

1 LeafByte: A mobile application that measures leaf area and herbivory quickly and accurately

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16 Running headline: LeafByte: measure leaf area and herbivory

17 Key Words: ecology methods, leaf area, planner homography, herbivory quantification.

## 18 **Abstract**

19 1. In both basic and applied studies, quantification of herbivory on foliage is a key metric in  
20 characterizing plant-herbivore interactions, which underpin many ecological, evolutionary, and  
21 agricultural processes. Current methods of quantifying herbivory are slow or inaccurate. We  
22 present LeafByte, a free iOS application for measuring leaf area and herbivory. LeafByte can  
23 save data automatically, read and record barcodes, handle both light and dark colored plant  
24 tissue, and be used non-destructively.

25 2. We evaluate its accuracy and efficiency relative to existing herbivory assessment tools.

26 3. LeafByte has the same accuracy as ImageJ, the field standard, but is 50% faster. Other tools,  
27 such as BioLeaf and grid quantification, are quick and accurate, but limited in the information  
28 they can provide. Visual estimation is quickest, but it only provides a coarse measure of leaf  
29 damage and tends to overestimate herbivory.

30 4. LeafByte is a quick and accurate means of measuring leaf area and herbivory, making it a  
31 useful tool for research in fields such as ecology, entomology, agronomy, and plant science.

32

### 33 **Introduction**

34 The amount of leaf tissue consumed, hereafter “herbivory”, is a fundamental metric used to  
35 understand plant-herbivore interactions in many disciplines spanning basic and applied science,  
36 including plant chemistry, plant-insect ecological and evolutionary dynamics, plant breeding,  
37 agronomy, and horticulture (Turcotte et al 2014). However, efficiently and accurately measuring  
38 amounts of herbivory remains challenging (Williams et al. 1991).

39 Herbivory from chewing insects is measured with software such as ImageJ (Abràmoff et al.  
40 2004), mobile apps such as BioLeaf (Machado et al., 2016), and manual methods such as grid  
41 quantification (Coley 1983) or visual estimation (Johnson et al. 2016). While all of these  
42 methods have advantages, there is significant room for improvement. One of the most commonly  
43 used options, the image processing program ImageJ, is accurate but not optimized for measuring  
44 herbivory, and is therefore incredibly time-consuming. Further, images must be scanned or  
45 photographed, saved on a computer, and then uploaded, which is also slow. The mobile app  
46 BioLeaf (Machado et al., 2016) allows for quick and efficient measurements of herbivory.  
47 However, it only measures percent herbivory, and not the absolute leaf area and herbivory,  
48 making it difficult to compare levels of herbivory when leaf sizes vary, which is commonly the  
49 case. Grid quantification entails placing a grid under a damaged leaf and counting the number of  
50 squares where an herbivore removed leaf tissue (Coley 1983). While measuring small amounts  
51 of herbivory is straightforward, measuring large amounts of herbivory or leaf area can be  
52 prohibitively slow. Finally, visual estimation of herbivory is quicker but sacrifices accuracy  
53 (Johnson et al. 2016).

54 We introduce LeafByte, a free and open source mobile app that solves common issues  
55 with the current tools and provides additional features. LeafByte can scan barcodes, measure  
56 light colored petals or leaves, and save results (with the date, time, and GPS coordinates) to a

57 spreadsheet on the phone or on Google Drive. LeafByte can be used non-destructively. We  
58 present a systematic comparison of the accuracy and efficiency of LeafByte and four of the most  
59 common herbivory measurement tools: ImageJ, BioLeaf, grid quantification, and visual  
60 quantification.

61

## 62 **Methods**

### 63 *How LeafByte works*

64 Users take or upload an image of a leaf surrounded by 4 dots in a square that act as a scale (see  
65 Supporting Information 1). LeafByte identifies the leaf and scale markings by separating the  
66 foreground of the image from the background in a process called "thresholding" (Otsu, 1979).

67 Each pixel in the image is considered individually. If the luma of the pixel's color, a measure of  
68 perceived intensity (ITU-R, 1982-2015), is above a certain cutoff value (the "threshold"), that  
69 pixel will be considered foreground; otherwise, it becomes background. Because the leaf and  
70 scale markings are much darker than the background (typically a green leaf and black scale  
71 markings on white paper), they are marked as foreground, while the rest is marked as  
72 background. LeafByte also supports light tissue (such as white flowers) against dark  
73 backgrounds by simply reversing the process.

74 LeafByte determines the luma level that separates foreground from background using an  
75 algorithm called Otsu's method (Otsu, 1979). Otsu's method considers a histogram of lumas in  
76 the image. This histogram is typically bimodal, with a mode of high luma, representing the leaf  
77 and scale markings, and a mode of low luma, representing the background. Otsu's method finds a  
78 luma that most clearly separates those two modes, effectively distinguishing foreground from  
79 background. This automatically-determined threshold is generally effective, but LeafByte allows  
80 users to tweak as needed (Fig. 1A).

81 Next, LeafByte determines what pixels represent the leaf and scale markings using an algorithm  
82 called connected-component labeling (Rosenfeld & Pfaltz, 1966) to separate pixels into groups  
83 representing different objects. LeafByte assumes that the largest group is the leaf, and the next  
84 four largest are the scale markings. This is right in most cases, and when it is not (e.g. there is  
85 another object in the image), the user can correct LeafByte's assumption by manually identifying  
86 scale markings (Fig. 1B).

87 If the image was taken at an angle, the scale markings no longer form a square, and the leaf itself  
88 is distorted, causing error (Supporting Information 2). To correct this skew, LeafByte uses a  
89 technique called planar homography (Wang, Klette, & Rosenhahn, 2006) to re-distort the image  
90 so that the scale markings once again form a square. LeafByte uses connected-components  
91 labeling again on background pixels to identify the holes within the leaf.

92 The user can draw missing margins onto the leaf image (Fig. 1C). Then, counting the number of  
93 pixels in the leaf and in the holes gives the relative amount of leaf eaten. Summing the number of  
94 pixels in the leaf and the holes gives the total size of the original leaf in pixels. Because there is a  
95 known distance between each scale mark, LeafByte can convert numbers of pixels into real  
96 world units. The photo and results are saved in a CSV file to Google Drive or the phone.

97

98

## 99 ***Methods for Testing LeafByte***

### 100 *Accuracy*

101 To confirm the accuracy of ImageJ and LeafByte, we used both methods to measure artificial  
102 "leaves" of known area". We printed out 16 black rectangles of known area with white "holes" of  
103 known size and analyzed them with both LeafByte and ImageJ, comparing theand compared  
104 their results to the known area.

105

106 *Comparisons of different methods*

107 We collected 67 leaves from 14 plant species (Supporting Information 3) from the Cornell  
108 Botanical Garden and grounds. Leaves were selected to represent a range of morphologies and  
109 were categorized by shape. If the leaf was undamaged, we created artificial herbivory using hole  
110 punches and razor blades to remove 0-50% of the leaf. We recorded whether the leaf was  
111 damaged on the margin (n=36) or only internally (n=22). Herbivory was estimated visually and  
112 using grid quantification (Coley 1983). For visual estimation, herbivory was estimated to the  
113 nearest 5%. Leaves with 0-2.5% herbivory were rounded to 5%. The leaves were then flattened  
114 between a sheet of printer paper with the scale printed on it and a Premium Matte Film Shield  
115 Screen Protector (J&D, Middleton, MA) and photographed. Each photograph was analyzed using  
116 LeafByte, BioLeaf, and ImageJ by at least two different researchers per method. LeafByte and  
117 ImageJ provided total leaf area, absolute herbivory, and percent herbivory. BioLeaf and visual  
118 quantification provided only percent herbivory, and the grid method provided only percent  
119 herbivory. We also recorded the time it took to analyze each leaf and record the data. For  
120 ImageJ, we did not include the time it took to photograph and upload the pictures.

121

122 *Statistics*

123 All statistics were performed using R, Version 3.5.2 (R Core Team, 2018). We built global  
124 mixed effects models using the nlme package (Pinheiro et al., 2018). We dropped non-significant  
125 predictors from the models in a backwards stepwise fashion, assessed pairwise differences  
126 between the methods using emmeans (Lenth, R., 2019), and adjusted for multiple comparisons  
127 using false discovery rate.

128

### 129 *Accuracy*

130 To test for differences in measurement accuracy between ImageJ and LeafByte, we ran linear  
131 mixed effects models with area and herbivory as response variables. In both models, method was  
132 included as a fixed effect, and the known size of each artificial leaf was set as the reference  
133 value. Additionally, we used an equivalency test (TOSTER, Lakens 2017) to evaluate whether  
134 the methods produced the same results (as opposed to linear models that test for differences). We  
135 used  $\frac{1}{4}$  of the standard deviation as upper and lower bounds of the model.

136

### 137 *Comparisons of different methods*

138 To analyze the effect of method on leaf area, we ran a linear mixed effects model with leaf area  
139 as the response variable and the interaction between method and leaf shape as predictor  
140 variables. Species and leaf ID were included as random effects in all models. Leaf areas were log  
141 transformed to meet assumptions of homoscedasticity.

142 To analyze the effect of method on herbivory, we ran a linear mixed effects model with  
143 herbivory as the response variable and the interaction between method and number of holes and  
144 the interaction between method and presence of leaf margin herbivory as predictor variables. To  
145 analyze the effect of method on percent area consumed data, we ran a binomial generalized  
146 linear mixed effects model with herbivory as a response variable and the interaction between  
147 method and number of holes and the interaction between method and presence of leaf margin  
148 herbivory as fixed effects. Because low levels of herbivory (0-2.5%) were rounded to 5% rather  
149 than 0% when using visual quantification, we analyzed both the full data set and data where  
150 percent herbivory was greater than 5% to ensure that rounding did not skew our results.

151

## 152 **Results**

### 153 *Accuracy*

154 We found no difference between the known area and LeafByte for total area (t-ratio=0.126,  
155 df=36, p=0.991, Fig. 2A) or herbivory (t-ratio=1.11, df=36, p=0.512, Fig. 2B) or between the  
156 known area and ImageJ for total area (t-ratio=-1.53, df=36, p=0.285, Fig. 2C) or herbivory (t-  
157 ratio=0.793, df=36, p=0.710, Fig. 2D). On average, LeafByte differed from the known area by  
158 1.3% while ImageJ differed from the known area by 3.2%. Based on the equivalence test  
159 comparing LeafByte to the known area, we can conclude that the difference between the  
160 treatments is equivalent to zero ( $t_{36}=20.4$ ,  $p<0.001$ ,  $t_{36}=-4.40$ ,  $p<0.001$ ) for both leaf area and  
161 hole area. Similarly, the difference between ImageJ and the known area is equivalent to zero for  
162 both leaf area and hole area ( $t_{36}=-20.2$ ,  $p<0.001$ ,  $t_{36}=-4.52$ ,  $p<0.001$ ).

163

### 164 *Comparisons of different methods*

165 On average, leaf area measured by LeafByte was 2% lower than the leaf area measured by  
166 ImageJ ( $t_{248}=0.627$ ,  $p=0.023$ , Fig. 3A). There was no effect of leaf shape on leaf area  
167 measurements using LeafByte or ImageJ (log likelihood=221 on 8 df,  $p=0.565$ ).

168 There was a significant interaction between method and number of holes in a leaf on the area of  
169 herbivory measurements (log likelihood = 979 on 8 df,  $p=0.003$ ), such that herbivory was  
170 underestimated when there were more holes using the grid method ( $t_{322}=-3.34$ ,  $p=0.001$ ), but not  
171 any of the other methods. When holding hole number constant, there was no significant  
172 difference in herbivory estimates between ImageJ and LeafByte (t-ratio=0.002, df= 322,  $p=1.0$ )  
173 or ImageJ and grid quantification (t-ratio=-2.02, df= 322,  $p=0.110$ , Fig. 3B).

174 There was a significant effect of method on percent herbivory ( $F_{3,107}= 35.8$   $p<0.001$ , Fig. 3C).

175 Neither BioLeaf (z-ratio=-0.871,  $p=0.820$ ) nor LeafByte (z-ratio= -0.955,  $p=0.775$ ) were

176 significantly different from ImageJ. Visual quantification overestimated percent herbivory  
177 compared to ImageJ (z-ratio= -5.12,  $p<0.001$ ), LeafByte (z-ratio=4.87,  $p<0.001$ ), or BioLeaf (z-  
178 ratio=-4.867,  $p<0.001$ ). The accuracy of each method was not affected by the presence of margin  
179 herbivory (log likelihood= -767 on 14 df,  $p=0.102$ ) or the number of holes (log likelihood = -770  
180 on 10 df,  $p=0.912$ ). The results were the same when analyzing the full data set or only the data  
181 >5%.

182 Different methods took different amounts of time to analyze a given leaf ( $F_{4,549}=202$ ,  $p<0.001$ ,  
183 Fig. 3D). ImageJ was by far the slowest option, taking twice as long as LeafByte (t-ratio=-15.0,  
184  $df=549$ ,  $p<0.001$ ) on average. Grid quantification and LeafByte took a comparable length of time  
185 (t-ratio=-0.508 ,  $df=549$ ,  $p=0.612$ ). BioLeaf was 40% faster than LeafByte (t-ratio=5.41,  $df=549$ ,  
186  $p<0.001$ ) while visual quantification was 85% faster (t-ratio=11.7,  $df=546$ ,  $p<0.001$ ). The  
187 presence of margin herbivory slowed down leaf measurements for LeafByte (t-ratio=-3.14,  
188  $df=52$ ,  $p=0.003$ ), ImageJ (t-ratio=-3.79,  $df=52$ ,  $p<0.001$ ), and BioLeaf (t-ratio=-2.67,  $df=52$ ,  
189  $p=0.0010$ ), but not the grid method (t-ratio=-1.69,  $df=52$ ,  $p=0.097$ ) or visual quantification (t-  
190 ratio=0.655,  $df=52$ ,  $p=0.515$ ). The number of holes increased the time to analyze for all methods  
191 ( $F_{4,549}=10.0$ ,  $p<0.001$ ), although it was drastically higher for ImageJ, which took ~8 seconds per  
192 additional hole, while all other methods were less than ½ a second per hole.

193

## 194 **Discussion**

195 LeafByte is a novel tool that combines and improves on the strengths of existing tools in a user-  
196 friendly application. LeafByte quickly and accurately measures leaf area, herbivory from  
197 chewing herbivores, and percent herbivory. It is the first herbivory measurement app to  
198 automatically save measurements to a spreadsheet, reducing time and transcription errors.  
199 LeafByte can read and record barcodes, handle both light and dark colored plant tissue, and be



200 used non-destructively. Our testing illustrates that while LeafByte produced average  
201 measurements 2% lower than ImageJ, both LeafByte and ImageJ were highly accurate when  
202 measuring "leaves" and "herbivory" of known sizes. LeafByte takes half as long as ImageJ to  
203 measure each leaf and can handle larger numbers of holes much more quickly. All electronic  
204 methods were significantly slower with margin damage.

205 We found that visual quantification led to overestimations. This was likely due to lack of training  
206 and the fact that most of our leaves had low levels of herbivory (Johnson et al. 2016).

207 Tilting a phone/camera more than 15° caused high rates of error. Using a skew-correcting box as  
208 a scale rather than a line was an effective and necessary means of reducing error (Supporting  
209 Information 2). Researchers using digital methods that do not automatically correct for skew  
210 should take care to ensure that their photographs are not taken at an angle greater than 15%.

211 LeafByte has several limitations. It is difficult to identify margin damage on needles and highly  
212 complex leaves. Highly ruffled or complex leaves have more shadows and are difficult to lie flat  
213 without overlap. Poor quality photos or photos with extensive shadows make it difficult to  
214 cleanly remove the background. These limitations hold for other image processing software  
215 including ImageJ and BioLeaf.

216 While LeafByte was designed to measure leaf area and herbivory, it can also measure disparate  
217 things like damage on butterfly wings, fungal growth on petri dishes, insect droppings on filter  
218 paper, and the efficacy of anilox rollers. LeafByte is a quick and accurate means of measuring  
219 leaf area and herbivory, making it a transformative tool for a wide variety of applications.

220

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227

## 228 **Author Contributions**

229 ZGP and AC designed the and created the app. ZGP, NA, TU, AG, and JD contributed to testing  
230 and improving the app. ZGP and JD collected and analyzed the data. ZGP, AC, NA, TU, JD, AG  
231 contributed to writing and editing the paper.

232

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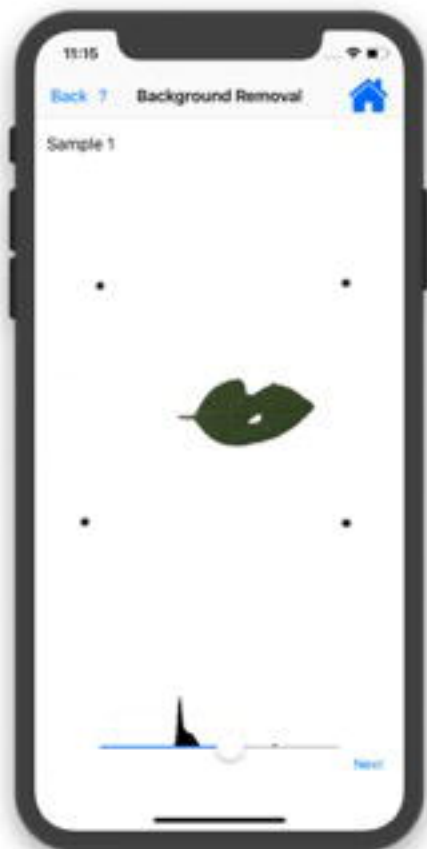
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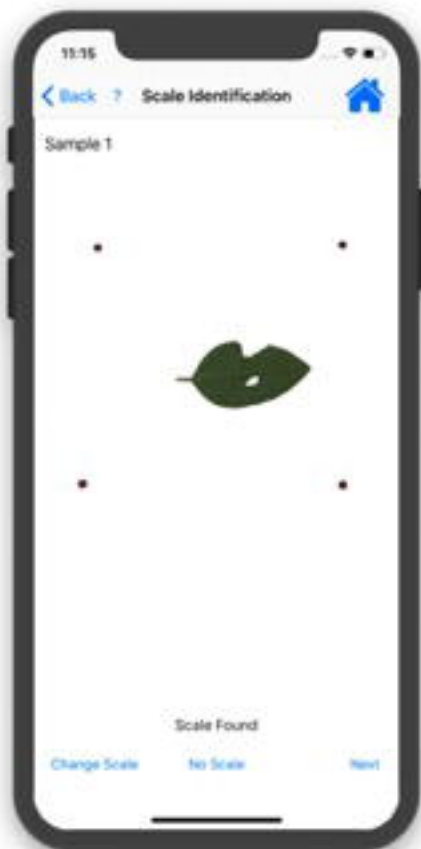
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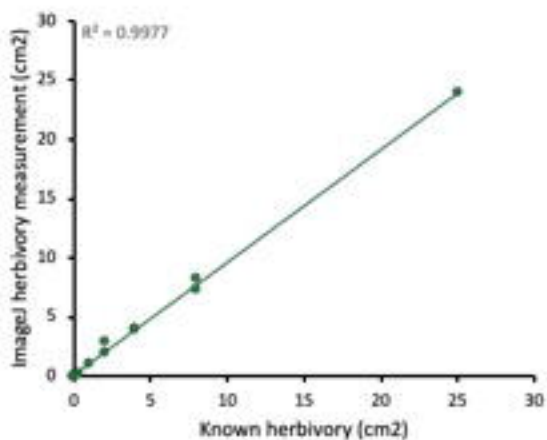
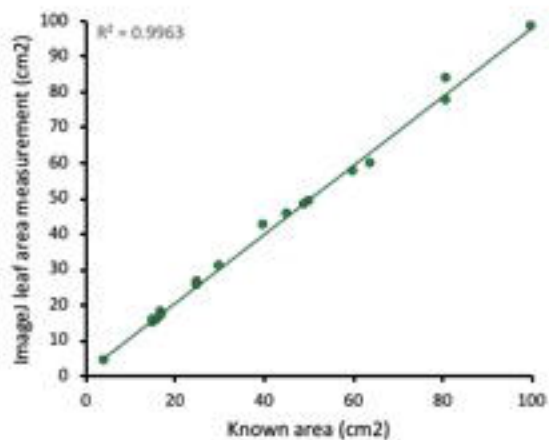
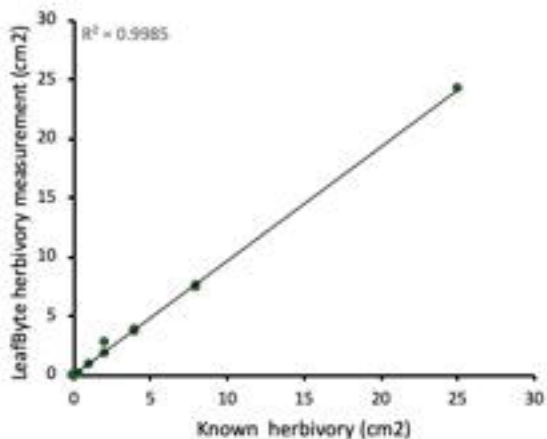
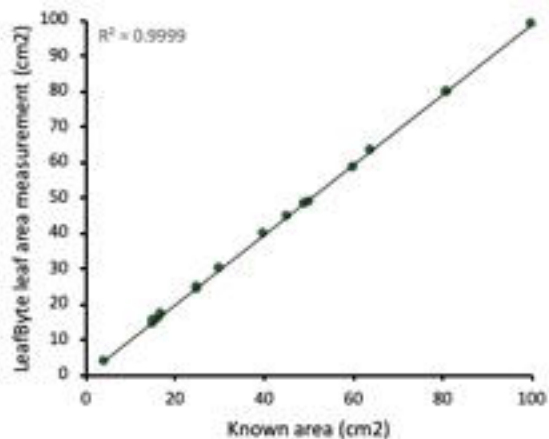
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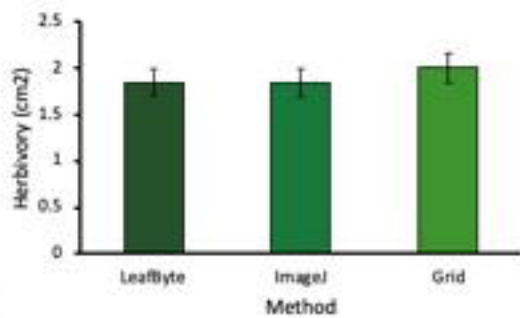
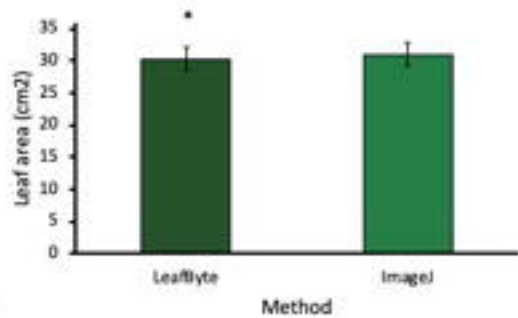


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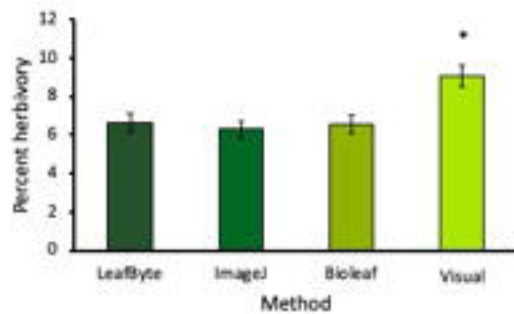
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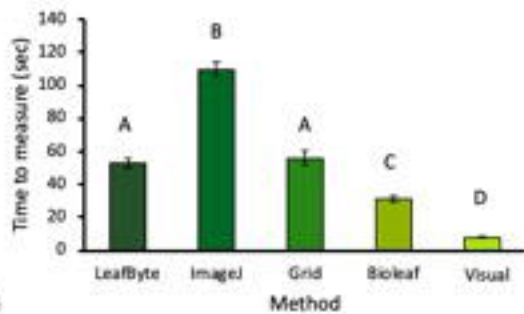


A)

B)



C)



D)



A )



B )



