree species and bark textures.

[3] The Author says that the method's ability to scale to many tree species or extensive datasets could be a limitation. Trunk12 and AFF serve as valuable resources for this purpose. Trunk12 is a dataset encompassing various tree species, offering distinct bark textures and variations in image quality. Similarly, the AFF (Australian Forest Faces) dataset is tailored for tree species classification, featuring diverse bark textures and species representation.

[4] This paper presents a deep learning-based model that can identify 50 species of trees found only based on the texture of their bark. Modern designs of convolutional neural networks allow them to extract feature vectors of any size or quality from picture input and are used in this case to extract features. Limited Data: The dataset used for training could be more extensive to enhance the model's performance and robustness. The model's capacity for accurate classification and generalization during the assessment stage has been confirmed. Additionally, The best-performing CNN-based architecture, ResNet101, was chosen after several were examined and tested.

[5] The data collection method involved taking pictures of tree species where bark was visible at varying distances. This approach could introduce bias as some tree species may be more challenging to photograph from a distance, leading to potential image quality and

Composition variations. Although the authors collected images under various conditions, such as different cameras and weather conditions, the dataset may not capture the full spectrum of environmental and seasonal variations that could affect bark appearance.

[6]The Author explains that Only ten tree species comprise the dataset used for the study. This little dataset might not represent the diversity of tree species found in the actual world. The research uses convolutional neural networks (CNN) as a deep learning technique to classify tree species based on their leaves. The authors' local dataset comprises ten thousand photos of leaves from ten other tree species, 1,000 images for each class. The study's test accuracy was high, coming in at 99.40%.

The application of deep learning—more particularly, transfer learning with the VGG-19. This work covers classification for identifying

plant species from color photographs of Swedish leaves. **[7]** The technique tries to reduce time by automating the process of leaf inspection, which botanists find to be Labour-intensive. When identifying plant species. According to the authors, their suggested model predicts an unknown plant's correct class with an accuracy of 99.70%, more significant than prior research reports. The Swedish leaf dataset, which has roughly 1125 photos and fifteen tree classes, is also mentioned in the paper as a tool for testing, validating, and training the model.

[8] The Author and the paper's organizational framework describe the dataset's collection, preparation, and structure. It also describes the architecture and features of the 3D CNN employed for categorization. The writers address the outcomes and conclude their research. The objective of this research is to improve the accuracy and efficiency of tree species identification through the use of deep learning, particularly with UAV-based hyperspectral sensors.

The Author explores the Problem Statement: Identifying tree species is of great practical importance, especially for conserving plant diversity and various real-world applications. However, **[9]** identifying tree species, especially in complex scenes, is challenging due to the wide variety of trees and the similarity in their shapes, requiring an automated solution. The paper introduces a method that can contribute significantly to the automatic identification of tree species, which has vital implications for conservation and various practical applications.

[10] The Data Imbalance: the dataset used in the paper is mentioned to have class imbalances, where some tree species have more images than others. The report addresses the importance of tree species identification for various forestry-related tasks. It emphasizes the significance of bark as a distinguishing feature for tree classification, as it remains consistent throughout the year. The Author uses the BarkVN-50 dataset, which comprises 50 different species of trees, to fine-tune a convolutional neural network (CNN), ResNet101. The model achieved an overall accuracy of over 94% during evaluation, validating its potential for real-world applications.

The paper offers a workable method for automatically detecting different species of trees using convolutional neural networks. By examining **[11]** tree leaves with multi-dimensional characteristics, including color, shape, and leaf, the work can identify different kinds of trees. CNN is used to combine multi-dimensional leaf information because it is difficult for tree species to do so. Several preprocessing stages are applied to strengthen the identification of the findings' robustness.

[12] The approach addresses the challenge of tree species identification in real-world scenarios with complex backdrops by combining multiple deep-learning models. Initially, many fresh photographs are created using the data augmentation technique. The aim is to identify tree species accurately and quickly from images, particularly in challenging natural settings. It uses a unique dataset called TreesNet and implements various deep learning models with transfer learning to achieve its objectives. The primary goal is to enhance the performance of tree species evaluation under challenging scenarios.

[13] The proposed model uses TLS data and 3D bark texture analysis to infer different types of trees. Using TLS data methodology saves time and eliminates the need for data fusion techniques that are not commonly used in single-tree species identification research problems.

[14] The study aims to obtain results by experimenting with data augmentation, model parameter modification, and comparisons with traditional classification approaches. Convincible results are derived through the architecture.

[15] The need for robotics and forestry applications is being addressed, which allows automatic tree species identification from bark photographs. To support deep learning research, it presents the BarkVN-50 dataset, which includes various high-resolution photos of different tree species. The primary objectives include demonstrating deep learning's effectiveness in species recognition, achieving high classification accuracy, and exploring factors impacting performance while fostering advancements in bark classification for robotics and forestry.

In order to classify plants, the study addresses the use of machine learning and image processing techniques, with a particular emphasis on identifying distinctive characteristics from plant leaves. The suggested model makes **[16]** use of an ideal feature set that combines characteristics from GIST, LBP, and Pyramid Histogram Oriented Gradient (PHOG). The model is tested on three datasets (Swedish Leaves, Flavia, and D-Leaf) and assessed using several classifiers (ANN, KNN, and RF). It achieves 98.99% accuracy in 353.39 seconds. The study

illustrates the higher performance of the suggested optimum feature set by contrasting it with alternative feature extraction techniques and classifiers.

[17] The research proposes an automated leaf recognition strategy for plant identification, which uses a combination of Bag-of-features (BOF) and Local Binary Pattern (LBP) textural characteristics as inputs to a multiclass Support Vector Machine (SVM) classifier. The structural risk reduction idea serves as the foundation for the SVM classifier, which uses a Gaussian kernel function. The Swedish leaf dataset, a publicly available leaf picture collection with leaves from 15 distinct tree species, is used to evaluate the proposed method. The usage of the Hessian-based blob detector SURF detector for locating interest spots in leaf image data is mentioned in the study.

The study examines and evaluates the use and efficacy of many plant classification approaches, with an emphasis on the identification and categorization of plant leaves. [18] Artificial neural networks (ANN), probabilistic neural networks (PNN), Convolutional neural networks (CNN), K-nearest neighbor (KNN), and support vector machines (SVM) are among the neural network approaches that are frequently utilized for classifying plant leaves. In order to effectively recognize leaf patterns, the paper's conclusion emphasizes the significance of solid image processing approaches that can ignore the picture's backdrop and manage a variety of lighting situations. The machine learning method must be established before leaf recognition and validation, and the quality of the leaf pictures is crucial to leaf recognition. A trustworthy source of leaf databases is also required.

[19]The study suggests a hierarchical architectural style that increases the resilience and efficacy of plant leaf categorization by employing many descriptors. Optimizing the performance of classifiers and feature extraction modules is part of the study. Using publically accessible databases, the suggested method is assessed and found to be superior to current methods for identifying green, non-green, simple, and complex leaves with differences in size, shape, and pattern. Other relevant publications that employ various plant leaf identification and classification methods—like Zernike moments, the Histogram of Oriented Gradient (HOG), local binary patterns, and shape descriptors—are also mentioned in the literature review.

[20] The necessity of employing CNNs and other image processing techniques for precise and effective leaf species identification is highlighted by this research, which jointly advances our understanding of and progress toward developing leaf classification algorithms. Explains the use of deep convolutional neural networks (CNNs) for categorizing tree leaves. In particular, the use of CNNs for image processing and classification problems is examined in the categorization of leaves. Give an overview of methods for identifying and classifying plant leaves. The paper discusses several techniques and strategies applied in the field, emphasizing how crucial precise leaf categorization is for identifying different plant species.

III. RELATED WORK

A. BARK :

Traditionally, bark categorization has depended on various hand-crafted features, often presented as a texture classification issue. For instance, some research [10-11] and others [6] used SIFT descriptors along support vector machine (SVM) to show 70% accuracy using the AFF dataset. [10] collected four statistical variables used in texture classification: uniformity, entropy, asymmetry, and smoothness, and utilized them to categorize images using a decision tree. Furthermore, [11] retrieved saliency, curvature, roughness, and form characteristics and then incorporated them into a Random Forest classification model, resulting in the development of a unique segmentation method based on watershed segmentation methodologies.

It is worth noting that early studies employed neural networks to classify bark. [8] deployed a classifier consisting of a radial-based probabilistic network to extract textural information based on Gabor wavelets. They achieved an accuracy of roughly 80% utilizing this strategy on a dataset of over 300 photos. However, this work occurred before the growth of deep learning algorithms led by AlexNet.

Some employed deep learning methods to achieve the more general objective of classifying trees. For example, deep learning was employed by all of the top-performing algorithms in the LifeCLEF competition, which tries to classify plants using photographs of different features like fruit or stem [8], [9], [10], [11]. However, their training database needs more images to meet their needs. Deep learning has also been used to identify trees from their bark, although with a different picture. [2] utilized LiDAR scans rather than RGB photos in their study. They created a 256x256 depth

picture from a point cloud at a distance of 10 meters that has a spatial resolution of 5 mm. On around 35,000 images, they improved a pre-trained AlexNet [10] for categorization.

Finally, using acquired characteristics from CNNs that had previously been trained using a range of area segmentation techniques and ImageNet, several authors have begun investigating deep learning on textures collected in RGB and have Based on the Flickr Material Dataset, an SVM was utilized to detect textural elements. Additionally, they enhanced the state-of-the-art neurotypical convolutional layer modified by [11] to include rotation-invariant filters on every dataset they examined. They grouped filters and connected the weights of every filter in each group such that all rs corresponded to a rotated version of each other. The three Outex [10] texture classification benchmarks were used to evaluate their layer, and they outperformed the state-of-the-art on one of them.

Photos in various weather situations, from clear skies to moderate rain, emphasize the variation in lighting. Finally, we chose trees from multiple places, including. Open spaces like university campuses, parks, and forests significantly impact how the bark looks, particularly in areas with a lot of foliage, where the canopy's reflection may alter the bark's color, adding several shades of green.

B. Leaf:

With over 391,000 vascular plant species worldwide, plant species are huge [1]. These days, machine learning, a subfield of artificial intelligence (AI), is a well-known and widely used method that has been used in many sectors, including biology, medicine, computer vision, speech recognition, and others [2– 5]. A contemporary AI technique called deep learning offers a strong foundation for supervised learning [6]. Even with an extensive dataset, it can quickly and effectively convert an input vector to an output vector [7]. Image enhancement draws attention to certain aspects of a picture [8]. Texture is one of the key elements of the plant identification system; it may be used to characterise leaves based on their surface structure. It is an asymmetrical spatial distribution pattern with variable picture brightness [9,10], mostly concentrating on individual pixels in an image. Cope et al. [11] introduced a developing vein classifier based on genetic algorithms (GA) and Ant Colony algorithms to extract the vein

anatomy.Anami et al. presented a technique for plant identification based on a combination of color and textural traits [12].

An automatic method for identifying leaves in legumes was developed by Larese et al. [13] using just the vein architecture. Basic measurements of the vein anatomy were made, and a Random Forests method was used to identify the veins. A different approach was suggested by Kadir et al. [14] using the Flavia and Foliage datasets. A CNN approach was presented by Lee et al. [15, 17] to identify 44 plant species obtained from the Royal Botanic Gardens of Kew, England. Following feature extraction, a Multilayer Perceptron and an SVM were used for classification. Two distinct datasets were used: leaf patches (D2) and the entire picture (D1). The accuracy of both datasets was over 97%.

Additionally, in [18], researchers merged local and global features and attained an accuracy rate of greater than 91%. Sladojevic et al. [19] also used CNN to identify plant illnesses. Grinblat et al. [20] suggested another study that would identify plants using deep learning techniques and leaf vein morphological features.

IV.   Architecture :

A. BARK :

The networks we employed were pre-trained on ImageNet, as is common in tasks involving image recognition. We also used the ResNet architecture [14], which is reliable and easy to train on everyday classification tasks. The DBH(Diameter at Breat Height) representation is provided in Fig 3 based on the number of trees with DBH level.
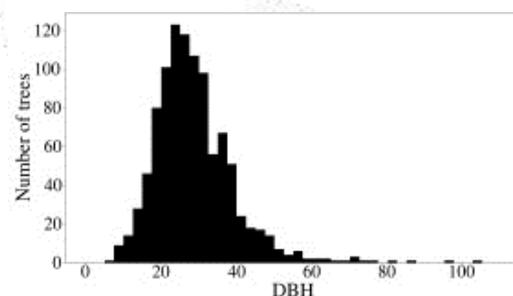

Figure. 1. DBH (Diameter at Breast Height)

The model architecture is depicted in Figure 4, and the description of the training model is as follows. For all tests,

we used PyTorch 0.3.0.post4 [30], and we used ImageNet to get the weights of the pre-trained

resnet18 and resnet34 networks. As the problem differed substantially from ImageNet, we used a typical method and froze the first layer before fine-adjusting the networks using 0.0001 as the starting learning rate. We trained for 40 epochs, resulting in a factor of 5 decrease in learning rate at fixed periods (16 and 33). We used Adam as an optimization technique, and the weight decay was set to 0.0001.

The high-resolution images were reduced to half of their initial dimensions, which might lead to quicker download and processing times for the images. This is required to assemble the minibatches. On color cameras, it additionally considers the image element's Bayer filter pattern, which only gathers colors for every other pixel.

We picked a random photo from a random tree and a random species (class) of the tree for each mini-batch. This allowed us to handle difficulties arising from an imbalanced dataset, such as class-aware sampling [14].

After that, we added to the data by randomly flipping horizontally, and the final step was to randomly crop the resulting image's 224 by 224 pixels. Additionally, we employed the ResNet architecture [16], which is solid and straightforward to train on everyday classification tasks.
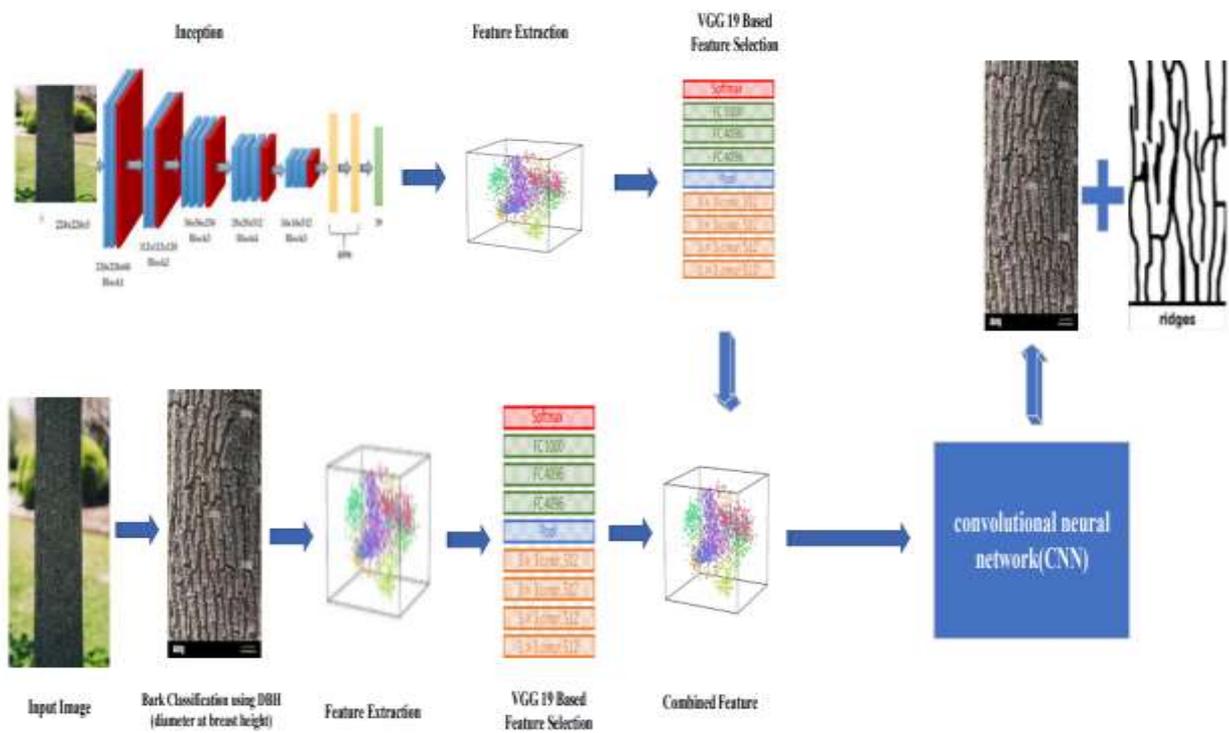
Figure. 2. Block diagram showing how to classify tree species using CNN and VGG-19

B. LEAF :

Proposed Work :
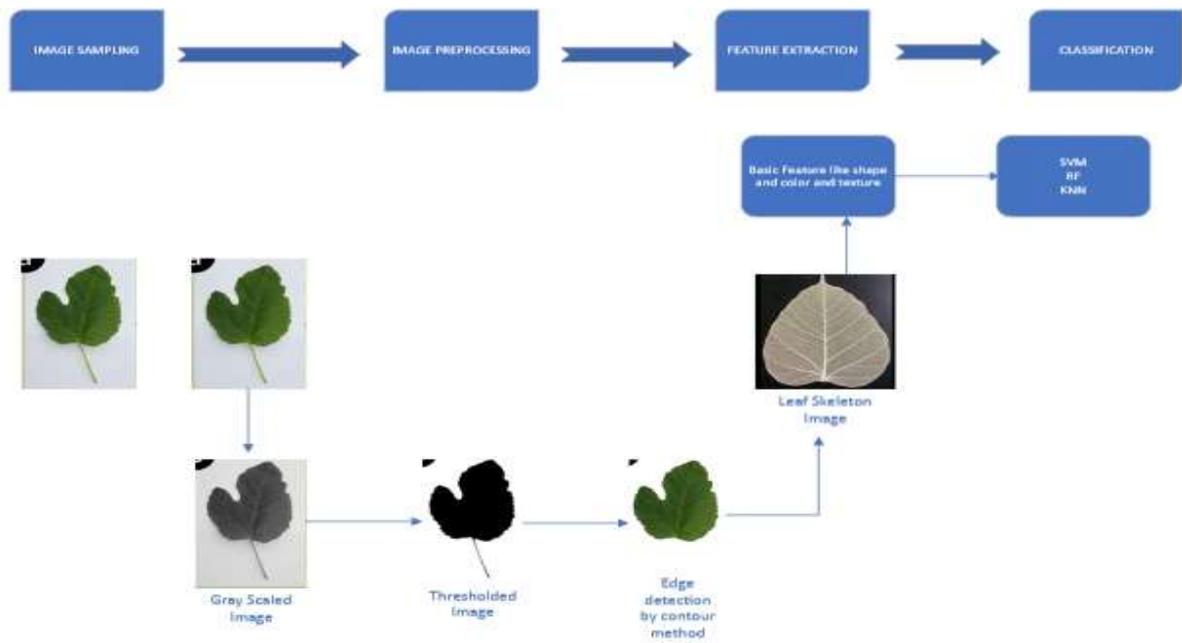
Figure. 3. Working Process of Leaf Classification using SAM, RF, KNN

1. Image Sampling: At this point, pictures of leaves are gathered. This can be carried out automatically or manually. Your machine learning model's performance will be impacted by the caliber and amount of pictures you utilize.

2. Image Preprocessing: Before the photos can be used for machine learning, they must be preprocessed. This frequently entails turning the photographs to grayscale and shrinking them to a consistent size. Image filtering can occasionally eliminate noise or highlight particular leaf characteristics.

3. Feature extraction: At this phase, the features of the preprocessed pictures are taken out. These leaf properties help differentiate between various species. The most appropriate feature extraction method for a given application will rely on the particular job at hand and the type of data involved. There are several feature extraction strategies available. These are a few typical methods for extracting features that are employed in leaf classification:

- **Shape features:** These characteristics, which include the leaf's aspect ratio, perimeter, and area, depict the leaf's general form.
- **Color features:** These characteristics record the leaf's color data, including its average color, color histogram, and dominating colors.
- **Texture features:** These characteristics depict the leaf surface's vein patterns, smoothness, and roughness.

4. Classification: To finally divide the leaves into several groups, a machine learning classifier is employed. An image dataset of labeled leaves is used to train the classifier. Throughout the training process, the classifier gains the ability to recognize the characteristics that are most crucial for differentiating between various leaf species. Upon training, the classifier may be used to new leaf pictures that still need to be viewed. The following are a few popular machine-learning classifiers for leaf classification:

Support Vector Machine (SVM) : Robust and versatile, the Support Vector Machine (SVM) is a machine learning technology that may be used to a variety of classification tasks. They are perfect for leaf classification because of their capacity to handle high-dimensional data and their efficacy with small datasets.

K-Nearest Neighbours (KNN): This machine learning technique is straightforward and simple

to comprehend. The labels of the new data points' closest neighbors in the training set are used to categorize them. While KNN can help classify

leaves, it can be computationally costly for big datasets.

V. METHODOLOGY :

A. BARK :

1. Data Collection and Preprocessing: Gather a diverse dataset of bark images from various tree species. Ensure that each image is labeled with its corresponding tree species. Preprocess the data by standardizing pixel values to a standard scale (e.g., [0, 1]) and shrinking pictures to a consistent resolution (e.g., 224x224 pixels).

2. Data splitting: Separate the dataset into training, validation, and test sets in order to assess model performance. (e.g., 70-15-15% split).

3. CNN Model Architecture: Create a CNN architecture for categorizing bark images. As a starting point, you may utilize pre-trained architectures like VGG, ResNet, or Inception, or you can construct your own model.

4. Data Augmentation: Data augmentation expands the variety of your training dataset by applying different changes to the original photos. It strengthens the model's resistance to changes in bark textures, lighting, and angles and improves its ability to generalize to new data. Standard methods for augmenting data include.

5. Model Training: The model's parameters (weights and biases) are updated depending on the training data to enable the model to identify patterns and characteristics in bark photos. This is how it operates.

6. Evaluation: Determine pertinent criteria, such as accuracy, and assess the model using the test set.

7. Continuous Improvement: Collect additional data and user feedback to fine-tune and improve your model over time.

8. Documentation: (output) Keep detailed documentation of your CNN model architecture, training process, and code for reference and collaboration.

This methodology uses bark pictures to organize the creation and training of a CNN model for identifying different kinds of trees. It strongly emphasizes data quality, model design, data augmentation, and iterative improvement to guarantee that the model successfully categorizes

tree species.

B. Leaf :

The proposed work consists of four basic steps: dataset collection, picture preprocessing, feature extraction, and classification. Initially, leaf samples were gathered, and photos were obtained from the Flavia dataset. The contours technique was then used to preprocess the leaf pictures and feed them into the feature extraction stage, which extracted the crucial information from the leaves. Finally, a variety of machine learning techniques were applied to train and classify the collected features.

A. Gathering the Dataset :

Figure. 4. Collection of leaf dataset

B. Preprocessing Data: As the data we use may contain noise that reduces or suppresses its quality, preprocessing data is essential for machine learning. Noises occur as pixel values that do not precisely reflect the actual intensities of a picture throughout the image-capturing process. A crucial first step in emphasizing or improving an image's main components is to remove visual noise. Rebuilding the leaf images into square dimensions (m x m) was required for the preprocessing data inputs. The original 6016 x 4016 resolution images were scaled to 1600 x 1200 resolution in order to maintain the leaf form ratio.. The image that has had the background removed is used for further processing. The divided images were previously processed.

C. Feature extraction: The primary way to differentiate between different hand signals is

based on their characteristics. However, selecting a feature requires accurately understanding and interpreting the obtained feature values. Initially, every picture was transformed from RGB to greyscale. Next, Contour extracted the region of interest (ROI) from the images. To ensure that a clean image of the leaf was created, the images underwent skeletonization and postprocessing after segmentation. In order to extract venous characteristics from the segmented pictures, vein morphological parameters were examined. Every attribute, such as form, colour, vein texture, endpoints, entropy, aspect ratio, areoles, inverse-difference-moments, rectangularity, and so on, was taken into account while computing the leaf area.

D. Classification: In the last phase of an automated plant recognition system, classification analyses training data to find the unique traits of each plant species and assigns a new sample to the appropriate group using an intelligent algorithm. The recommended machine learning methods for plant identification include k-nearest Neighbour (kNN) and support vector machines (SVM).
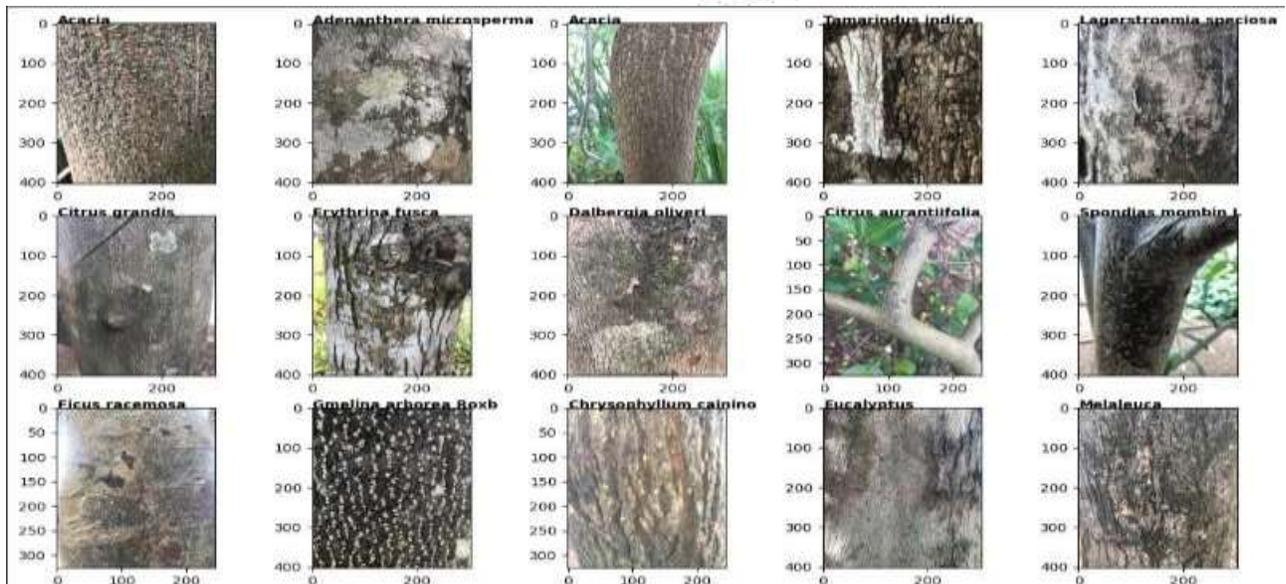
Figure. 5
BarkVN-50 includes high-resolution bark photos of several tree species. (Images of bark)

VI. Results

A. BARK :

In testing, we examined how network depth affected categorization accuracy. We also examined its regularization effectiveness using varying batch sizes.
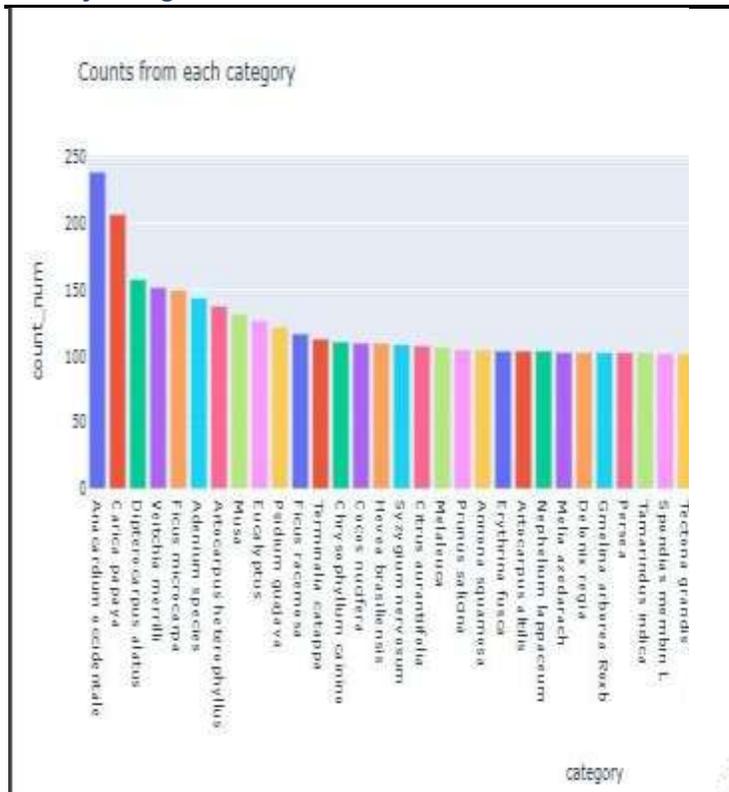
TABLE I (Classification Report)

contains 1,584 binary images and 16 examples from 99 different species.

	Model	Score
2	K Neighbors Classifier	94.444444
1	Random Forest Classifier	97.979798
4	svm	98.484848

Figure .8. Accuracy scores for machine learning models used in leaf classification.
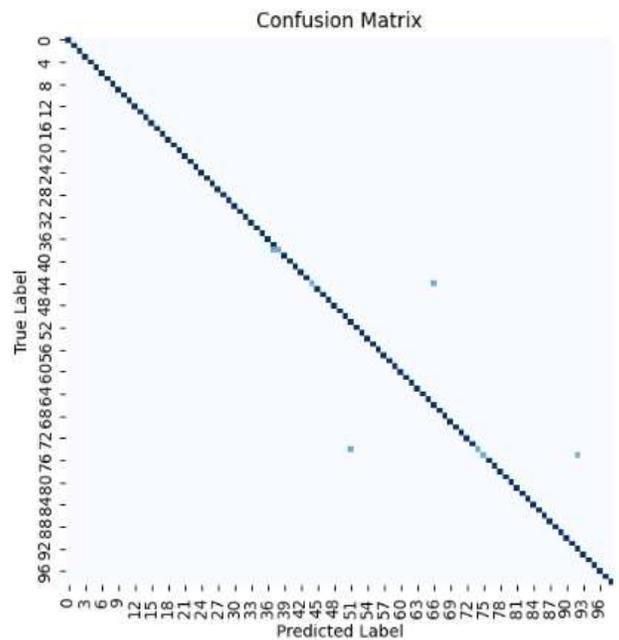
Confusion Matrix :

Figure.9. Confusion Matrix

The four parameters are TP, TN, FP, and FN. The confusion matrix's diagonal value in a multiclass setting represents the associated class's TP. The total number of TN for that class is the sum of all the columns and rows, except the column and row for that class. The total number of FPs for a class is equal to the sum of the values in the corresponding column if the TP values are not included. FN is the total values in the relevant row minus the TP value.

VIII. CONCLUSION :

This study empirically shows that ResNets can identify tree species from bark photographs for twenty Canadian species. The obtained dataset, the method's accuracy is much greater than the 5%

Figure. 6 Bar Chat plot a bar plot along with their categories and count

B. LEAF :

Figure 7. The collection of leaf specimens

chance classification, ranging for several crops on a single picture for all trunk images) increased from 93.88% to 97.81%. We determined through actual investigation that the number of trees in the database has a much more significant impact on training than the total number of images. This outcome will assist in focusing on future data collection efforts. Along the way, we created BarkVN 1.0, a large publicly accessible dataset that comprises tagged photographs of the barks. This database can help expedite research on bark classification for robotics or forestry applications. Furthermore, it can help the computer vision community create algorithms to address the challenging issues related to the classification of fine-grained textures.

For leaf classification, we suggested a shape-based method that involves several processes, such as picture preprocessing, edge detection, feature extraction, classification, and comparison. This approach's strengths include its simplicity, accuracy, time management, ease of implementation, and lack of significant training or postprocessing requirements. It also yields a greater recognition rate with less calculation time. This method's flaw is that it needs to follow a systematic approach to leaf detection. Therefore, we have to specify some parameters and threshold values experimentally. The maximum parameters used in this technique are also dependent on assumptions established after examining many photos.

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