



Comparison of Support Vector Machine and k -Nearest Neighbor Classifiers for Tree Species Identification

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Tree species are a group of organisms that have different characteristics, and the identification of tree species has become essential to protect biodiversity, ecosystem balancing, as well as for medicinal purposes. It takes too much time for experts to identify individual tree species, so research based on automatic tree species identification is required to save time. Remote sensing-based satellite Image Processing (IP) techniques are useful for detecting features of different tree species like shape, texture, color, etc., but IP techniques alone are not sufficient for automatic detection of tree species. So, some Machine Learning (ML) algorithms are useful for the identification of tree species. Here, Histogram of Oriented Gradient (HOG) features have been introduced to identify different tree species like, banana, coconut, lemon, mango, oil palm, papaya trees, and those which do not belong to any category, are recognized as a not specified class. So, the combination of IP and ML techniques are useful. Here, comparison of k -Nearest-Neighbor (k NN) and Support Vector Machine (SVM) classifiers with HOG has been introduced, and overall accuracy (OA) for k NN and SVM can be obtained 85.71% and 93.33% respectively. For further evaluation, K-fold cross-validation is used, and it gives 88.39% and 94.34% OA for k NN and SVM respectively.

Keywords: HOG feature descriptor, K fold cross-validation, k -Nearest-Neighbor (k NN), Support vector machine (SVM), Tree species identification

1 Introduction

Today, remote sensing makes an important contribution to the research field, and it has made research possible in many fields. Generally, researchers use multi spectral, hyperspectral, or aerial-based image processing (IP) algorithms to extract different features and objects from satellite images. Other than that, land use and land cover (LULC) classification, segmentation, and object-based image analysis (OBIA), crop or tree identification, crop area estimation¹, crop disease identification, and much more researches are going on using DL² and ML techniques. Single tree detection can be done using IP based smoothing, thresholding, and morphological techniques³. While vegetation type can be explored using Landsat and Rapid Eye images⁴. Hassan⁵ and Nourabakr *et al.*⁶ have performed maximum likelihood classifier for LULC, while Natallia *et al.*⁷ have introduced multi layers deep learning approach to with 1D Convolution Neural Network (CNN) in spectral domain and 2D CNN in spatial domain, along with a Random Forest (RF) and ensemble of Multilayer perceptron (MLP)

As per seasonal changes, land cover mapping and changes in vegetation areas will be affected. So, to avoid misclassification, D Simonetti E *et al.*⁸ have suggested a phenology-based synthesis classifier, while Katharina Heupel *et al.*⁹ have suggested classification based on their phenological development and spectral characteristics using Landsat-7, Landsat-8, Sentinel 2A and Rapid Eye. Sarchil H. Qader *et al.*¹⁰ have introduced the SVM classifier to classify crop land in arid and semiarid areas using MODIS data based on phenology using an ML technique. But a disadvantage of phenology-based classification is that crops may have similar phenology, so it has become difficult to distinguish different crops. To overcome this problem, the Feature Filtering & Enhancement (FFE) method¹¹, the regression model¹², and vegetation indices can be useful¹³. Hsiao-Chien Shih *et al.*¹⁴ have used the modified soil adjusted vegetation index (MSAVI) to distinguish vegetation and non-vegetation areas. Fateme Mostajer *et al.*¹⁵ have introduced the GIST feature along with PCA to extract the features of different leaves of plants and classifying them using Artificial Neural Network (ANN), SVM, and Cosine k NN classifier.

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Other than these techniques, 3D CNN¹⁶, object-based image analysis (OBIA), ML algorithms¹⁷ as well as Green Leaf Area Index (GLAI)¹⁸ are much useful for different crop classification.

Due to high spectral information in hyperspectral images, identification of crop or tree has become difficult. It can be overcome by using Aerial Images. Rick Archibald and George Fann¹⁹ have introduced SVM classifier for image classification to eliminate various bands, Jose A J berni *et al.*²⁰ have introduced helicopter based Unmanned Aerial Vehicle (UAV) imagery for identification of crops. To identify the shape of palm trees, scale invariant feature transform (SIFT) to detect key points of palm trees can be useful²¹, as well as to detect²² and to count²³ the oil palm trees CNN and SVM classifier can be played vital role²⁴.

2 Materials and Methods

2.1 Dataset collection

To perform any machine learning algorithm, a dataset is the primary requirement. So, for tree species identification, images of different tree species like banana, coconut, lemon, mango, oil palm, and papaya are required. These images are collected from Wikimedia, and they are used to train and test the classifier results. Each class contains 600 images, so a total of 4200 images are collected. Among all the 80% dataset, it means 3360 images are used for training purpose and remaining 20% means 840 images are used for the testing purpose.

Before giving any image as an input to a classifier, feature extraction is the first step to extract significant information from an image and remove extra features. Feature descriptors like HOG, Scale Invariant Feature Transform (SIFT), and Speeded Up Robust Feature (SURF) are used to extract the necessary information.

Here, HOG feature vectors are used to extract tree species features. HOG feature vectors are not useful for viewing images, but they are useful for extracting the features of tree species such as structure, shape, and color. These feature vectors are fed as input to classifiers such as, *k*NN and SVM. But for further evaluation of both models, K-fold cross validation has been performed. The value of K is defined as 10. Figure 1 shows an algorithm for tree species identification using ML approaches.

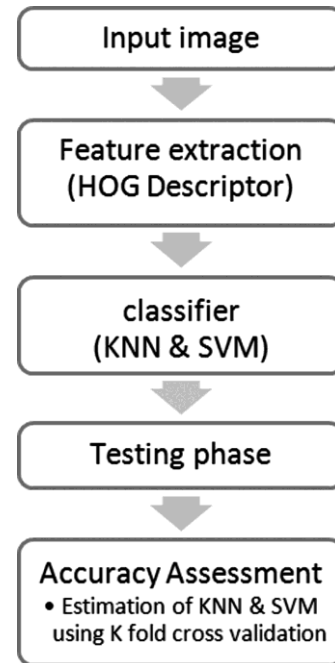


Fig. 1 — Algorithm for tree species identification.

2.2 Feature extraction using Histogram of Oriented Gradient (HOG)

In tree species identification, HOG descriptors are used to detect the structure of leaves. To perform HOG feature descriptor, all images should be equal in size for training and testing. After resizing the image to 256×256 patches, horizontal gradient (g_x) and vertical gradients (g_y) are calculated by the kernel or sobel operator. Now, the magnitude and direction of gradients are calculated using the following formula:

$$\text{Magnitude (g)} = (g_x^2 + g_y^2)^{1/2} \quad \dots(1)$$

$$\text{Direction } (\theta) = \tan^{-1}(g_y/g_x) \quad \dots(2)$$

For each and every pixel, the gradient has magnitude and direction for RGB images. So, maximum magnitude and direction are used among the three channels. The magnitude of the gradient is large around the edges and abruptly changes near the corner. So, according to edges and corners, the shape of the leaves is identified.

To calculate HOG feature vectors, the image is divided into 16×16 cells. It means each 16x16 image patch contains 16×16×3 = 768 pixels and then each pixel has a magnitude and direction i.e., 16x16x2 = 512 and cell_per_block is 2×2 for input images.

The histogram contains 9 bins with degrees of 0, 20, 40, 60...160 and the gradient of 16×16 patches is divided into 9 bins according to magnitude and direction. Here, gradients are sensitive to lighting. So, histogram normalization is required to reduce lighting variation. The normalization of the vector is achieved by the following formula:

$$L2 \text{ Norm} = (R^2 + G^2 + B^2)^{1/2} \quad \dots (3)$$

This length of vector is called the A normalized vector can be obtained, after dividing each element using L2 Norm value.

According to the 16×16 vector size, 36x1 histogram bins and 8100 HOG feature vectors can be obtained that can be used as an input to the classifier.

Figure 2 shows sample images of database and its HOG features that is useful to find the shape of a different tree's leaves.

2.3 Support Vector Machine (SVM) classifier

SVM classification is widely used in the field of remote sensing to classify features from hyperspectral, multispectral, or aerial-based satellite images as well as to find hyperplanes in *N*-dimensional space. Here, 4200 images of different

tree species are used for classification, where each folder contains 600 images, but the images can't be given directly as an input to the classifier. So, feature vectors that are obtained from the HOG descriptor are given as an input to the classifier.

These features are in the form of $(x_1, y_1), (x_2, y_2), \dots \dots \dots (x_n, y_n)$. Where x_i ($i = 1$ to n) is a feature vector and y_i ($i = 1$ to n) is the output class label. An SVM classifier separated the different tree species in the different classes with a hyperplane and was used to maximize the margin between the classes. For tree species identification, the linear kernel is used because it is faster than others, and fewer hyperparameters are required to optimize. A hyperplane for linear kernel can be written by,

$$W * x - b = 0 \quad \dots(4)$$

Where *W* is the weight value, and *b* is the bias value, $b/||w||$ determines the margin of the hyperplane.

A predicted class is defined as the sum of feature vectors that identify the tree species. As per the Pareto principle, training and testing data are divided into 80% and 20% respectively. SVM classification for tree species identification is performed with the

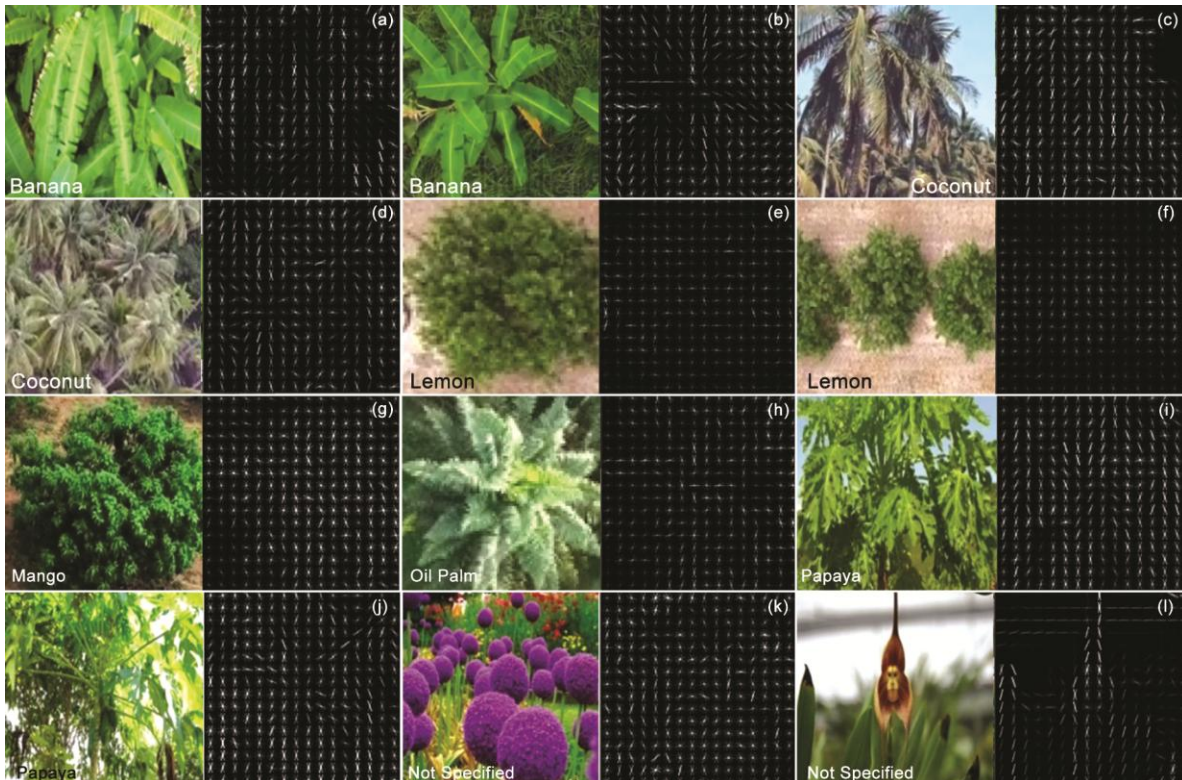


Fig. 2 — (a - k) Samples of database image and its Histogram of Oriented Gradients features²⁵⁻³¹.

help of sklearn, scikit-image, and opencv libraries of python.

2.4 k- Nearest Neighbor (kNN) Classifier

The kNN classifier is the simplest classifier, and it classifies data based on the measure of similarity. Same as SVM classifier, HOG feature vectors are given as an input to the kNN classifier and it defines a class for the particular pixel using distance function such as the Euclidean, Manhattan, or Minkowski distance formula. For tree identification and to separate the features of one tree from another, the Euclidean distance formula has been introduced:

If pixel location-1 is defined as (x_1, y_1) and pixel location-2 is defined as (x_2, y_2) then Euclidean distance can be measured as:

$$D = ((x_1 - x_2)^2 + (y_1 - y_2)^2)^{1/2} \quad \dots(5)$$

A particular class is defined for a particular pixel by measuring the distance between pixels. The advantages of kNN are that it is simple and easy to implement, and there is no need to tune several parameters.

After performing classification, to estimate the competence of the ML models such as kNN and SVM, the K-fold cross-Validation technique is used.

It gave information about how accurately the model would perform in practice. It involved the partition of the dataset into a K number of complementary subsets. For tree species, K is defined as 10. It means the dataset is divided into $K = 10$ groups.

3 Results and Discussion

Accuracy assessment is an essential part of any classification project and is used to compare the classified images to ground truth data. In tree species identification, accuracy assessment plays a vital role in getting the information about tree species, whether they are correctly classified or not. Overall accuracy (OA) gives a piece of information about an individual tree, whether it is correctly classified or not. OA can be calculated from a confusion- matrix as follows:

$$OA = (\text{sum of all diagonal elements}) / (\text{total number of images}) \quad \dots(6)$$

$$UA = (\text{correctly classified image for particular class}) / (\text{total number of images in class}) \quad \dots(7)$$

$$PA = (\text{number in diagonal cell element} / \text{number in column total}) \quad \dots(8)$$

Figure 3 shows the predicted result by kNN and SVM classifiers, as well as Table (1 and 2). giving

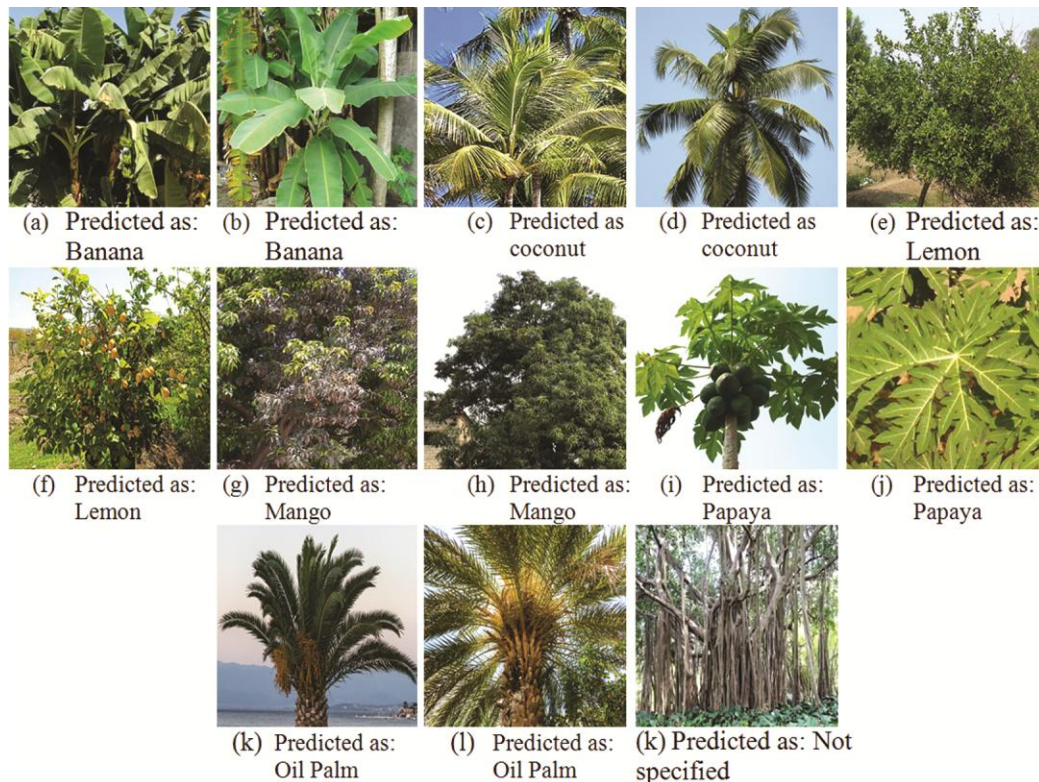


Fig. 3 — (a - m) Performance of classifier on test images³²⁻⁴⁴.

Table 1 — Accuracy assessment of *k*NN classifier

Ground truth class	Classifier: <i>k</i> -Nearest-Neighbors (<i>k</i> NN)							User's class	No. of classified images	User's accuracy (%)
	<i>Banana</i>	<i>Coconut</i>	<i>Lemon</i>	<i>Mango</i>	<i>Not specified</i>	<i>Oil Palm</i>	<i>Papaya</i>			
Banana	105	0	1	1	0	0	0	107	98.13	
Coconut	2	109	13	4	1	0	1	130	83.84	
Lemon	5	0	105	0	0	0	0	110	95.45	
Mango	1	0	12	136	0	0	0	149	91.27	
Not Specified	1	3	57	17	33	0	0	111	29.72	
Oil palm tree	0	0	1	0	0	112	0	113	99.15	
Papaya	0	0	0	0	0	0	120	120	100	
No. of ground truth images	114	112	189	158	34	112	121	840		
Producer's accuracy(%)	92.10	97.32	55.55	86.07	97.05	100	99.17			
Overall accuracy	85.71%									

Table 2 — Accuracy assessment of SVM classifier

Ground truth class	Classifier: Support vector machine (SVM)							User's class	No. of classified images	User's Accuracy (%)
	<i>Banana</i>	<i>Coconut</i>	<i>Lemon</i>	<i>Mango</i>	<i>Not specified</i>	<i>Oil Palm</i>	<i>Papaya</i>			
Banana	120	0	1	0	0	0	0	121	99.17	
Coconut	2	97	3	3	3	0	0	108	89.81	
Lemon	1	1	105	4	0	0	0	111	94.59	
Mango	1	1	8	102	0	0	0	112	91.07	
Not Specified	4	12	4	2	95	1	0	118	80.50	
Palm	2	1	1	0	1	137	0	142	96.47	
Papaya	0	0	0	00	0	0	128	128	100	
No. of ground truth images	130	112	122	111	99	138	128	840		
Producer's accuracy(%)	92.30	86.60	86.06	91.89	95.95	99.27	100			
Overall Accuracy	93.33%									

the information accuracy assessment of *k*NN and SVM classifier respectively. Here, diagonal elements show the number of correctly classified images.

By comparison of SVM and *k*NN classifiers, it is clear that the SVM classifier performed better than *k*NN, but the SVM classifier took more computation time (around 15-20 minutes) as the complexity of SVM is $O(N^3)$, while *k*NN took less time as its complexity is $O(Nd)$, where N is the input feature and d is the dimension.

A producer's and user's accuracy showed that papaya trees are correctly classified in both classifiers, but some trees are wrongly classified, such as mango, which is classified as a lemon, and banana and oil palm trees are classified as a coconut.

Similarly, some images that are labelled as "Not specified" are also wrongly classified as banana, coconut, lemon, mango, or oil palm. So, the false positive rate for 'Not Specified' class is higher than the other classes. The reasons for a misclassification are, similar features of trees, poor visibility of the image, overfitting while the model learns the details, and noise.

To overcome that problem, further evaluation of classifiers is required. For further evaluation of the *k*NN and SVM models, a K-fold cross-validation resampling technique has been introduced that decides how much more accurate both models will perform for the new testing dataset. So, Table 3 gives information about the evaluation of *k*NN and SVM classifiers with K-fold cross-validation.

Table 3 — Estimation of *k*NN and SVM classifiers using K-fold cross-validation

Classifier	Accuracy
Evaluation of <i>k</i> NN with K-fold cross validation	88.39%
Evaluation of SVM with K-fold cross validation	94.34%

4 Conclusion

The study has presented that HOG feature vectors are used to identify different types of tree species like banana, coconut, lemon, mango, oil palm, and papaya as well as features that do not belong to any class, which are categorized as a 'not Specified'. By performing, *k*NN and SVM classifiers, the overall accuracies are 85.71% and 93.33%, respectively. For further appraisal, K-fold cross-validation is used to estimate that *k*NN has performed 88.39% and SVM has performed 94.34% accurately in practice. A drawback of performed classifiers is that their false positive rate is higher for the not Specified class as well as the limitation of the HOG features is that they are sensitive to image rotation. So, sometimes it is not good for classification. So, this problem can be overcome by using deep learning algorithms such as CNN, Region-based CNN (R-CNN), and fast R-CNN.

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