Estimating the severity of sugarcane aphids infestation on sorghum with machine vision

Xiaoling Deng[1], J. Alex Thomasson[2,6], N. Ace Pugh[3], Junxi Chen[1], William L. Rooney[3], Michael J. Brewer[4], Yeyin Shi[5*]

(1. College of Electronic Engineering, South China Agricultural University, Guangzhou 510642, China;
2. Department of Biological and Agricultural Engineering, Texas A&M University, 333 Spence St, College Station, TX 77843;
3. Department of Soil and Crop Sciences, Texas A&M University, 370 Olsen Blvd, College Station, TX 77843;
4. Department of Entomology, Texas A&M AgriLife Research, 10345 Hwy 44, Corpus Christi, TX 78406;
5. Department of Biological Systems Engineering, University of Nebraska-Lincoln, 3605 Fair Street, Lincoln, NE 68583, USA
6. Ddepartment of Agricultural and Biological Engineering, Mississippi State University, MS 39762)

Abstract: Sugarcane aphid (SCA), Melanaphis sacchari, is one of the most prominent insect pests of grain, forage and bio-energy sorghum in the southern US since 2013.   The timing and dosage of a pesticide application for SCA depend on a close monitoring of its pressure or severity change in the field.   To assist the field scouting, digital images were taken using a smart phone in proximity of infected leaves and corresponding image processing algorithms were developed later to estimate the infestation severity in this study.   Image samples were grouped into four classes according to the infestation severity for aphid management considerations: no threat (0-10 SCA/leaf), insecticide use should be considered (11-125 SCA/leaf), insecticide should be used and yield loss likely (126-500 SCA/leaf), and plant death possible (more than 500 SCA/leaf).   With 5-fold cross validation, results showed that the best average classification accuracy across the four SCA classes was 85.0% with the modified OVO-SVM algorithm.   The SCA quantification accuracies achieved in this study using the SVM algorithm showed the promise of using machine learning algorithms in this case of aphid density estimation on sorghum leaves.   The methodology developed in this study can be modified with more sophisticated machine learning algorithms and more data in the future to be incorporated into a handheld or a mobile remote sensing system to assist growers and researchers with automatically quantifying SCA in a fast and objective manner.
Keywords: IPM, machine vison, SVM, sugarcane aphid, severity estimation

Citation: Deng X L, Thomasson A J, Pugh A N, Chen J X, Rooney L W, Brewer J M, Shi Y Y.   Estimating the severity of sugarcane aphids infestation on sorghum with machine vision.   Int J Precis Agric Aviat, 2020; 3(2): 89–96.

1 Introduction

Sorghum is one of the top five cereal crops in the world[1]. Ranked the first in the world's grain sorghum producers, the United States harvested 10.1 million tonnes grain sorghum[2] with an estimated economic value of $1.35 billion[3] in 2016.   Texas

contributed over $388 million which was the second largest producer in the US after Kansas[3].   However, the North America sorghum industry is threatened by a new invasive pest, the sugarcane aphid (SCA), *Melanaphis sacchari* (Zehntner) (Hemiptera: Aphididae).   Since the first report in 2013, the aphid has been found on sorghum in 17 states and over 400 counties in the US as well as all sorghum producing regions in Mexico by 2015, with significant yield loss ranging from 10% to greater than 50%[4].   SCA damage to sorghum results from direct loss of plant nutrients through their feeding on plant sap, and leads to leaf chlorosis and necrosis, and eventual seed head decline and yield loss.   They also produce honeydew which deposits on the upper side of the leaf underneath the leaf they cluster on its underside.   This sticky substance attracts black sooty mold and can also clog equipment during harvesting[4]. One avenue of management is the use of foliar-applied insecticides which are applied according to guidelines based on density of aphid infestation on the leaves[5].   In most common situations of sorghum production in the U.S., insecticide use is advised if the field average is 40 to 100 sugarcane aphids per leaf or greater[5].   An immature SCA takes only 4 to 12 days to become an adult and lives for another 10 to 37 days with a reproductive potential of 34 to 96 nymphs[4,6,7] . With such a rapid reproductive potential, pest monitoring to obtain estimates of aphid density on the leaves is recommended once or twice per week.

Unfortunately, manual estimation of the number of SCA on

leaves is a difficult and time-consuming task prone to wide variation in estimation due to variation in observer assessment[8]. Immature and adult SCA colonize in clusters on the underside of sorghum leaves so leaves need to be turned over for observation, and the structure and composition of the aphid cluster can range from small number of aphids forming a cluster to large cluster with many aphids of multiple sizes (development stages)[9]. Educational materials on the identification of the pest and estimation of its population densities on leaves have been developed. The educational formats included a 6-min instructional video and a 22-min pre-recorded slideshow which were shown to south Texas pest managers. The instructional video significantly modified their accuracy at aphid density estimation[8], however, the process is time-consuming and field use varies.

If a computer vision system can partially automate this estimation process, it will not only reduce the observer variation, but also better document the original infestation situation with imagery for further studies. Such a computer vision system can be ultimately integrated in a field robot with a mechanical arm which can conduct automatic scouting to save human labor. For the computer vision system, however, challenges exist in the SCA quantification algorithm. The size of SCA clusters and density of aphids in a cluster varies. Moreover, the color and size of SCA can vary from pale yellow, tan to gray depending on the maturity level and species, as showed in Figure 1. These challenges can be addressed better by advanced supervised machine learning algorithms.

The methods based on machine learning method can help farms reduce damage and increase their incomes, and can be applied to various crops [10]. Machine learning algorithms have been applied in agriculture, such as to detect citrus greening disease at leaf level with two-stage back propagation neural network[11], to recognize insects on sticky traps with feed-forward neural network[12], to recognize moths in surveillance videos using deep convolutional neural networks[13], and to count pests in the paddy field using image analysis[14].

Figure 1 Sugarcane aphid clusters on a sorghum leaf. SCAs were in different maturity stages with different colors and sizes and were highly overlaid with each other. Image was taken by authors in fall, 2015, in Texas

Among machine learning methods, support vector machine (SVM) classifier is one of the most classical supervised machine learning models[15]. Compared with some other popular machine learning algorithms such as artificial neural network, SVM often suffers less with the overfitting issue and can work with small training data sets. Given a set of training data with class labels, SVM maps the data into a higher dimensional space where an optimal hyperplane can be constructed to linearly separate the data into classes; new data are then assigned into one of the classes using the developed model[16]. Inputs of the SVM model are often the features extracted from the imagery to recognize pests including color in different color spaces, shape, and texture features. Cost-support vector classification (C-SVC) was applied on true-color imagery to detect citrus greening disease (HLB) based on the texture and histograms features in gray-scale and hue, saturation and intensity color spaces were extracted from the digital images of citrus leaves with different disease severities under natural lighting, resulted in an accuracy of 91.9%[17]. In another application of identifying and counting five rice pests on rice light traps, SVM was used with 156 inputs including color, shape and texture features extracted from digital images of the rice light traps and achieved an average accuracy of 97.5% with 7-fold cross validation[18]. Similarly, SVM with different kernel functions and with both morphological and color features was used to detect thrips on strawberry flowers[19], evaluate leafminer damage on cucumber leaves[20], and evaluate the browning degree on mongo[21].

To the best of our knowledge, no study has been conducted to develop an SVM based on machine learning model for estimation the severity of SCA on sorghum using digital images. The goal of this study is to partially automate the current manual scouting and classification for SCA infestations on sorghum leaves using true-color digital imagery and SVM based machine learning modeling. The specific objectives were to (1) develop a feature extraction method to effectively represent the severity of SCA infestation on images, (2) evaluate the improved multi-class classification model performance on severity assessment of SCA infestation.

2   Materials and methods

2.1   Field image collection

Field data collection was conducted in a SCA-infested bioenergy sorghum field located on the Texas A&M University Farm in College Station, TX, in September 2015 and 2016. The sorghum was in their mid to late growth stage at the data collection. Each leaf was detached from the plant, quickly flattened against the black surface of a notepad case and imaged using a smart phone (iPhone 5S) with auto focus at a proximity of about 20 cm. The undersides of all leaves were imaged; and both sides of the leaf were imaged if the upper side was evidently covered by honeydew. Imaging angle was selected to ensure uniform lighting on the images. Limited by the field of view and the pixel resolution of the camera, only part of the leaf where the SCA clustered or evident black sooty mold caused by the honeydew were imaged.

2.2   Ground truth, sample size and summary of SVM modeling

Ground truth number of SCA in each image of the leaf underside was manually counted by three different persons. Images were zoomed in and each SCA was marked by a red dot after being counted in GIMP2 image manipulation software (The GIMP Development Team) to ensure no multiple or missing count. According to the number of SCA, each image of the leaf underside was assigned into one of the four classes based on sorghum damage assessments from SCA infestations taken across multiple years, locations in the southern U.S., and sorghum hybrids[5,22]: Class A, 0-10 SCA per leaf, no threat; Class B, 11-125 SCA per leaf, indicating a building population to be monitored weekly to determine if insecticide use is warranted; Class C, 126-500 SCA per leaf, insecticide must be applied quickly and some yield loss may be expected; Class D, greater than 500 SCA per leaf, significant yield reduction and plant death possible. Example image of each class was shown in Figure 2.

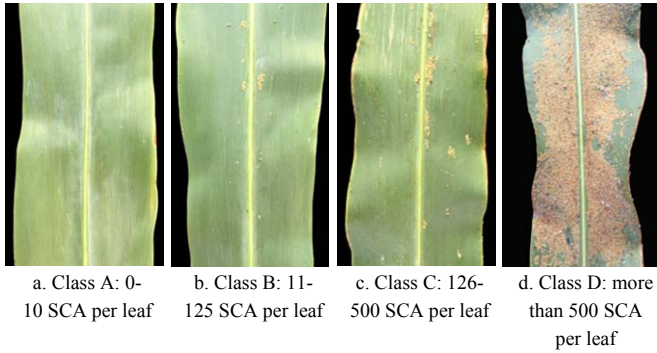| a. Class A: 0-10 SCA per leaf | b. Class B: 11-125 SCA per leaf | c. Class C: 126-500 SCA per leaf | d. Class D: more than 500 SCA per leaf |

Figure 2   Example images of underside leaves in each class

Figure 3 shows a framework of the research work in this study. After texture and color features were extracted and input to each classifier, two multi-class classifiers were optimized and compared for the severity SCA estimation: improved One-Versus-One SVM (OVO-SVM) and improved Hierarchical SVM (H-SVM). Grid search was used to optimize model parameters. Finally, the classification results of the two classifiers with and without optimization were compared using 5-fold cross validation.
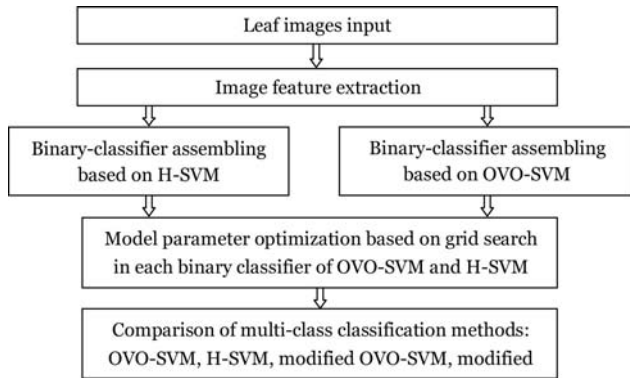

Figure 3   The framework of the research proposal

2.3 Image feature extraction

Texture and color features were extracted to be inputs to the SVM models. The digital images were first converted from the original Red, Green and Blue (RGB) color space to the Hue, Saturation and Value (HSV) color space to better separate pixel intensity variation from color variation in the images. Then texture feature was extracted based on the Gray Level Co-occurrence Matrix (GLCM) calculated from the gray level image. It is a measure of how often different combinations of neighboring pixel values occur. Equation (1) shows how each element in the GLCM was calculated according to Soh and Tsatsoulis[23] :

$$p(g1, g2) = \sum_{x=1}^{X}\sum_{y=1}^{Y} \begin{cases} 1, G(x, y) = g1 \quad \text{and} \quad G(x+dx, y+dy) = g2 \\ 0, G(x, y) \neq g1 \quad \text{or} \quad G(x+dx, y+dy) \neq g2 \end{cases}$$

(1)

in which p is the ($g1$, $g2$)th entry in a normalized GLCM; $g1$ and $g2$ vary from 1 to the number of grey levels which was down sampled to 256 in this study; $G(x, y)$ is the gray level of the center pixel and $G(x+dx, y+dy)$ is the gray level of the neighboring pixel; x and y are the order of pixel by their row-column designations. In this study, GLCMs were calculated along four directions – 0-degree, 45-degree, 90-degree and 135-degree – and at the offset of one, in total 16 statistics of texture features. Four statistics including energy, entropy, contrast and dependency (Table 1) were derived from the calculated GLCMs.

Besides the texture features, three color features – the first rank moment (mean value), the second rank moment (standard deviation),

and the third rank moment – were extracted from each channel of the HSV and RGB color space which resulted in 18 statistics of color features (Table 2). Hence, there were 34 statistics extracted for the texture and color features all together for each image.

Table 1   Equations of texture features derived from the calculated gray level co-occurrence matrices

Feature	Equation
Energy	$Q_1 = \sum_{g1}\sum_{g2}[p(g1, g2)]^2$
Entropy	$Q_2 = -\sum_{g1}\sum_{g2} p(g1, g2)\lg p(g1, g2)$
Contrast	$Q_3 = \sum_{g1}\sum_{g2}(g1-g2)^2 p(g1, g2)$
	$Q_4 = \dfrac{\sum_{g1}\sum_{g2} g1g2\, p(g1, g2) - \mu_x\mu_y}{\delta_x\delta_y}$
Dependency	$\mu_x = \sum_{g1} g1\sum_{g2} p(g1, g2),$
	$\mu_y = \sum_{g2} g2\sum_{g1} p(g1, g2)$
	$\delta_x = \sum_{g1}(g1-\mu_x)^2 \sum_{g2} p(g1, g2),$
	$\delta_y = \sum_{g2}(g2-\mu_y)^2 \sum_{g1} p(g1, g2)$

Table 2   Equations of color features derived from HSV and RGB channels

Feature	Equation
1st rank moment	$\bar{X} = \dfrac{\sum_{i=1}^{N} X_i}{N}, \ (i = 1, 2, 3, ..., N)$
2nd rank moment	$\sigma = \sqrt{\dfrac{\sum_{i=1}^{N}(X_i - \bar{X})^2}{N}}, \ (i = 1, 2, 3, ..., N)$
3rd rank moment	$\kappa = \sqrt[3]{\dfrac{\sum_{i=1}^{N}(X_i - \bar{X})^3}{N}}, \ (i = 1, 2, 3, ..., N)$

2.4 SVM Modelling for severity of sugarcane aphid infestation

SVMs were originally designed for binary classification. For multi-class classification such as the case in this study, often binary classifiers were constructed first and then combine for the multi-class classification. Some of the typical multi-class SVM classification methods include One-versus-Rest SVM (OVR-SVM), One-versus-One SVM (OVO-SVM), direct acyclic graph SVM (DAG-SVM), hierarchical tree based SVM (H-SVM). Among these methods, the H-SVM and the OVO-SVM are two of the most popular ones and were used in this study.

2.4.1 SVM model parameter optimization

After image feature extraction, SVM was implemented and optimized based on the LIBSVM library developed by Chang and Lin[24]. Among some common kernel functions including linear, polynomial, RBF and sigmoid, the RBF kernel has fewer numerical difficulties compared with the polynomial kernel which has more hyper parameters. It has excellent generalization performance and low computational cost to nonlinearly maps samples into a higher dimensional space to handle the case when the relation between class labels and attributes in nonlinea[16]. After comparison, radial basis function (RBF) kernel was selected in this study to project the original inputs to a high-dimensional feature space so the data points that belong to different classes become mostly linearly separable.

An important step in this study was to optimize the RBF kernel of the SVM model. Two parameters of the RBF kernel were optimized: C and γ. Parameter C is a penalty coefficient for the soft margin cost function which trades off misclassification of training

data points against the decision surface. A smaller C results in a smoother decision surface while a larger C results in a decision surface with more correctly classification for all training data points. Parameter γ defines how far the influence of a single training data point reaches in determining the decision plane. An excessively large value for parameter γ results over-fitting and a less generalized model, while a disproportionately small value of γ leads to under-fitting[25]. To find the optimal combination of C and γ, grid-search algorithm was used in this study. Compared with some other optimization algorithms, the grid search method is one of the most simple and common methods by setting the upper and lower search bounds and the search interval and search the best value within the entire search area[26,27]. Too large a search interval wastes computational resource, while too small a search interval might render a satisfactory outcome impossible. In this study, the search intervals of both parameters of C and γ were all set to 0.5, and the lower and upper search bounds of both parameters were all set from –10 to 10.

2.4.2 Modified multi-class SVM classifications

Considering the individuality of each training subset in the classical multi-classification methods, OVO-SVM and H-SVM were both modified by performing parameter optimizing in every binary classifier in this study.

As for the H-SVM, a two-layer architecture was used for the four classes in this study[28,29]. The first layer was a binary classifier which distinguished the data from a combined class AB which corresponded to less than 126 SCA per leaf, and a combined class CD which corresponded to more than 125 SCA per leaf. The second layer was two binary classifiers, one to distinguish the data that were classified to combined class AB to either Class A or B, the other to distinguish the data that were classified to combined class CD to either Class C or D.

In the traditional H-SVMs, the process of parameter optimization for C and γ only perform once which result in neglecting the individuality of every training subset. To increase the accuracy of multi-class classification, the strategy of multiple level parameter optimization was conducted in H-SVMs, specifically, parameter optimization for C, γ are performed in every level of training process of H-SVMs, the flowchart of training process is showed as Figure 4.
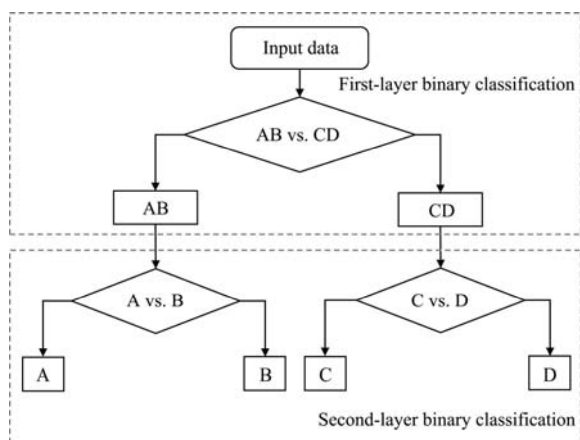

Figure 4   Flowchart of the multi-class classification process of the Hierarchical SVM (H-SVM) used in this study with four infestation severity levels.   Class A: 0-10 SCA per leaf; Class B: 11-125 SCA per leaf; Class C: 126-500 SCA per leaf; Class D: more than 500 SCA per leaf.   AB stands for the combination of Class A and Class B; CD stands for the combination of Class C and Class D

The OVO-SVM trains a separate binary classifier for each different pair of classes, which in the case of this study were six ($=n_{class}(n_{class}-1)/2=4*3/2$) separate classifiers between each two of the four different classes. Similar like improved H-SVMs, the improved strategy is that parameters optimization based on grid search was conducted in each of 6 binary classifiers in the training process. In the predicting process, the final classification is decided by the majority vote[30,31]. The flowchart of prediction process in OVO-SVMs is showed in Figure 5.
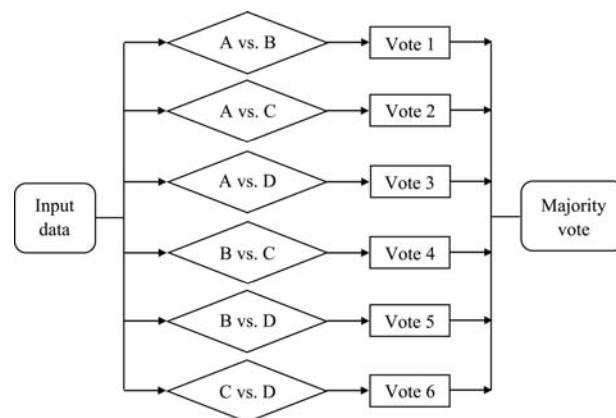

Figure 5   Flowchart of the multi-class classification process of the improved OVO-SVM used in this study with four infestation severity levels.   Class A: 0-10 SCA per leaf; Class B: 11-125 SCA per leaf; Class C: 126-500 SCA per leaf; Class D: more than 500 SCA per leaf

3   Results and discussion

To evaluate the SVM classification accuracy, 5-fold cross-validation was used considering the limited samples in this study. All 180 images were randomly partitioned into five equal-sized groups. Each time one group was retained as the validation dataset and the remaining four groups were used as training dataset. The process was then repeated 5 times, with each of the five groups used once as the validation data. Finally, the average of the five accuracies for each class was reported as the model prediction performance.

3.1   Classification accuracies with different infestation severity

Table 3 illustrates the classification accuracy for each class of SCA quantification with the modified H-SVM and OVO-SVM, respectively. The accuracies for class A (less than 10) and class D (more than 500) were good for both methods. However, the accuracies of class B (between 10-125) and class C (between 126-500) were lower, especially for class C.

Table 3   The SCA quantification accuracy using modified H-SVM and OVO-SVM methods

Class	Modified H-SVM	Modified OVO-SVM
Class A (0 – 10 aphids/leaf)	100%	100%
Class B (10 – 125 aphids/leaf)	76.0%	80.0%
Class C (126 – 500 aphids/leaf)	57.8%	60.0%
Class D (> 500 aphids/leaf)	100%	100%
Mean	83.5%	85.0%

Table 4 illustrates the recognition accuracy of modified H-SVM and OVO-SVM for all samples using 5-fold cross validation. From this table, obvious differences between different fold can be observed, to estimate the performance of predicting modeling. To avoid the randomness of data, the average recognition accuracy was adopted to estimate the performance of modified H-SVM and OVO-SVM.

Table 4 Average classification accuracy across the four classes of each fold of the 5-fold cross validation using modified H-SVM and OVO-SVM.

	Modified H-SVM	Modified OVO-SVM
1st fold	82.9%	83.9%
2nd fold	88.6%	89.3%
3rd fold	77.1%	83.7%
4th fold	91.4%	91.6%
5th fold	71.4%	75.5%
Mean	83.5%	85%

3.2 Performance of binary classifiers

Figure 6 and Figure 7 show the binary classification accuracies from the grid search optimization for different combinations of parameters C and γ for the H-SVM and OVO-SVM, respectively. The performance of each binary classifier directly indicates the effectiveness of feature extraction and parameter optimization of SVM and influences the overall performance of the multi-class classification.

Figure 6 shows the results of the first- and second-layer binary classifiers using H-SVM. A highest classification accuracy of 91.03% was achieved for the first-layer binary classification between the combined Class AB (0-125 SCA per leaf) and the combined Class CD (more than 125 SCA per leaf) when parameter C was equal to 8.000 and γ was equal to 0.5000 in the RBF kernel (Figure 6a). For the second-layer binary classifications in the H-SVM, a highest classification accuracy of 100% was achieved for the classification between Class A (0-10 SCA per leaf) and Class B (11-125 SCA per leaf) when parameter C was equal to 5.657 and γ was equal to 0.03125 in the RBF kernel (Figure 6b); and a highest classification accuracy of 100% was achieved for the classification between Class C (126-500 SCA per leaf) and Class D (more than 500 SCA per leaf) when parameter C was equal to 256.0 and γ was equal to 0.1768 in the RBF kernel (Figure 6c).

a. Accuracies of the first layer binary classification between Class AB
(0-125 SCA per leaf) and Class CD (more than 125 per leaf)

b. Accuracies of the second layer binary classification between Class A
(0-10 SCA per leaf) and Class B (11 to 125 SCA per leaf)

c. Accuracies of the second layer binary classification between Class C
(126 to 500 SCA per leaf) and Class D (more than 500 SCA per leaf)
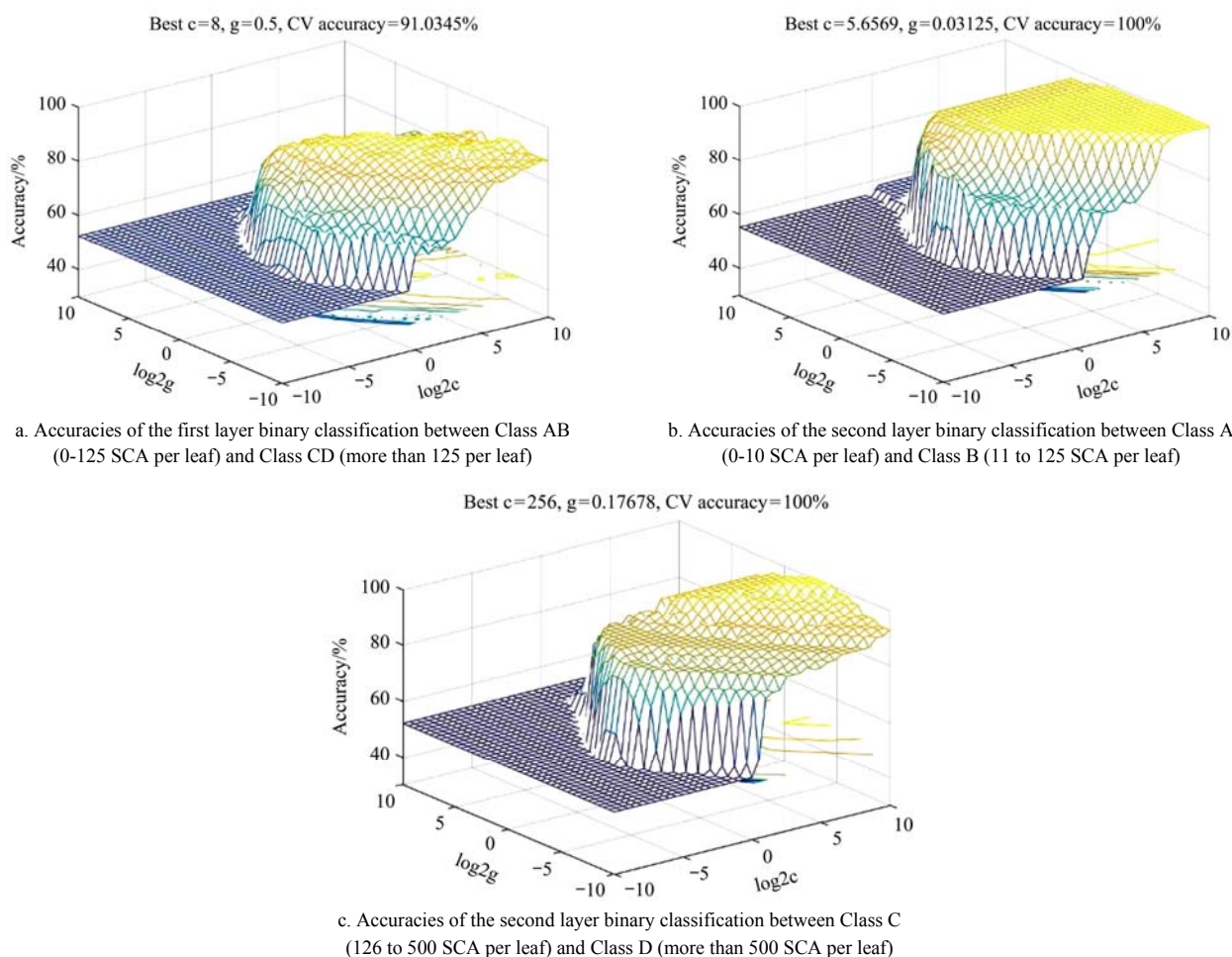
Note: C and γ values in the plots are shown in the logarithm to base 2.

Figure 6   Waterfall plots illustrate accuracies from the grid search with different parameters C and γ combinations for each binary classifier in the H-SVM

Figure 7 shows the grid search results of the six different pairs of binary classifiers in the OVO-SVM.   Class A (0-10 SCA per leaf) was well distinguished from Class B (11-125 SCA per leaf), Class C (126 to 500 SCA per leaf) and Class D (more than 500 SCA per leaf) with 100% highest classification accuracies when parameter c was equal to 5.657, 2.8284 and 0.35355, and γ was equal to 0.03125, 0.044194 and 0.35355, respectively, in the RBF kernel (Figure 7a, b and c). Similar highest classification accuracies were achieved for the binary classifier of Class B and Class D (100%), and the one of Class C and D (97.10%), when parameter c was equal to 1.4142 and 362.0387, and γ was equal to 4 and 0.044194, respectively, in the RBF kernel (Figure 7e, and f).   The high classification accuracies of these binary classifiers indicated effectiveness of image feature extraction, SVM models and parameter optimization. Similar as the results of the H-SVM, the binary classifier with the lowest classification accuracy was still for Class B and Class C at 83.33% when parameter c was equal to 724.0773 and γ was equal to 0.003906 in the RBF kernel (Figure 7d).

Best c=5.6569, g=0.03125, CV accuracy=100%

a. Class A vs. Class B

Best c=2.8284, g=0.044194, CV accuracy=100%

b. Class A vs. Class C

Best c=0.35355, g=0.35355, CV accuracy=100%

c. Class A vs. Class D

Best c=724.0773, g=0.0039363, CV accuracy=83.3333%

d. Class B vs. Class C

Best c=1.4142, g=4, CV accuracy=100%

e. Class B vs. Class D

Best c=362.0387, g=0.044194, CV accuracy=97.1014%
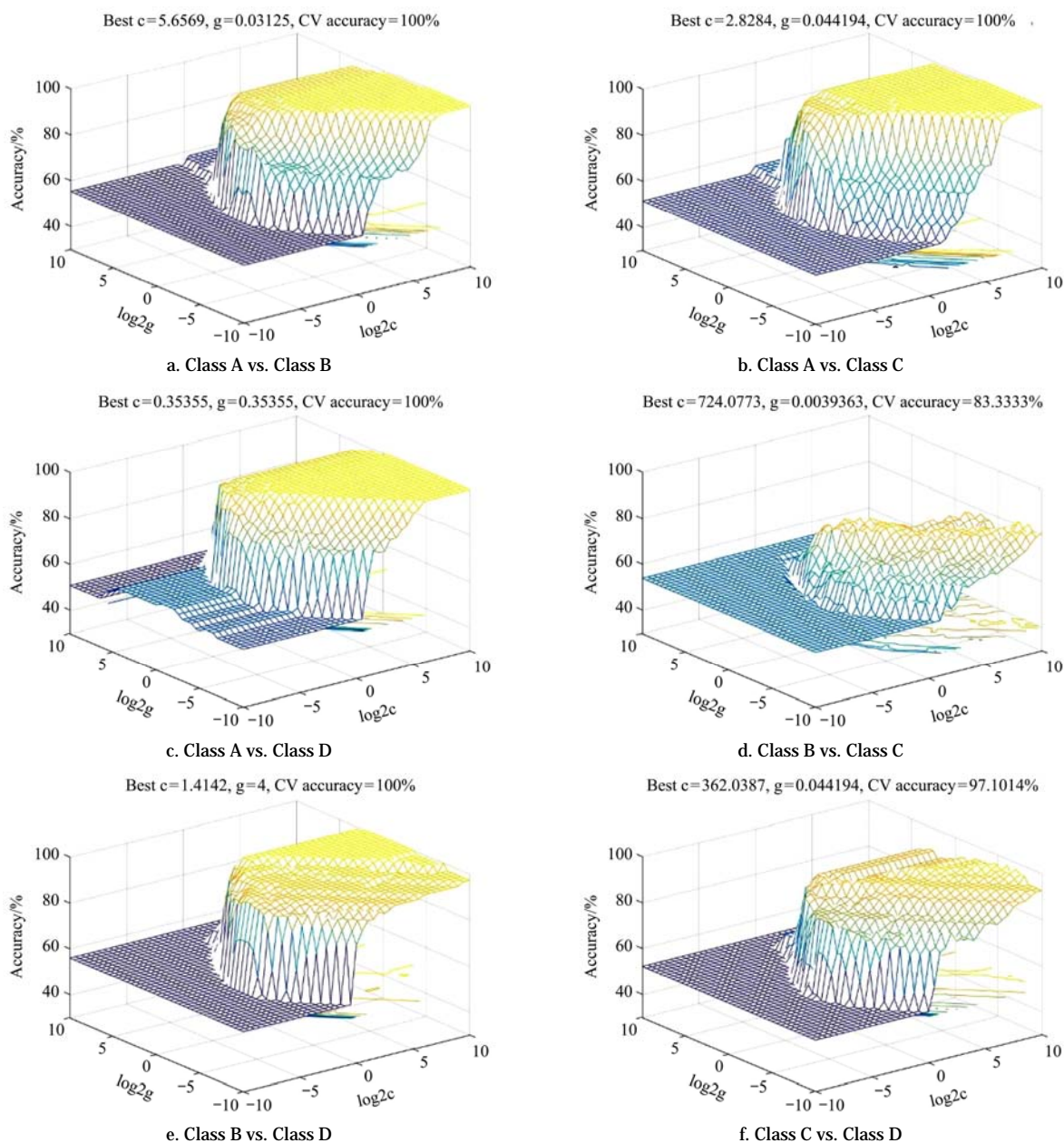

f. Class C vs. Class D

Figure 7   Waterfall plots illustrate accuracies from the grid search with different parameters C and γ combinations for each binary classifier in the OVO-SVM.   Class A: 0-10 SCA per leaf; Class B: 11-125 SCA per leaf; Class C: 126-500 SCA per leaf; Class D: more than 500 SCA per leaf.   C and γ values in the plots are shown in the logarithm to base 2

3.3 Comparison of classical and modified multi-class SVM classifications

In this study, modified multi-class SVM models slightly increased the classification accuracy of SCA infestation levels. Figure 8 showed the average recognition rate across the four SCA infestation classes using 5-fold cross validation with the classical and modified SVM classifiers.   The modified OVO-SVM model performed the best with an accuracy of 85.0% compared with the classical OVO-SVM model which had an accuracy of 74.1%.   The modified H-SVM model had similar performance than the classical H-SVM model which had a slight accuracy increase from 82.3% to 83.5%.   The customized parameter optimization for each binary classification in the modified SVM models did slightly improve the accuracy over the classical multi-class classification in which the parameter optimization was general over the multiple binary classes. However, the customized parameter optimization increased the computational complexity for the training process.   The modified models are recommended when computation complexity and time is

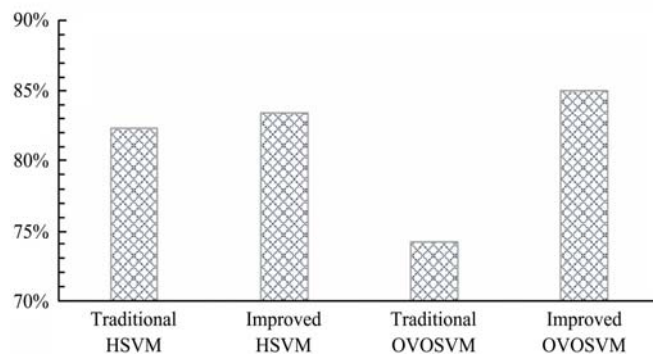not a concern for the training process.

Figure 8   The average recognition rate across the four SCA classes using 5-fold cross validation with classical and modified SVM classifiers.   For the H-SVM classifier, the recognition rate increased from 82.3% to 83.5%; for the OVO-SVM classifier, the recognition rate increased from 74.1% to 85.0%

3.4 Limitations and future work

This study provided a framework of using smart phone based digital imagery and SVM based machine learning algorithm to assess the level of SCA infestation at leaf level in sorghum production. The results were promising; however, the limited sample size prevented the SVM models investigated in this study from reaching their best performances. The total sample size was 180 and, with four classes, the sample size of each infestation level was about 45. The results in this study was also reported using the cross validation due to the limited sample size in this study. To further increase the estimation accuracy, the latest deep learning-based methods, such as various convolutional neural networks, can be investigated. Those methods usually require huge amount of training samples. A significant increase on sample size is recommended for further study on using machine learning methods for automatic pest infestation level assessment. Sampling under various illumination conditions, shadow casting and with different imaging angles are recommended to increase the adaptability and generalization of the machine learning model development.

4 Conclusion

This study developed an automatic leaf level sorghum SCA infestation assessment method using digital images taken by a smart phone. Two multi-class SVM models, the H-SVM and the OVO-SVM, and their modified versions were investigated to evaluate their performance in classifying the digital imagery into four infestation levels: 0-10, 11-125, 126-500, and more than 500 SCA per leaf. The best mean classification accuracy across the four classes was 85.0% with the modified OVO-SVM model. The modified SVM models with customized parameter optimization for each binary classification slightly improved the accuracy over the classical multi-class classification in which the parameter optimization was general over the multiple binary classes. More image samples under various illumination conditions, shadow casting and imaging angles as training data can increase the accuracy of the SVM models. Future work can be conducted to investigate other machine learning models such as convolutional neural networks to improve the infestation assessment accuracy. The digital imagery-based machine learning model for SCA quantification developed in this study can be improved and eventually integrated in an IoT system to assist researchers and producers in making more effective and sustainable spray decisions.

Acknowledgments

[References]

[1] FAOSTAT. Production Quantities of Sorghum by Country 2014. 2017. doi: http://www.fao.org/faostat/en/#data/QC/visualize.

[2] USDA-NASS. Crop Production. 2016.

[3] USDA-NASS. Crop Values 2016 Summary. 2017.

[4] Bowling R D, Michael J B, David L K, John G, Nick S, Norman E E, G D Buntin, M O Way, T A Royer, and Stephen B. 2016. "Sugarcane Aphid (Hemiptera: Aphididae): A New Pest on Sorghum in North America." Journal of Integrated Pest Management 7 (1): 12. doi: 10.1093/jipm/pmw011.

[5] Gordy J.W., M.J. Brewer, R.D. Bowling, G.D. Buntin, N.J. Seiter, D.L. Kerns, F.P.F. Reay-Jones, and M.O. Way. 2019. Development of economic thresholds for sugarcane aphid (Hemiptera: Aphididae) in susceptible grain sorghum hybrids. J. Econ. Entomol. 112: 1251-1259.

[6] Singh, B.U, P.G Padmaja, and N Seetharama. 2004. "Biology and Management of the Sugarcane Aphid, Melanaphis Sacchari (Zehntner) (Homoptera: Aphididae), in Sorghum: A Review." Crop Protection 23 (9): 739–55. doi: 10.1016/J.CROPRO.2004.01.004.

[7] Chang, C. P., Fang, M. N., Tseng, H. Y. 1982. "Studies on the Life History and Varietal Resistance in Grain Sorghum Aphid, Melanaphis Sacchari Zehntner in Central Taiwan." Chinese Journal of Entomology 2: 70–81.

[8] Thomas J L, Robert B, and Michael J B. 2018. "Learning Experiences in IPM Through Concise Instructional Videos." Journal of Integrated Pest Management 9 (1). doi: 10.1093/jipm/pmx030.

[9] Dixon A F G. 2012. Aphid Ecology an Optimization Approach. Springer Science & Business Media.

[10] Kim Y H, Seong J Y, Yeong H G, Jin H L, Dongil H, and Sung W B. 2014. "Crop Pests Prediction Method Using Regression and Machine Learning Technology: Survey." IERI Procedia 6: 52–56.

[11] Deng, X L, Lan Y B, Xing X Q, Mei H L, Liu J K, and Hong T S. 2016. "Detection of Citrus Huanglongbing Based on Image Feature Extraction and Two-Stage BPNN Modeling." International Journal of Agricultural and Biological Engineering 9 (6): 20.

[12] Espinoza K, Diego L.V. , José A.T. , Alejandro L. , and Francisco D. M. . 2016. "Combination of Image Processing and Artificial Neural Networks as a Novel Approach for the Identification of Bemisia Tabaci and Frankliniella Occidentalis on Sticky Traps in Greenhouse Agriculture." Computers and Electronics in Agriculture 127: 495–505. doi: 10.1016/j.compag.2016.07.008.

[13] Ding W.G., and Graham T. 2016. "Automatic Moth Detection from Trap Images for Pest Management." Computers and Electronics in Agriculture 123 (Supplement C): 17–28. doi: 10.1016/j.compag.2016.02.003.

[14] Shariff A R M, Yap Y A, Wong T H, Shattri M, and Radzali M. 2006. "Automated Identification and Counting of Pests in the Paddy Fields Using Image Analysis." In Computers in Agriculture and Natural Resources, Proceedings of 4th World Congress Conference. Orlando, Florida USA. doi:10.13031/2013.21969..

[15] Vapnik V. 2013. The Nature of Statistical Learning Theory. Springer science & business media.

[16] Suykens, Johan A K, and Joos V. 1999. "Least Squares Support Vector Machine Classifiers." Neural Processing Letters 9 (3): 293–300.

[17] Deng X L, Lan Y B, Hong T S, and Chen J X. 2016. "Citrus Greening Detection Using Visible Spectrum Imaging and C-SVC." Computers and Electronics in Agriculture 130 (November): 177–83. doi: 10.1016/j.compag.2016.09.005.

[18] Yao Q, Lv J, Liu Q J, Diao G Q, Yang B J, Chen H M, and Tang J. 2012. "An Insect Imaging System to Automate Rice Light-Trap Pest Identification." Journal of Integrative Agriculture 11 (6): 978–85. doi: 10.1016/S2095-3119(12)60089-6.

[19] Ebrahimi M A, M H Khoshtaghaza, Saeid M, and B Jamshidi. 2017. "Vision-Based Pest Detection Based on SVM Classification Method." Computers and Electronics in Agriculture 137: 52–58.

[20] Wu D K, Xie C Y, and Ma C W. 2008. "The SVM Classification Leafminer-Infected Leaves Based on Fractal Dimension." In Cybernetics and Intelligent Systems, 2008 IEEE Conference On, 147–51. IEEE.

[21] Zheng H, and Lu H F. 2012. "A Least-Squares Support Vector Machine (LS-SVM) Based on Fractal Analysis and CIELab Parameters for the Detection of Browning Degree on Mango (Mangifera Indica L.)." Computers and Electronics in Agriculture 83 (Supplement C): 47–51. doi: 10.1016/j.compag.2012.01.012.

[22] Brewer, M.J. , J.W. Gordy, D.L. Kerns, J.B. Woolley, W.L. Rooney, and R.D. Bowling. 2017. Sugarcane aphid population growth, plant injury, and natural enemies on selected grain sorghum hybrids in Texas and Louisiana. J. Econ. Entomol. 110: 2109-2118.

[23] Soh, L-K, and Costas T. 1999. "Texture Analysis of SAR Sea Ice Imagery Using Gray Level Co-Occurrence Matrices." IEEE Transactions on Geoscience and Remote Sensing 37 (2): 780–95.

[24] Chang C C, and Lin C J. 2011. "LIBSVM." ACM Transactions on Intelligent Systems and Technology 2(3): 1–27. doi: 10.1145/1961189.1961199./ 1961189.1961199.

[25] Pardo M, and Giorgio S. 2005. "Classification of Electronic Nose Data with Support Vector Machines." Sensors and Actuators, B: Chemical 107 (2): 730–37. doi: 10.1016/j.snb.2004.12.005.

[26] Hsu C W, C C Chang, and C J Lin. 2003. "A Practical Guide to Support Vector Classification." Taipei.Wang, Lipo. Support Vector Machines : Theory and Applications. Springer. Springer, 2005.

[27] Wang L. 2005. Support Vector Machines : Theory and Applications. Springer. Springer.

[28] Chen Y C, M.M. Crawford, and J. Ghosh. N.D. "Integrating Support Vector Machines in a Hierarchical Output Space Decomposition Framework." In IEEE International IEEE International IEEE International Geoscience and Remote Sensing Symposium, 2004. IGARSS '04.

Proceedings. 2004, 2:949–52. IEEE. Accessed June 3, 2018. doi: 10.1109/IGARSS.2004.1368565.

[29] Liu Z G, Shi W Z, Qin Q Q, Li X W, and Xie D H. 2005. "Hierarchical Support Vector Machines." In Proceedings. 2005 IEEE International Geoscience and Remote Sensing Symposium, 2005. IGARSS '05., 1:4 pp.-. IEEE. doi: 10.1109/IGARSS.2005.1526138.

[30] Duan K B, and S. Sathiya Keerthi. 2005. "Which Is the Best Multiclass SVM Method? An Empirical Study." In , 278–85. Springer, Berlin, Heidelberg. doi: 10.1007/11494683_28.

[31] Chen J, Wang C, and Wang R S. 2009. "Adaptive Binary Tree for Fast SVM Multiclass Classification." Neurocomputing 72 (13–15): 3370–75. doi: 10.1016/j.neucom.2009.03.013.