FAST CLASSIFICATION OF LEAF IMAGES FOR AGRICULTURAL REMOTE SENSING APPLICATIONS

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ABSTRACT

This paper introduces a method of classifying leaves using machine learning. Considerable emphasis has been put on leaf classification for use in remote sensing applications such as plant phenotyping and precision agriculture. Convolutional neural networks (CNN) have been extensively used in computer vision for image classification. However, CNN can be computationally expensive. This paper describes a method that achieves a comparable accuracy, with a lower computational burden, using a support vector machine (SVM) classifier. This method uses image processing algorithms to extract features from Hough transform and Hough Lines. These features are then integrated with those extracted from binary images, and "eigenleaves" extracted from grayscale, gradient, and different color-space images of leaves as data preprocessing for classification. The classifier is implemented on two publicly available datasets: Flavia and Swedish; and is able to achieve state-of-the-art accuracies using a SVM classifier.

INTRODUCTION

Precise identification of leaves has applications such as site-specific weed management in agriculture and plant phenotyping. With a growing population, there is an increasing demand for efficient agricultural methods. The ability to identify weeds in the field using an autonomous robot, perhaps one which has a robotic arm to remove weeds, or a drone which can spray herbicide on the desired area could be helpful. Such automated systems need a way to differentiate desirable plants from undesirable weeds. One way to do this is with an imaging system that can recognize different species of plants. Some recent machine algorithms use convolutional neural networks (CNN) for this operation. However, they are computationally expensive operations. This paper proposes using a SVM classifier instead of using CNN, which can substantially reduce the computational burden. This new classifier was trained using two publicly available datasets named Flavia and Swedish. The classifier was able to analyze images using the processing power available on conventional agricultural drones. There was no need to augument the processor with a graphics processing unit (GPU) or similar hardware. Nor was there a need to relay data to a ground station for processing

A way to improve the accuracy of leaf classification by training auxiliary data for classification of leaves when training dataset is small has been previously shown by Wu [1]. This method compares leaf shapes by aligning their angle sequences to one another, rather than extracting features from leaf shapes. It was shown by Ling [2] that using inner-distance as a descriptor for an image can be helpful in improving the performance of identification of leaves. Im [3] and Wang [4] used hierarchical polygon approximation representation for leaf shape and hypersphere classifier respectively to classify leaves. Segmentation of leaves from the background using 3-D point cloud was done by Teng [5], which would be a bridge between the system for capturing the images and classifying them. Elliptic Fourier transforms were used to identify weed species by Neto [6] with an accuracy of 89.4%.

Our proposed method extracts distinctive features from images in binary, monochrome (grayscale and gradient) and different color-spaces (RGB, HSV, and YCbCr). Binary images are used to extract binary object features such as area and perimeter of the object. Grayscale images are used to calculate Gray-Level Co-occurrence Matrix (GLCM) from which feature vectors are extracted. Grayscale images are also used to calculate Hough transform and Hough lines which help in extracting features related to the vein structures and the contour of the leaf. We find the number of corners in a leaf image using the method described by Rosten [15], the number of speeded up robust features (SURF) points using the method described in Bay [16], and the number of binary robust invariant scalable keypoints (BRISK) using the method described by Leutenegger [17]. Using the entire feature vectors instead of using the number of points can be helpful in improving the accuracy of the system, but as the feature vectors are very large it would be computationally expensive. Later we show that we can achieve the desired accuracy even without using the entire feature vectors of BRISK and SURF. The grayscale images along with the all the different color-space images are used to extract eigenleaves which are eigenvectors of the leaves projected on the leaf images. The idea of eigenleaves is inspired from [18] where the authors use eigenfaces to classify faces, where eigenfaces are the eigenvectors of the set of faces.

All these features extracted from the images are then used to train a SVM classifier. The features are also tested on various other classifiers too to test the accuracy. By using the hand-crafted features, and SVM classifier, we can achieve accuracy rates of 97.71% on the Flavia dataset [7] and accuracy of 99.56% on the Swedish dataset [19].

PREVIOUS WORK

Wu [7] developed a leaf recognition algorithm using a probabilistic neural network (PNN) and achieved an accuracy of 90% on the Flavia dataset. Singh [8] was able to achieve 96% accuracy on the Flavia dataset using SVM based on a binary decision tree. Kadir [9] used principal component analysis (PCA) to reduce the dimension of the features and improve the performance of classification using PNN. Nguyen [10] combines SURF features with bag-of-words to achieve an accuracy of 95.94% on the Flavia dataset. Kumar [11] developed the first android classification application LeafSnap which used leaf's contour over multiple scales for classification. Kadir [12] uses Zernike moments extracted from leaf images to train the PNN along with features extracted from gray level co-occurrence matrix and achieves an accuracy of 94.69% on the Flavia dataset. Wu [13] used CNN for classification of leaves using PReLU activation function and were able to get an accuracy of 94.8% on the ICL dataset with 25 different species of leaves. Wick showed in [14] that almost perfect accuracy can be achieved on Flavia dataset using Deep CNN.

PROPOSED METHOD

Our method can be divided into two major steps: Extraction of features from images, and training and testing of the classifier. The extraction of features is summarized in Figure 1.

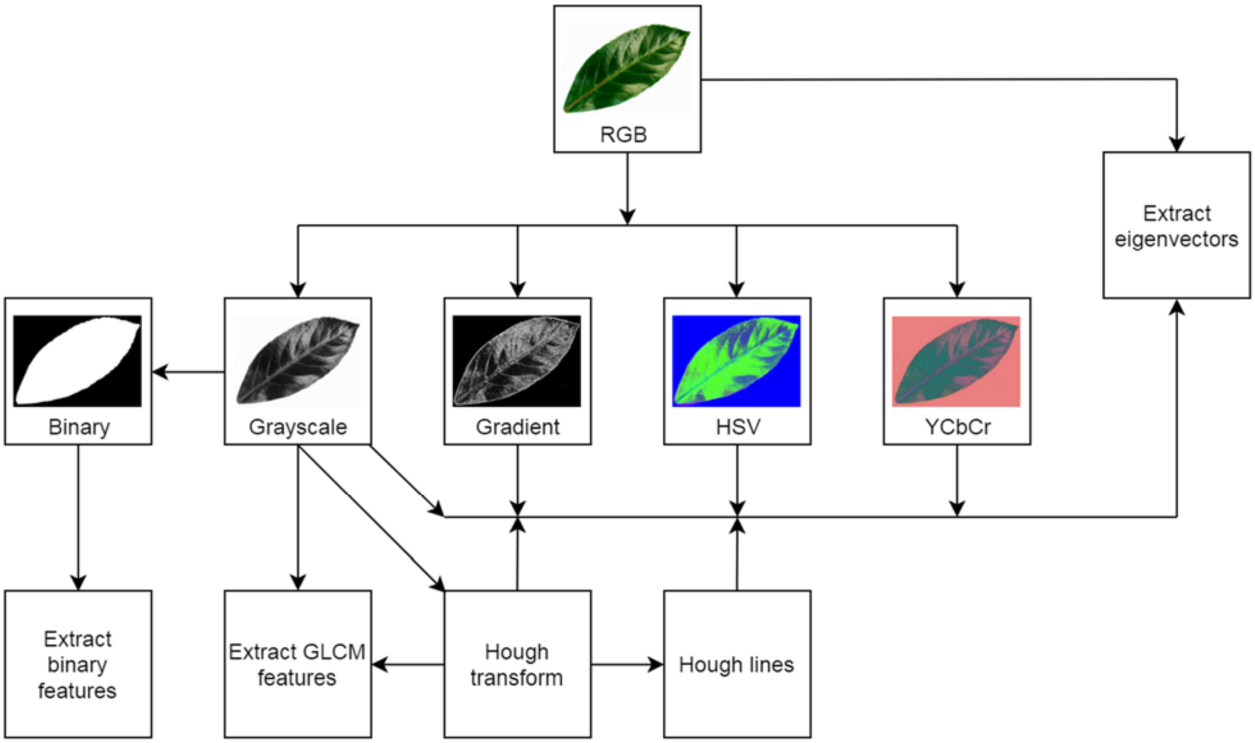

Figure 1 Feature extraction

Extracting features from the binary image

To extract features from a binary image, the RGB image of the leaf is first converted into a grayscale image and then to binary. Then some morphological operations such as closing, removing objects smaller than a certain area, and filling the holes are applied to the binary image to get rid of small erroneous objects and to get leaf as the only object in the image. Figure 2 summarizes the preprocessing step:

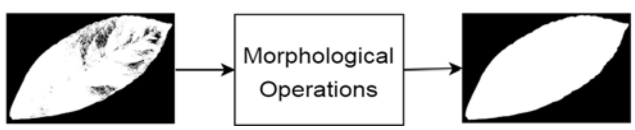

Figure 2 Performing morphological operations on the binary image to remove errors

Once the preprocessing step is done following features are extracted from the binary images:

1. Eccentricity

   Since the shape of a leaf resembles an ellipse, eccentricity can be used as a feature for classification. The eccentricity of an ellipse can be calculated as:

$$eccentricity = \frac{distance\ between\ two\ foci}{length\ of\ major\ axis} \tag{1}$$

2. Ratio of minor axis to major axis of an ellipse
3. Perimeter to area ratio

   This is the ratio of the distance around the boundary of the leaf object to the number of pixels in the region of the leaf object.
4. Solidity:

   Solidity is defined as the proportion of the pixels in the convex hull which are also in the region. The solidity of an object can be calculated as:

$$Solidity = \frac{Area}{Convex\ Area} \tag{2}$$

   Where convex area can be defined as the number of pixels in the smallest convex polygon that can contain the object.
5. Centroid

   In this case, a centroid is the center of mass of the leaf object.
6. Aspect ratio

   Aspect ratio is defined as the ratio of the height of bounding box containing the object to the width of the bounding box. Aspect ratio can be calculated as:

$$Aspect\ Ratio = \frac{height\ of\ the\ bounding\ box}{width\ of\ the\ bounding\ box} \tag{3}$$

Extracting features from a grayscale image

Following features are extracted from grayscale images:

1. GLCM features

Several features can be calculated from GLCM and four of them are used as features for training the classifier.

a. Contrast

   Calculates the contrast between each pixel and its neighbor and is given as

$$Contrast = \sum_i \sum_j (i-j)^2 c(i,j) \tag{4}$$

   Where $c(i,j)$ denotes an element in GLCM

b. Correlation

   Calculates how correlated each pixel is to its neighboring pixel and is given as

$$Correlation = \sum_i \sum_j \frac{(i-\mu i)(j-\mu j)c(i,j)}{\sigma_i \sigma_j} \tag{5}$$

   Where μ and σ denote mean and standard deviation respectively.

c. Energy

Calculates the energy of each element in GLCM and is given as

$$Energy = \sum_i \sum_j c(i,j)^2 \tag{6}$$

d. Homogeneity
Calculates the closeness of the distribution of elements in GLCM to the diagonal of GLCM and is given as

$$Homogeneity = \sum_i \sum_j \frac{c(i,j)}{1+|i-j|} \tag{7}$$

2. Number of corner points
Leaves from different species could have a different number of corner points so using the number of corners as a feature would help to boost up the accuracy of the system. We use the high-speed machine learning algorithm presented by Rosten [15] to calculate the number of corner points in a leaf image.
3. Number of SURF and Brisk points
SURF features were introduced by Bay [16] which are scale- and rotation-invariant detector and descriptor. BRISK features were introduced by Leutenegger [17] which detects, describes and matches keypoints in a grayscale image. In this step, rather than using the entire description of the features vector, we just use the number of SURF and BRISK points in an image as a descriptor as the leaves from the same species should have a similar number of SURF and BRISK points.
4. Hough transform
One of the most distinctive features of the leaves is the vein pattern. Hough transform is a technique that finds aligned points in an image that create, so it helps in detecting vein features of a leaf image. Hough transform can be applied to a grayscale image by detecting the edges in the image and then applying the Hough transform algorithm, as summarized in Figure 3.

As it can be seen from Figure 3 that Hough transform of one leaf differs from another, so GLCM features of Hough transform images too are calculated.
5. Hough lines
The most significant Hough peaks in the figure can be used to find Hough lines and as shown in Figure 3 different leaves have significantly different Hough lines.

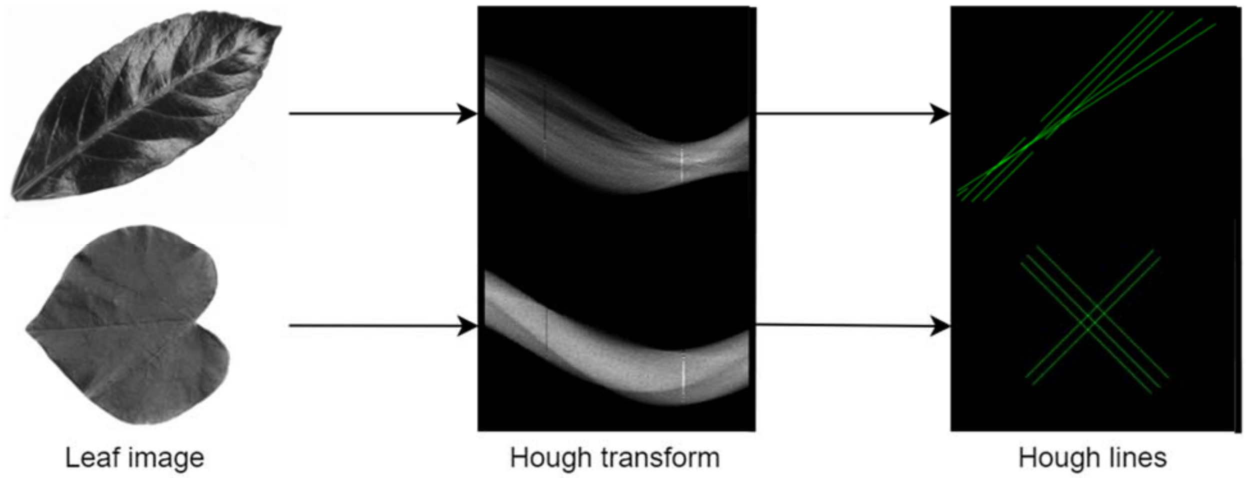

Figure 3 Hough transform and Hough lines of grayscale leaf images

Extracting eigenleaves

As seen from Figure-1 Eigenleaves are extracted from seven different images. Eigenleaves are calculated for different color-spaces and for grayscale and gradient images following the steps described below:

1. Convert image into the desired colorspace
2. Vectorize all images and put in a matrix → $\boldsymbol{X}$
3. Calculate mean of corresponding pixels of each image → $\boldsymbol{\mu}$
4. Subtract the mean from all images → $\overline{\boldsymbol{X}} = \boldsymbol{X} - \boldsymbol{\mu}$
5. Perform eigen-decomposition of the of $\overline{\boldsymbol{X}}^{\boldsymbol{T}}\boldsymbol{X}$ and get K eigenvectors corresponding to K largest eigenvalues → $\boldsymbol{v_k}$
6. Calculate eigenleaves → $\boldsymbol{l_k} = \overline{\boldsymbol{X}}\boldsymbol{v_k}$, where $k \in [1, K]$.

Thus, there are eigenleaves of length K associated with each leaf image which are used as features for training the classifier. The eigenleaves are also calculated for Hough transform and Hough lines images as they too provide distinctive features for training the classifier and helps boosting the accuracy.

EXPERIMENT AND RESULTS

Our approach is tested on two of the publicly available datasets: Flavia and Swedish. Flavia dataset consists of 1907 leaf images of 32 different species and the Swedish dataset consists of 1125 images of 15 different species. SVM classifier is trained for both the datasets using the hand-crafted features that are extracted from the leaf images. The classifier is tested on 10% images from the Flavia dataset and 20% images from the Swedish dataset respectively. Then we fine-tune training and testing data-size to get an optimal accuracy of 97.91% for the Flavia dataset and 99.56% for the Swedish dataset. Figure 4 shows how the accuracy of the system changes as we reduce the number of training images.

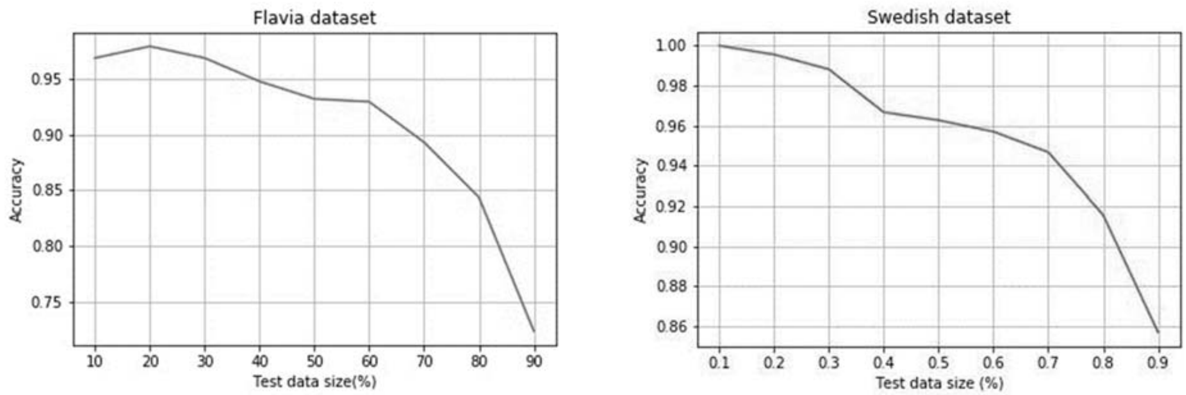

Figure 4 Accuracy of the SVM with changing test data size.

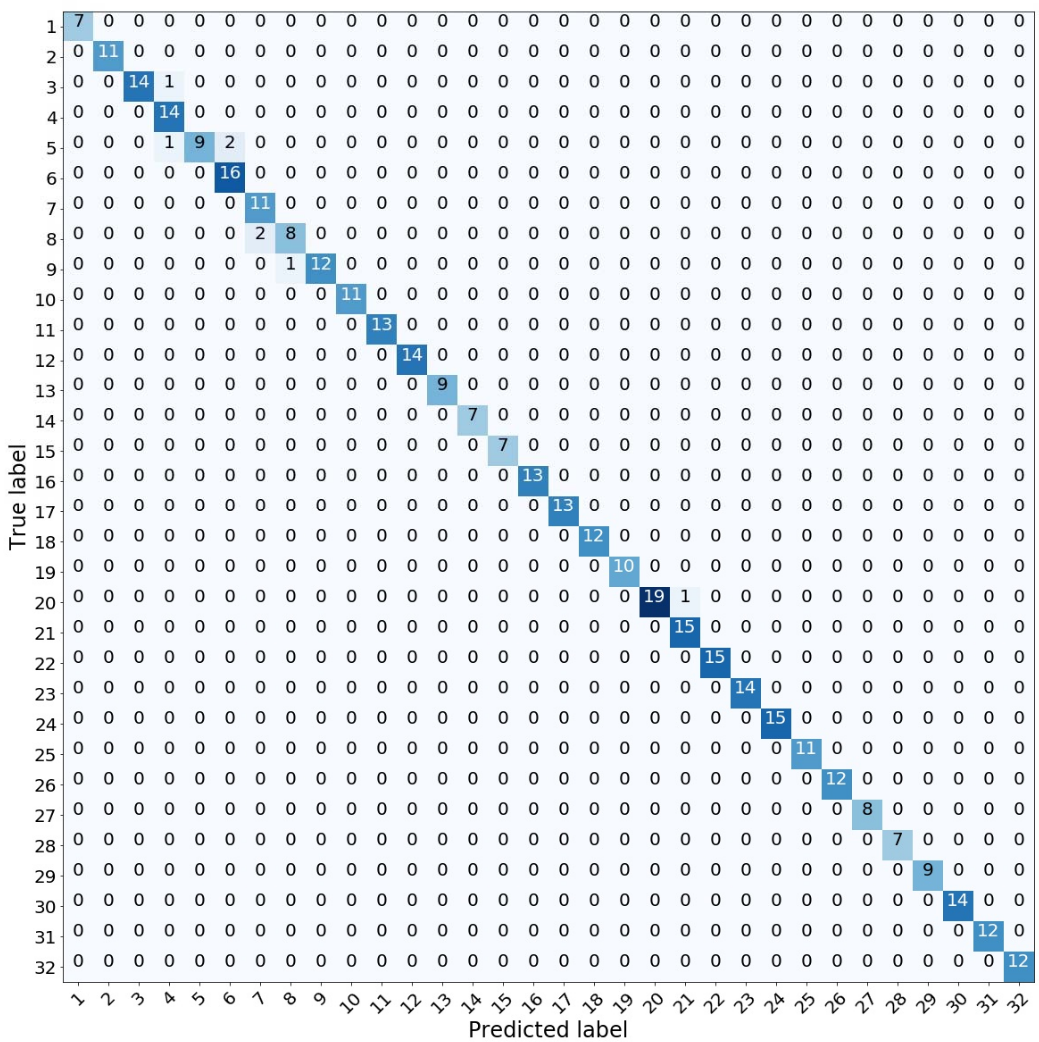

Figure 5 Confusion matrix for Flavia dataset

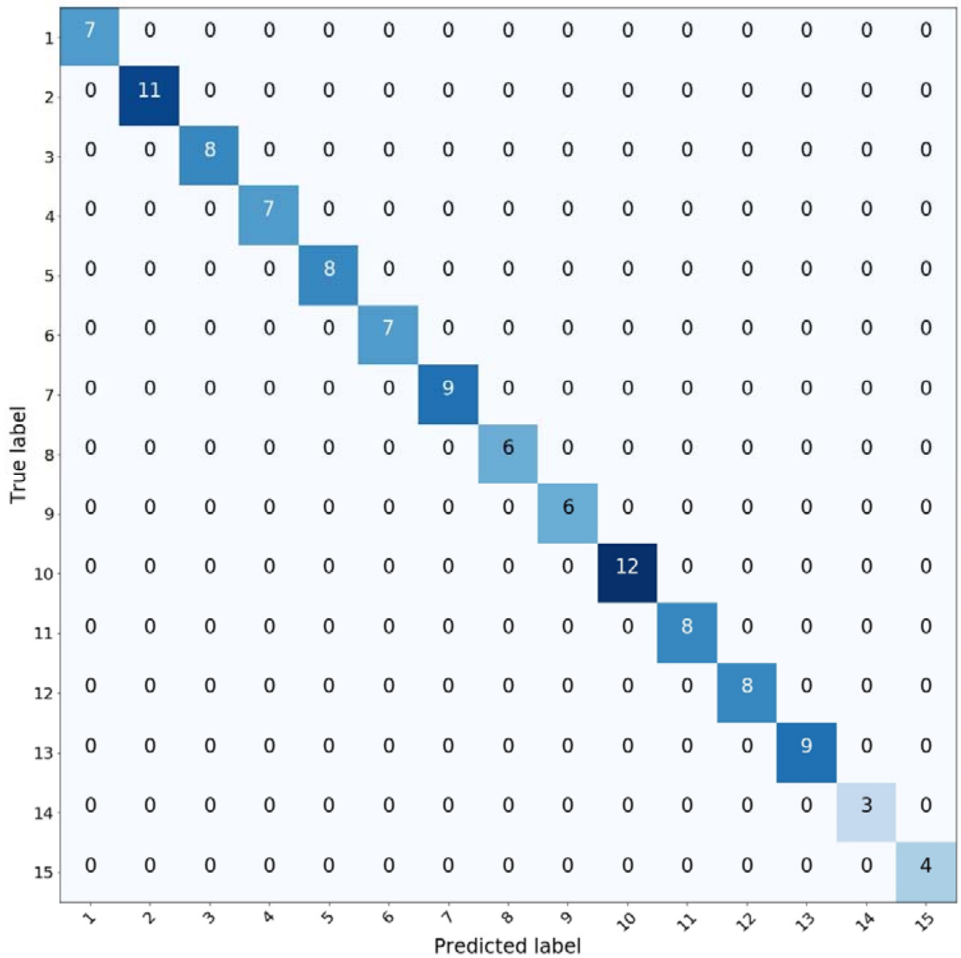

Figure 6 Confusion matrix for Swedish dataset

We also tested our features on several other classifiers, with the results summarized in Figure 7.

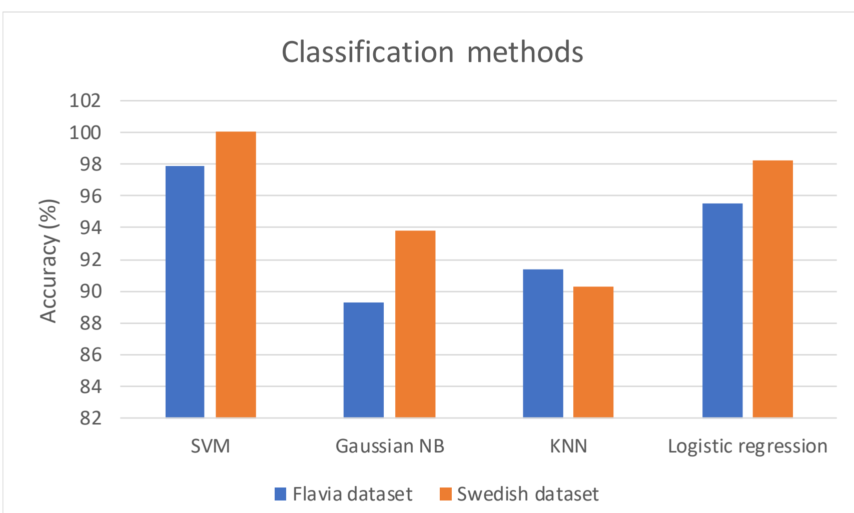

Figure 7 Comparison between different classification methods

CONCLUSIONS AND FUTURE WORK

We are able to achieve state-of-the-art accuracy for Flavia and Swedish datasets using SVM classifier. Features are extracted from leaf object in binary images and features from GLCM are extracted by calculating GLCM for grayscale images. Grayscale images were also used to calculate Hough transform to extract GLCM features and Hough lines. Finally, eigenleaves are calculated from images in different color-spaces and from the monochrome images to be used as features. We are successfully able to get comparable accuracy to the state-of-the-art using a computationally efficient method. Furthermore, we calculate features from the Fast Fourier Transform (FFT) and Curvelet transform but those features are redundant with respect to the features we already have and are not able to improve the accuracy. The algorithm remains to be tested on other publicly available datasets namely: Foilage, LeafSnap, ICL, and ImageCLEF.

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