Convolutional Neural Networks for Image-based
Corn Kernel Detection and Counting

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Abstract

Precise in-season corn grain yield estimates enable farmers to make real-time accurate harvest and grain marketing decisions minimizing possible losses of profitability. A well-developed corn ear can have up to 800 kernels, but manually counting the kernels on an ear of corn is labor-intensive, time consuming and prone to human error. From an algorithmic perspective, the detection of the kernels from a single corn ear image is challenging due to the large number of kernels at different angles and very small distance among the kernels. In this paper, we propose a kernel detection and counting method based on a sliding window approach. The proposed method detect and counts all corn kernels in a single corn ear image taken in uncontrolled lighting conditions. The sliding window approach uses a convolutional neural network (CNN) for kernel detection. Then, a non-maximum suppression (NMS) is applied to remove overlapping detections. Finally, windows that are classified as kernel are passed to another CNN regression model for finding the \((x, y)\) coordinates of the center of kernel image patches. Our experiments indicate that the proposed method can successfully detect the corn kernels with a low detection error and is also able to detect kernels on a batch of corn ears positioned at different angles.

1 Introduction

Commercial corn (Zea mays L.) is processed into numerous food and industrial products and it is widely known as one of the world’s most important grain crops. Corn serves as a source of food for the world and is a key ingredient in both animal feed and the production of bio-fuels. Corn grain yield is driven by optimizing the number of plants per given area and providing sufficient inputs to maximize total kernels per ear within a given environment.

Determining corn grain yield is complicated and requires a detailed understanding of corn breeding, crop physiology, soil fertility, and agronomy. But accurate estimates using simple data inputs can provide reliable information to drive certain management decisions. A well-developed corn ear can expect to have over 650-750 kernels per ear. However, various environmental stresses can affect corn ear development impacting the total number of kernels per ear. For instance, drought and heat stress will have a negative correlation with the number of kernels on an ear. Moreover, soil fertility limitations and intense pest pressure throughout a growing season can have adverse effects on total kernels developed resulting in lower total grain yield. Plant breeders work to maximize the amount of material we gain from corn by breeding existing corn with the most resilient, high-yielding genetics. If total kernels per ear, kernel depth, kernel width and estimated kernel weight can be quickly and accurately measured; additional information could be gathered about the crop and allow farmers to make early accurate management decisions.

1.1 Motivation

Precise in-season corn grain yield estimates enable farmers to make real-time accurate harvest and grain marketing...
decisions minimizing possible losses of profitability [21].

Due to the manual labor needed to count the number of kernels on an ear of corn, high-throughput phenotyping is not possible due to the necessary manual labor and the possibility to human error. Executing yield estimates in digital applications can be done more efficiently and consistently, compared to past methods, while providing the ability to make historical comparisons following harvest [23]. Agronomically, accurate yield estimates in-season delivers unique potential for agronomists to diagnose potential issues that have or may impact corn grain yield.

With this as motivation, this work proposes new deep learning approach to corn kernel estimations, that can be used in real-time decision making. This methodology takes an image of a single ear of corn and outputs the estimated number of kernels on the entire ear with no assumptions on the environmental lighting conditions.

1.2 Related Works

In 2014, Zhao et al. [22] applied traditional image processing based approaches i.e. filtering, watershedding, thresholding, etc. to count kernels. Grift et al. [5] invoked a machine vision approach but limits ear images to be taken within a soft box fitted with controlled lighting conditions. Moreover, the images in their study contained 360 degree photos, that is, they designed a special lighting box so that lighting conditions were controlled and to take complete photos of the ear.

Ni et al. [16] in 2018 and Li et al. [14] in 2019 both utilized deep learning to count corn kernels, however, their algorithms were designed to count kernels which already removed from the cob. Although both were able to accurately count kernels, their problem is easier than directly counting kernels while on the ear, due to the distinct spacing between kernels in their images. Additionally, this process does not allow for real-time in-field decision making.

Deep learning models have also been used to solve other problems in agriculture such as phenotype prediction [10, 11, 9], image-based crop disease detection [15, 17], and crop stress classification [8]. In most of these studies, deep learning models showed promising performance compared to other methods.

Due to the difficult nature of this problem, we propose a deep learning approach to counting kernels where kernels are still intact on an ear, no assumptions are made on the lighting conditions, and we simply use a 180 degree photo of an ear of corn.

2 Methodology

The goal of this study is to localize and count corn kernels in a corn ear image taken in uncontrolled lighting conditions. To solve this problem, we first detect all kernels in a corn ear image and then estimate the total number of kernels by counting the number of detected kernels. As a result, the underlying research problem is a single class object detection problem. As shown in Figure 1, Figure 8, and Figure 9 the number of objects (kernels) in a corn ear is extensive (up to 800 kernels) and the objects are in close proximity to one another, making the problem more challenging.

![Figure 1: Three different corn ears.](image)

We use a sliding window approach for kernel detection in this study. At each window position, a convolutional neural network classifier returns a confidence value representing its certainty that the current window contains a kernel or not. After computing all confidence values, a NMS is applied to remove redundant and overlapping detections. Finally, windows that are classified as a kernel are passed to a regression model. The regression model predicts \((x, y)\) coordinates of the center of kernels given image patch of kernels. Detailed description of the kernel classifier and the regression model is provided as follows.

2.1 Corn Kernel Classifier

In this paper, we apply sliding window approach for kernel detection problem which requires a supervised learning model to classify the current window as either kernel or non-kernel. We use a CNN to classify image patches as CNNs have been shown to be a very powerful method for the image classification task [13, 6, 19]. The CNN model takes in image patches with size of \(32 \times 32\) pixels. The CNN architecture for kernel classification is defined in Table 1. All layers are followed by a batchnorm [7] and ReLU nonlinearity except the final fully connected layer which has a sigmoid activation function to produce a confidence value representing the CNN’s certainty that an input image patch contains a kernel or not. Down sampling is performed with average pooling layers. We do not use dropout [18], following the practice in [7].
### 2.2 Regression Model

As shown in Figure 1, the kernels are very close to each other on corn ears. As such, if we visualized all detected kernels with bounding boxes in a corn ear image, it would be almost impossible to see the corn ear, especially on the left and right sides of the ear due to having many close bounding boxes. Furthermore, some kernels have different shapes and angles which might not fit perfectly in a rectangle bounding boxes. As such, we use a convolutional neural network as a regression model which takes in an image of kernel with size of $32 \times 32$ pixels and predicts $(x, y)$ coordinates of the center of the kernel. The primary reason for not simply using the center of the windows being classified as kernel as the center of detected kernels is that the center of the kernels are not always in the center of the windows, especially for the kernels on the sides of the corn ear. The CNN architecture for finding the $(x, y)$ coordinates of the center of a kernel image is defined in Table 2. All layers are followed by ReLU nonlinearity except the final fully connected layer which has no nonlinearity. Down sampling is performed with max pooling layers. We did not use dropout for this model as it did not improve overall performance. The regression model is applied only on the final windows being classified as a kernel after the NMS. As such, the proposed regression model does not add a lot of computational cost to the kernel detection approach considering the number of final windows being classified as kernel is small.

### 3 Experiments and Results

This section presents the dataset used for our experiments, the training hyperparameters, and the final results. We consider standard evaluation measures such as false positive (FP), false negative (FN), accuracy, and f-score. All our experiments were conducted in Python using the TensorFlow library on a NVIDIA Tesla V100 GPU.

#### 3.1 Dataset

Sliding window approach requires a trained kernel classifier before it can be applied. Therefore, positive samples of kernels and negative samples of non-kernel are necessary. We manually cut and labeled kernel and non-kernel images from 43 different corn ear images to generate the training dataset. Each kernel sample is cut out and scaled to $32 \times 32$ pixels. Negative samples are generated in the same way using random crops at different positions. The positive samples only include image of one kernel. If the image patch contains two or more kernels, it is considered a negative sample. The training dataset consists of 6,978 kernel and 9,413 non-kernel samples. Figure 2 and 3 show a subset of kernel and non-kernel images, respectively. For the regression model, we only used the kernel image part of the dataset. We manually labeled the kernel images by finding the $(x, y)$ coordinates of their centers using Labelme software. Figure 4 depicts a subset of annotated kernel images.

![Figure 2: A random subset of kernel images.](image-url)
3.2 Corn Kernel Classifier Training

We trained the CNN as described in section 2.1 for kernel classification using the following training hyperparameters. The weights were initialized with the Xavier initialization [4]. A stochastic gradient descent (SGD) was used with a mini-batch size of 128. The learning rate started from 0.03% and was reduced to 0.01% when error plateaued. The model was trained for 25,000 iterations. Adam optimizer [12] was used to minimize the log loss. For our data, we randomly took 20% of the data as the test data (3,278 images) and used the rest as the training data (22,292 images). We augmented around 70% the training data with flip and color augmentations. Figure 5 shows the plot of training and test losses for the CNN. To better evaluate the CNN classifier, a comparison of the CNN classifier with the HOG+SVM model was performed [2]. This model uses the Histogram of Oriented Gradient (HOG) to extract edge features to describe the objects shape and then trains a support vector machine (SVM) classifier based on the extracted features. The best results achieved for the HOG+SVM were with the parameters $4 \times 4$ pixels per cell, 2 cells per block, and 9 histogram bins. Table 3 compares the performances of the CNN and HOG+SVM classifiers on the training and test datasets. We used the CNN model as our final kernel classifier because it resulted in a more reliable kernel detection and counting. Moreover, the CNN model can successfully generalize the prediction to different backgrounds.

| Classifier | Evaluation Measures |
|------------|----------------------|
|            | FP | FN | Accuracy | F-score |
| Training   |    |    |          |         |
| HOG+SVM    | 596 | 595 | 0.947    | 0.937   |
| CNN        | 0  | 0  | 1.0      | 1.0     |
| Test       |    |    |          |         |
| HOG+SVM    | 135 | 135 | 0.918    | 0.906   |
| CNN        | 19  | 22  | 0.987    | 0.985   |

Table 3: Performance comparison of the CNN and HOG+SVM classifiers on the training and test datasets.

Table 3 indicates that the CNN model outperforms the HOG+SVM model with respect to all evaluation measures. One of the reasons for the higher accuracy of the CNN classifier compared to the HOG+SVM is that the CNN automatically extracts necessary features from the data. However, the HOG+SVM model is faster to train and test from computational perspective.

3.3 Regression Model Training

The CNN model was trained as described in section 2.2 for finding the $(x, y)$ coordinates of the center of a kernel.
image using the following training hyperparameters. The weights were initialized with the Xavier initialization. A stochastic gradient descent (SGD) was utilized with a mini-batch size of 45. The model was trained for 25,000 iterations with the learning rate of 0.03%. Adam optimizer was used to minimize the smooth $L_1$ loss as in [3], which is less sensitive to the outliers compared to the $L_2$ loss. We randomly took 20% of the data as the test data (1,396 images) and used the rest as the training data (5,582 images). Figure 6 shows the plot of the training and test losses for the CNN regression model.

![Figure 6: Plot of the smooth $L_1$ loss of the CNN regression model during training process.](image)

3.4 Final Results

We applied sliding window approach with the trained CNN classifier on several test images. After applying the NMS, the windows that were classified as kernel were passed to the regression model for finding their corresponding centers. We used window size of $32 \times 22$ for the sliding window approach. To fully evaluate the proposed approach, we tested the approach on the multiple corn ears with different angles. Farmers and breeders usually assume that corn ears are symmetric. As such, they count the number of kernels on the one side and then double it to approximately find the total number of corn kernels on a corn ear. We used a similar approach except that we multiplied the number of detected kernels on the one side by 2.5 because around 2 columns of kernels on the very left and right sides of the ear are not captured in the image and consequently not counted. The inference time for a corn ear is 5.79 seconds.

Figure 8 shows the results of the proposed approach on a batch of two corn ears. As shown in Figure 8, the proposed approach successfully found the most of kernels in the image. Figure 9 shows the results of the proposed approach on the image of an angled corn ear. This image is considered a difficult test image because we did not include any angled kernel image in the training dataset. But, the results indicate that the approach can generalize the detection to the images of angled corn ears. We also applied the approach on another difficult test image of a corn ear whose kernels are slightly angled, and as shown in Figure 10, the proposed approach is still able to detect most of the kernels. Figure 11 and Figure 12 also show the performance of the proposed method on two other test corn ears. Our proposed approach has the following advantages for kernel counting: (1) our proposed approach can be used on a batch of corn ears, and (2) our proposed approach can be used on a slightly angled corn ear. To completely evaluate our proposed approach, we manually counted the number of kernels on 20 different corn ears and used the proposed method to predict the number of kernels on these corn ears. Table 4 compares the performances of the proposed method with respect to the root-mean-squared error (RMSE) and correlation coefficient. Figure 7 shows the plot of the predicted number of kernels versus the ground truth number of kernels.

| Method         | RMSE | Correlation Coefficient |
|----------------|------|-------------------------|
| Proposed Method| 33.11| 95.86                   |

Table 4: The performance of the proposed method on the kernel counting task of 20 different corn ears.

![Figure 7: The plot of the predicted number of kernels versus ground truth number of kernels.](image)
Figure 8: The results of the proposed approach on a batch of corn ears in the straight position. The total predicted and the ground truth numbers of the kernels on the ears are 1,012 and 1,046, respectively.

Figure 9: The results of the proposed approach on an angled corn ear. The predicted and the ground truth numbers of the kernels on the ear are 312 and 323, respectively.

Figure 10: The results of the proposed approach on a corn ear whose kernels are slightly angled. The predicted and the ground truth numbers of the kernels on the ear are 550 and 585, respectively.

Figure 11: The results of the proposed approach on a corn ear in the straight position. The predicted and the ground truth numbers of the kernels on the ear are 342 and 296, respectively.

Figure 12: The results of the proposed approach on a corn ear in the straight position. The predicted and ground truth numbers of the kernels on the ear are 390 and 394, respectively.

4 Conclusions

In this paper, we propose a kernel detection and counting method based on the sliding window approach. The proposed method detects and counts all corn kernels in a corn ear image taken in uncontrolled lighting conditions. The sliding window approach uses a CNN classifier for kernel detection. Then, a non-maximum suppression is applied to remove overlapping detections. Finally, windows that are classified as kernel are passed to a regression model for finding the \((x, y)\) coordinates of the center of kernel image patches. Our experiments suggest the effectiveness of the proposed method in detection and counting of corn kernels. Our proposed method is able to detect kernels on a batch of corn ears at different angles. This approach could be extended to address several future research directions. For example, similar approach could be used to detect diseased kernels with blue or black color on a corn ear.
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