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Research Article

Using Realistic Images for Plant Classification and Effect on Classification Difficulty

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ABSTRACT

We proposed a hybrid computer-vision framework that distinguishes different plant species (such as radish and weeds) that combines machine learning methods (such as Support Vector Machine (SVM) and Random Forest (RF) classifiers) with application-specific features and image processing methods such as our own plant leaf isolation algorithm. The designed features include geometrical features that are sensitive to plant shape, as well as moment-invariant and texture features. The accuracy obtained using the combination of the designed features, and the isolation algorithm was 81.1% using SVM and 88.4% using Random Forest. We used 10-fold cross-validation to illustrate the importance of designing and selecting good features. We compared our designs with generic deep neural networks. We also compared our features with other features, such as SURF features classification, and our methods were more robust and produced better results. Throughout, we used realistic images obtained in the field, where the quality of the images depends on many factors such as lighting, seasons, occlusions, etc. We therefore include a careful discussion of the difficulty of classification problems and its dependence on the quality of images, and we propose computable definitions of problem difficulty, robustness, level of corruption, and degree of performance degradation due to corruption in the context of precision agriculture.

Keywords: Computer vision; Crop classification; Weed classification; Machine learning; SVM; Random forest; Measures of image corruption; Classification difficulty

INTRODUCTION

The recent trend toward organic food and the push to meet the food needs of the world's populations pose a significant challenge to current agricultural techniques. The world population is increasing and is expected to reach nine billions by 2050 Hasan et al.; Radoglou-Grammatikis et al. One of the most important challenges facing organic farmers is weed control without using labor-intensive practices or pesticides. Weeds cause more losses in agricultural production than any other lesion Sen et al. Direct damage to crops from weeds occurs from competition between for light, nutrients, water, and space. Faced with this competition, crops are unable to reach their full potential for growth, so their yields are constrained Pantazi et al.; Strothmann et al.; Patel et al.; Jinglei et al.; Garcia-Navarrete et al. Organic agriculture can be defined as a production system characterized by the ability to avoid or prevent the use of pesticides and synthetic fertilizers Kim et al. Hand weeding is too costly and labor-intensive Abou Chehade et al.

Technologies for precision agriculture have emerged that enable robotic weeding. They require advanced computer vision techniques that can distinguish crop from weeds using realistic images of plants at the early stages of growth Nejati et al. Realistic farm images have many artifacts that make the classification harder, such as occlusion, variable lighting, the percentage of the image occupied by "confusing junk," and overlap of species and backgrounds that make the classification harder, leading to a typical degradation of performance of about 10% [1].

Our research is dedicated to assisting small rural areas and economically challenged farms in effectively managing weed growth right from the early stages of production. This emphasis on cost-effectiveness is purposeful. Our scope deliberately

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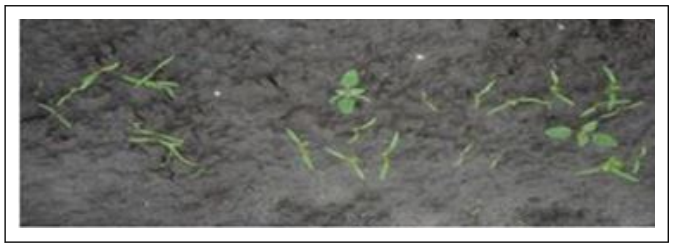
excludes the application of drones or interventions for commercial farms. We specifically tailored our approach to ground-level, small-scale micro plantations, as opposed to a canopy level. The focus remains on aiding small-scale farmers with limited resources to address weed-related challenges at the outset of the cultivation process. Looking ahead, there is potential for our algorithm to be expanded into a tool or other applications suitable for use on larger farms or for processing images captured *via* Unmanned Aerial Vehicles (UAVs). Most of our designed features are scale-invariant. If we want to apply them on a large scale, we can divide the features by the altitude of the drones. Furthermore, this research could potentially pave the way for the implementation of advanced technologies, such as ground-level robots, to combat weed-related issues effectively [2].

This paper presents a computer vision approach to classify radish *vs.* weed in the early stage of production, starting at the two-leaf growth stage for the actual organic farm using realistic images collected in the field, and illustrates and discusses the performance degradation due to the complexities of realistic images. Previous work is described in Section II. Section III presents the proposed image prepossessing and the overall proposed framework. Section IV presents and compares the various classifiers combining component isolation, specific invariant features and ML techniques. Section V illustrates the effect of corrupting the original image dataset on various parts of the classifiers and proposes and illustrates how to compute measures that quantifies the difficulty of the classification problem that arises from using realistic images. Finally, Section VII presents the conclusions.

Accuracy tends to suffer when plants are small and not fully formed, although this stage may be the most effective for weeding. There may also be differences in the quality of the images between commercially cultivated lands and those organically farmed: In the former, larger machines and more pesticides lead to more uniform soil, making images clearer and the classification easier. Therefore we may conclude that the excellent classification performance reported in the literature may not be applicable to organic farms at the early stage of production. Table 1 presents some images used in the literature, with clear backgrounds and apparent plant shapes [3].

Table 1: Some images that have been used in literature review.

Note that the background is smooth, and only one plant is in the picture. The plant shape is apparent		
Bakhshipour et al. achieved 96.7% and 93.3%. Note that the background is black, and only one plant is in the picture. The plant shape is apparent		
Espejo-Garcia et al. obtained a 99%. Note that the background is smooth, and only one plant is in the picture		

Jiang et al. obtained 97.8%, 99.4%, 98.9%, and 96.5%. The background is smooth, and the picture has one plant only		
Knoll et al. achieved an accuracy of 96.8%. Note the picture has two types of plants, but the shape is clear for each one, and the background is very smooth		
Le and et al. reached 98.6%. Note the background is black, and only one plant is in the picture. The plant shape is apparent, and the plant is mature		

The impact of image quality on classification has been documented in the literature. Huang et al., collected a diverse set of images for both training and testing, including hazy photos, motion-blurred images, fish-eye images, underwater images, low-resolution images, salt-and-peppered images, images with white Gaussian noise, Gaussian-blurred images, and out-of-focus images, each with six degradation levels. They observed a significant decrease in the image classification performance as the image quality degrades, especially when the training images cannot sufficiently reflect the degradation levels of the test images [4].

Karahan et al., conducted an analysis of the influence of image degradation on deep CNN-based face recognition performance. They assessed three popular deep CNN models: The AlexNet, VEG-Face, and GoogLeNet. Their findings highlighted how image degradation can dramatically lower face recognition accuracy. Blur, noise, and occlusion cause a significant deterioration in performance. For instance, when the noise level was increased by 50 gray levels, the VGG-Face accuracy dropped from 79% to 22%, and AlexNet dropped from 78% to 18%. Consequently, performance was significantly affected when the quality of images changed by approximately 60% [5].

MATERIALS AND METHODS

Component isolation and feature design and computation

The proposed framework is shown in the workflow chart in Figure 1. The first part is an image database collected under various conditions at the small Urban Teaching Farm in Guilford County, North Carolina. The images were prepossessed to isolate the wanted species. Features were described how calculated for each isolated component in the image. After that, SVM and Random Forest classifier have been applied to classify radish and weeds [6].

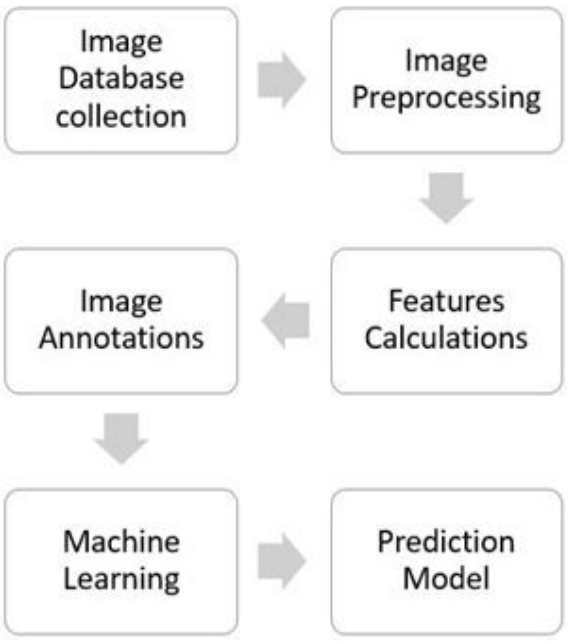


Figure 1: Workflow.

Isolation algorithm

A crucial step that will improve the accuracy of classification is correctly identifying and isolating the plant images. This step prepares and enhances the image for further calculations by removing the background and unwanted species. Since we are dealing with green leafy plants, we isolate the green color only from the background. Figure 2 shows the original image of a radish plant with a cluttered background and weeds present [7].



Figure 2: Original image for the radish plant with background and weed.

From Figure 3A, there are still unwanted objects from the background, so we apply morphological operations to remove small objects and fill small holes, as shown in Figure 3B. The final colored isolated image is shown in Figure 3C. A more detailed discussion of the isolation algorithm is presented in our previous work. The output image from isolation will be used for feature calculations [8].



Figure 3: The isolation algorithm: A) The green channel image, B) Binary isolated image after morphological operations, C) Colored isolated image.

Image annotation

We used the image labeler in MATLAB for image annotation in deep learning. The Image Labeler app allowed us to draw labeled bounding boxes around the regions of interest. Each image had three main classes: Radish, weed, and gravel. The output is a ground-truth object containing information about the photo's source and marked label annotations. Figure 4 shows a labeled image in the Image Labeler app. We conducted the image annotation manually for our classification method to use in machine learning.

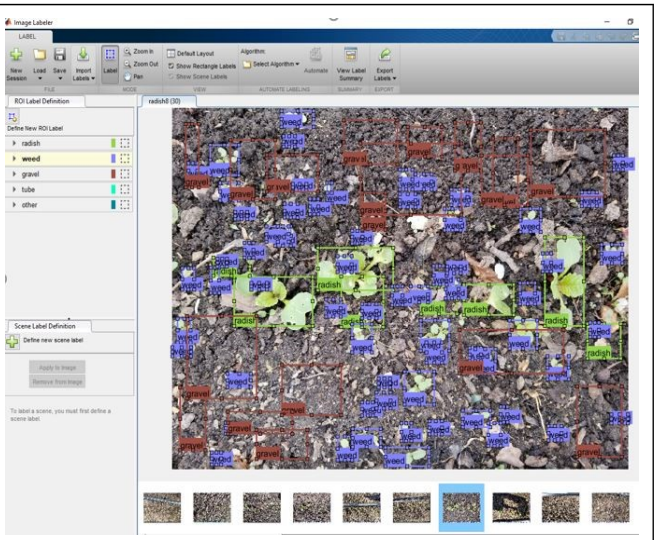


Figure 4: Image Labeler app of MATLAB.

Feature design

As shown in Figure 3B, the binary isolated image contains several components of crops and weeds. Here, a component is defined as a disjoint sub-image containing plants in a tightly fit hull, not necessarily convex. The components are labeled, as shown in Figure 5, to easiest select a single component inside the bounded box [9].

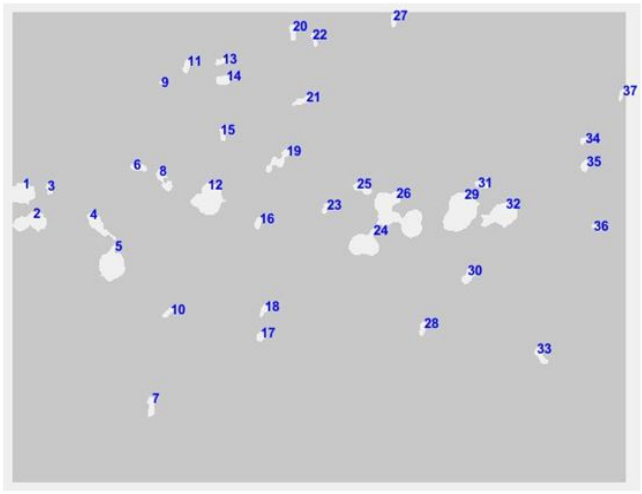


Figure 5: Components of an image, each containing plant(s) sub-image.

We will take component 26 inside the bounding box as an example to explain the proposed designed features. Figure 6 shows the binary silhouette images within a tightly-fit rectangular bounding box for component 26.

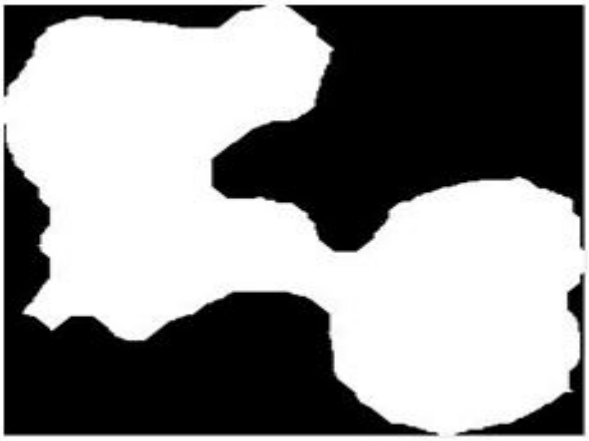


Figure 6: Binary image within the bounding box for component number 26.

The above discussion is well aligned with many results in the literature. Numerous researchers have delved into the study of spurious features. For example, Newsome et al., conducted investigations involving causative attacks on the Polygraph virus detector. One of their significant findings was that the correlated outlier attack can be categorized as a causative availability attack. This attack targeted the Naive-Bayes-like component of the Polygraph detector by introducing spurious features into positive training instances, resulting in erroneous blocking of benign traffic exhibiting these spurious features. Newsome et al., also devised a causative integrity attack targeting the conjunction learner component of the polygraph. In this red herring attack, spurious features were introduced alongside their payload. Once the learner had constructed their signature using this manipulated data, the spurious features were discarded to avoid detection in later stages.

Sagawa et al., investigated the counterintuitive phenomenon wherein over parameterization, characterized by a significant increase in model size beyond achieving zero training error, could lead to higher test errors within minority groups despite improving the average test error in scenarios with spurious correlations in the data. Their findings highlighted a difficulty regarding the choice between employing over parameterized models and utilizing the entire training dataset to achieve lower worst-group error rates.

RESULTS AND DISCUSSION

Classification using machine learning

Random forest classification and feature importance: A Random Forest (RF) is a supervised learning algorithm, and it is also the most flexible and easy to use. A forest comprises several decision trees. The more trees it has, the more robust the forest becomes. Random forests create decision trees on randomly selected data samples, obtain a prediction from each tree, and select the best solution using voting.

We selected random samples from a given dataset (70% for training and 30% for testing) and presented them to an RF learning process that constructs a decision tree for each sample and obtains a prediction result from each decision tree. Afterwards, the RF performs a vote for each predicted result to select the prediction with the most votes as the final prediction. Random forests also provide a good feature selection indicator. In each Data Frame, there are 28 features.

The Coefficient of Degradation (CD) β reflects both the difficulty of the problem and the robustness of the algorithm. The performance of difficult problems is expected to degrade more rapidly than that of easy problems for the same corrupted dataset. Moreover, the degradation of robust algorithms is likely to grow more slowly than that of non-robust algorithms.

Since the CD reflects both the difficulty of the problem and the robustness of the algorithm, it can be used to evaluate one when the other is held fixed.

Application

We applied the procedure outlined above, which yielded a dataset of corrupted radish images by altering their contrast ratios.

Subsequently, we applied our isolation algorithm to the corrupted images. It's evident that as corruption increased, we observed a greater number of missed components. The shapes and the sizes of the bounding boxes and the components masks are also severely degraded. The similarity between the isolated components, when identified, quantifies the performance of the isolation algorithm, and it deteriorates as image corruption intensifies. We quantified the Level of Corruption (LC) by calculating the difference between the standard deviation of the original image and the standard deviation of the corrupted image.

Figure displays the degree of corruption on the horizontal axis and the similarity ratio between the isolated original images and

the corrupted images on the vertical axis. As observed, the similarity ratio decreases as the level of corruption increases. The slope of the graph serves as an indicator of the robustness of the problem.

We automatically labeled the newly detected components based on the intersection between the bounding boxes from the original images and those from the corrupted images. Subsequently, we computed relevant features for these labeled components. Finally, we employed a random forest classifier under different scenarios.

In the first scenario, we utilized the corrupted datasets' training and testing sets. In the second scenario, the training dataset was derived from the original dataset, while the testing dataset was from the corrupted dataset. In the last scenario, the training dataset was sourced from the corrupted dataset, and the testing dataset came from the original dataset.

It is evident that as the level of corruption increased, the accuracy of the classifier decreased. Also, high accuracy was achieved when the training and testing were conducted using the same datasets.

CONCLUSION

In this paper, we classified radishes and weeds using machine learning. The accuracy using SVM was 81.1%, and the random forest classifier achieved the highest accuracy at 88.4%. We calculated various features, including geometrical, texture, and moment-invariant features. Some of the texture features were particularly effective in classifying plants that are similar to each other, especially the features contrast, energy with angle zero and energy with angle 90. Geometrical features also played a crucial role in the classification of green leafy plants in our work, with features like convex hull perimeter ratio and form factor being the most important. The aspect ratio, convex hull area ratio, rectangularity ratio, green over gray of the RGB image, and Mean over Standard Deviation (MoSD) of Rho were also essential features, approximately equally important in classification. On the other hand, the Average Vertical Cut Number (AVCN) and standard deviation were the least important features.

The seven moment-invariant features in our work did not improve the classification but reduced accuracy. Hence they are recommended. This is largely due to significant over-parameterization and the emergence of spurious features, which will impact the accuracy.

We have compared our method with other built-in methods like CNN and SURF, but our application-specific features performed better. Our results were obtained using realistic photos collected in the A&T farm during the early production stage. We demonstrated that cleaned images have an impact on accuracy and emphasized the importance of isolation in improving accuracy. In conclusion, we can say that classification from the first appearance of plants is very complex.

We elucidated the critical dependence of algorithmic performance on the quality of initial data in classification and machine learning problems. The proposed measures of problem difficulty provide a systematic approach to assess algorithm robustness and data quality. By characterizing the rate of degradation in performance as data corruption increases, the Coefficient of Degradation (CD) serves as an insightful metric reflecting both problem difficulty and algorithm robustness. The study's application to a dataset of corrupted radish images highlights the significance of data quality in affecting algorithm performance, as evidenced by the deterioration of the isolation algorithm's accuracy with increasing corruption levels. The findings emphasize the need to account for the interplay between data quality and problem complexity when evaluating algorithmic performance, indicating that superior performance achieved with high-quality data may not be replicable under realistic conditions. We performed as an essential step toward understanding the intricate relationship between data quality, problem complexity, and algorithmic robustness, laying the groundwork for more comprehensive investigations into these fundamental aspects. Further research in this area holds promise for enhancing the reliability and applicability of classification and machine-learning solutions in real-world settings.

In the literature, previous classification studies have been praised for their astronomical accuracy. We believe such conclusions to be premature because an inherent complexity of the problem was ignored: Namely, the significant degradation of performance due to the corruption present in realistic images. Often, researchers present classification results without measuring or commenting the quality of the data. Therefore, we advocate that standard robustness tests, such as difficulty of the problem, proposed above, be included in every classification studies.

DATA AVAILABILITY STATEMENT

The datasets generated and/or analyzed during this study, including experimental images, are not publicly available due to privacy or ethical restrictions. However, they can be made available upon reasonable request. Researchers interested in accessing the dataset for replication or validation purposes may contact the corresponding author *via* email at yasalatneh@gmail.com.

Informed consent was obtained from all individual participants included in the study (or their legal guardians) for the publication of identifying information/images in an online open-access publication.

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