Leaf Wilting Detection Using Support Vector Machine and Random Forest Classifiers

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I. Dataset Description

The given dataset contains images of soybean crops at various times of the day. The training dataset contains 1025 images and annotations corresponding to the level of wilting observed. The level of wilting is defined from 0-4, 0 means there is no/minimum wilting and 4 means the maximum level of wilting. The test dataset contains 300 images. Each image in both train and test dataset has dimension of 640*480. The distribution of each label in the training dataset is given in Figure 1.

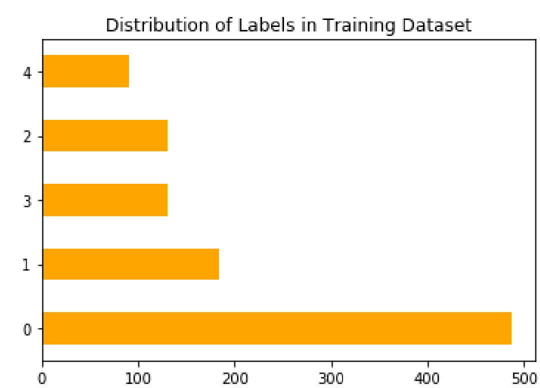

Fig. 1. Distribution of Labels in Training Dataset

As can be observed from Figure 1, the training data contains highest number of samples for crops with "0" level of wilting and the crops with "4" level wilting is lowest in number, less than one-fifth of the samples for crops with "0" wilting level.

II. Methodologies

The objective of this project is to automate leaf wilting ratings of soybean crops, given images of the crop at various times of the day. In this section, we discuss the key components of our model including feature extraction and classifiers used in the experiment. Figure 2 shows the architecture and key components of our classification model.

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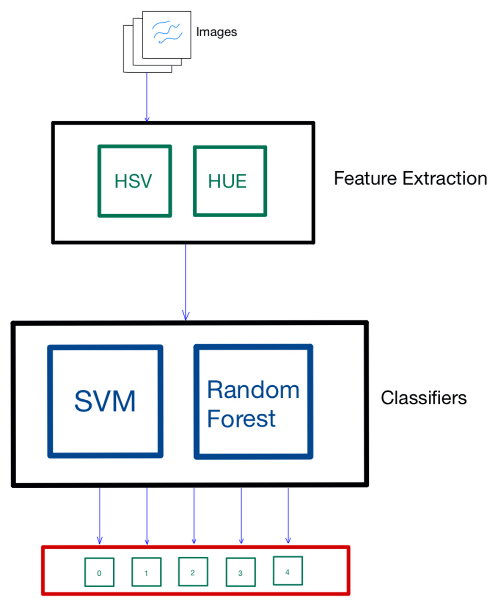

Fig. 2. Image Classification Model

A. Feature Extraction

Image feature extraction is an essential step in any image classification task. We manually inspected an image from each class for different image features. After visual inspection of representative images of each wilting rating, we noticed that different levels of wilting had different leaf's hue as shown in Figure 3.

Further inspection of color histograms of these images in the Hue-Saturation-Value (HSV) space confirmed this observation (Figure 4). As a result, we converted all images into HSV space and trained our models using the converted images; no other pre-processing was done.

HSV color histograms also showed that different levels of leaf wilting had different distributions of hue. As a result, we trained secondary models using only the hue channel of

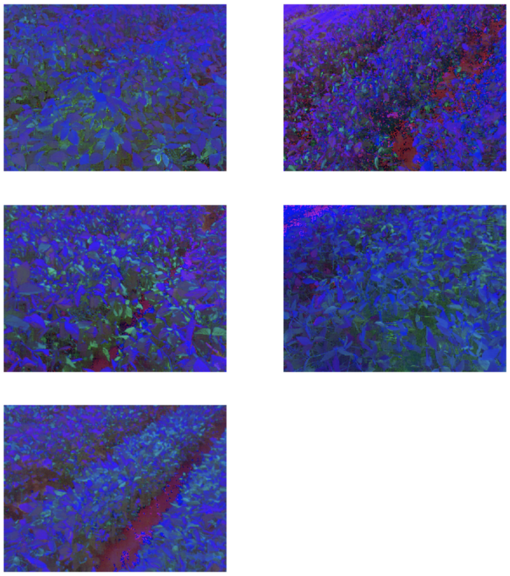

Fig. 3. Illustration of different levels of leaf wilting (using representative images) in HSV space. (From left to right, top to bottom) No wilting; leaflets folding inward at secondary pulvinus, no turgor loss in leaflets or petioles; slight leaflet or petiole turgor loss in the upper canopy; moderate turgor loss in the upper canopy; severe turgor loss throughout the canopy

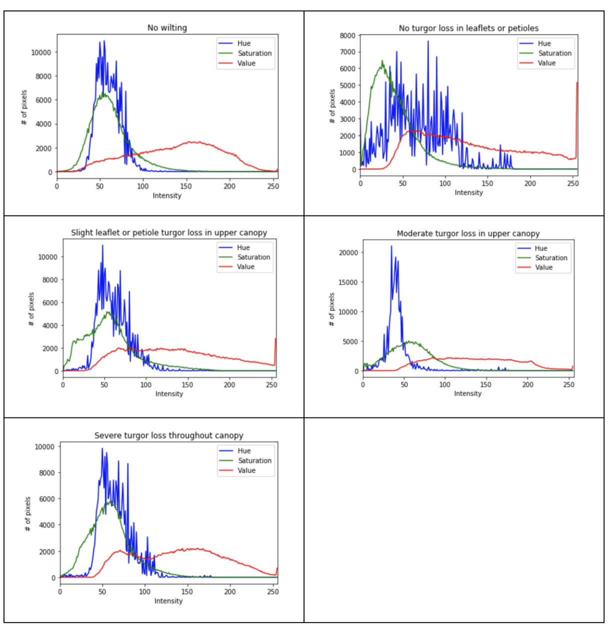

Fig. 4. HSV color histograms of representative images of different levels of leaf wilting

converted images.

B. Support Vector Machines

Support Vector Machines (SVMs) [1] is a commonly used method in pattern recognition and image classification. A SVM algorithm takes data as input and creates a hyperplane which separates the data into classes. SVM algorithm finds the points closest to the hyperplane from both classes, which are called support vectors. Then, the distance between the hyperplane and the support vectors is computed. The goal is to maximize this distance, so that the separation between the classes is as wide as possible.

1) SVM Kernel Functions: SVM algorithm builds an optimal hyperplane using the kernel function. The function of a kernel is to take data as input and transform it into different form. In our experiment, we used linear, polynomial, radial basis function (RBF) kernels.

C. Random Forest Classifiers

Random forest [2] is an ensemble model and it uses results from many several decision trees to calculate a response. A random forest model calculates a response variable by creating forests of decision trees and the putting each item (in our case, the extracted image) in each decision tree. The final response is based on the response from all the decision tree. In our task, an image is assigned a class that is predicted the most.

In our study, we experimented with random forest classifiers with 100, 300, 500 and 700 trees.

III. Experiment and Results

A primary and secondary analysis was conducted on all of SVM and Random Forest classifiers using HSV and HUE features, respectively. The training images were randomly split into two for model evaluation: a training set and a testing set. The training set contained 717 images (70% of the dataset); the remaining images were used for testing.

Figure 5 shows the test accuracy for the three SVM models with HSV and HUE features. Full models are the models that represent images in HSV features and secondary models are the models that represent images in HUE features. As can be seen from the figure HSV features were more representative of the image and using HSV features improved the accuracy of the SVM models.

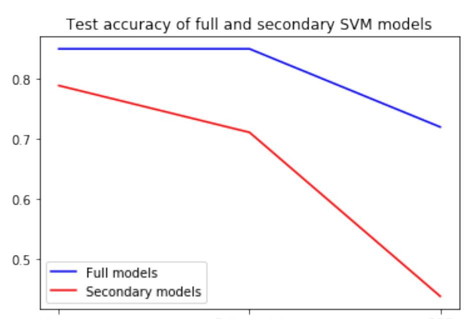

Fig. 5. Test Accuray for SVM Models using HSV and HUE Features

Like SVM models, the random forest classifiers performed better with HSV features compared to HUE features (Figure 6).

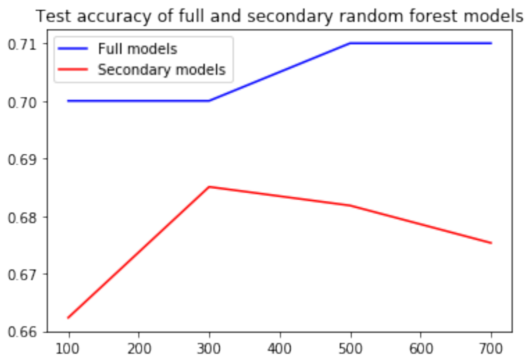

Fig. 6. Test Accuray for SVM Models using HSV and HUE Features

Overall the SVM model with linear kernel performed the best. The model performed the best for both HSV and HUE features. SVM with polynomial kernel performed as good as the model with linear kernel for HSV features. All variants of Random Forest classifiers performed worse than SVM with Linear and Polynomial kernels. However, all the random forest classifiers outperformed the SVM model with RBF kernel. The precision, recall, F1-score and accuracy for each model with both HSV and HUE features are reported in Table 1.

TABLE I
RESULTS FOR DIFFERENT MODELS FOR HSV AND HUE FEATURES

Model	**Feature**	**Precision**	**Recall**	**F1-score**	**Accuracy**
SVM - Linear	HSV	0.85	0.85	0.85	0.85
SVM - Poly	HSV	0.85	0.85	0.84	0.85
SVM - RBF	HSV	0.75	0.72	0.68	0.72
SVM - Linear	HUE	0.79	0.79	0.79	0.789
SVM - Poly	HUE	0.71	0.71	0.71	0.711
SVM - RBF	HUE	0.44	0.44	0.44	0.438
Random Forest - 100	HSV	0.72	0.70	0.67	0.70
Random Forest - 300	HSV	0.72	0.70	0.67	0.70
Random Forest - 500	HSV	0.72	0.71	0.67	0.71
Random Forest - 700	HSV	0.73	0.71	0.67	0.71
Random Forest - 100	HUE	0.66	0.66	0.66	0.66
Random Forest - 300	HUE	0.69	0.69	0.69	0.69
Random Forest - 500	HUE	0.68	0.68	0.68	0.68
Random Forest - 700	HUE	0.68	0.68	0.68	0.68

IV. Conclusion and Future Work

In our experiment, we observed that HSV features were more representative of the image data than HUE features. Using HSV features increased the performance of our best model i.e. SVM with linear kernel by 6%. Although our SVM - Linear and SVM- Poly performed fairly same for HVS features, SVM-linear performed better than SVM - Poly when using HUE feature by 7.8%. For the second part we plan on experimenting with Convolution Neural Networks for the task of image classification. Since, of dataset is not balanced, in the next experiment we will handle the issues associated with the imbalanced data as well.

References

[1] C. Cortes and V. Vapnik, "Support-vector networks," *Machine learning*, vol. 20, no. 3, pp. 273–297, 1995.
[2] A. Liaw, M. Wiener *et al.*, "Classification and regression by randomforest," *R news*, vol. 2, no. 3, pp. 18–22, 2002.