In this project, high AI Future efforts will focus on enhancing the identification (c)12/21/2022 0.34 400 cultivars, 5 replications, 2,000 selections in total. Larger training data led to a better performance (Table 1).

Traditional methods of visually identifying runners in the Characterizing strawberry trials in high throughput.

HIGH-THROUGHPUT IMAGING

A ground imaging system comprises an electric vehicle, a GNSS receiver, and 6 DSLR cameras positioned at various angles (Fig. 2).

1 image/sec/camera, weekly collection for 400 varieties.

RUNNER IDENTIFICATION

In this project, high-resolution RGB images collected at early growth stage (on Dec. 1st, 14th, and 21st, 2022) were used to train and test an image-based deep learning model for runner identification.

(a) 12/01/2022 (b) 12/14/2022 (c) 12/21/2022

Figure 2. A ground imaging system for strawberry phenotyping

Figure 3. Canopy top-view of the same strawberry cultivar on three dates

Following the same Mask R-CNN architecture (Fig. 4), two models were trained using two datasets for performance comparison: 1) images from Dec. 1st, 2022, and 2) images from Dec. 1st and 12th, 2022.

The two models were tested separately on images from all three dates.

Figure 4. Output examples from the Mask R-CNN display dashed bounding boxes to show identified runners

PRELIMINARY RESULTS

Trained by a small number of images (from 3 dates only), the Mask R-CNN model could reach the runner identification accuracy of 84%.

Larger training data led to a better performance (Table 1).

Table 1. Performance of runner identification on different dates using two Mask R-CNN-based models

<table>
<thead>
<tr>
<th>Date for model testing</th>
<th>No. of runners detected</th>
<th>No. of correctly identified runners (TP)</th>
<th>Precision (TP/TP+FP)</th>
<th>Recall (TP/TP+FN)</th>
<th>F1 Score (2<em>recall</em>precision)/(recall+precision)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trained by 12/01</td>
<td>20221201</td>
<td>95</td>
<td>59</td>
<td>0.50</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td>20221214</td>
<td>140</td>
<td>68</td>
<td>0.69</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td>20221221</td>
<td>174</td>
<td>78</td>
<td>0.77</td>
<td>0.34</td>
</tr>
<tr>
<td>Trained by 12/01 and 12/14</td>
<td>20221201</td>
<td>95</td>
<td>83</td>
<td>0.43</td>
<td>0.87</td>
</tr>
<tr>
<td></td>
<td>20221214</td>
<td>140</td>
<td>90</td>
<td>0.74</td>
<td>0.64</td>
</tr>
<tr>
<td></td>
<td>20221221</td>
<td>174</td>
<td>107</td>
<td>0.84</td>
<td>0.62</td>
</tr>
</tbody>
</table>

TP: true positives, the positive class is correctly predicted as the positive class
FP: false positive, the negative class is predicted to be a positive class
TN: true negatives, the negative class is correctly predicted to be a negative class
FN: false negative, the positive class is predicted to be a negative class

CONCLUSIONS

Preliminary results from this study successfully proved the concept of runner identification using machine vision.

AI-powered machine vision technique has great potential to identify complex plant tissues for crop breeding, management, and production applications.

Future efforts will focus on enhancing the identification accuracy, expanding the system’s capacity in larger-scale strawberry trials, and evaluating the efficacy of this method across multiple cultivation periods.

ACKNOWLEDGEMENT

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