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Predicting yield attributes of maize through image processing

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Abstract
Currently, the yield attributes of maize ears (such as ear length, kernel count, kernel weight, and so on) are often assessed by hand throughout the breeding process, which necessitates a large number of workers. Furthermore, subjective mistakes are difficult to prevent, and manual measuring efficiency is quite poor. The method described in this work can quickly assess yield attributes linked to breeding traits of numerous maize ears, significantly improving maize variety evaluation efficiency. From photographs of ears taken from field trial plots, a low-cost ear digital imaging system was developed that offers estimations of ear and kernel characteristics such as ear number and size, kernel number and size, and kernel weight. Image J, an open-source program, is used here to process the images using a script that runs in batch mode. The total kernel number was determined from the number of visible kernels on the picture and the average kernel size was used to calculate kernel weight. Ground truth measurements and data obtained by image processing have an excellent agreement in terms of accuracy and precision. The procedure also entails utilizing a mobile camera to picture scattered kernel samples and counting them using the software. Results demonstrate that this is a fast (less than a minute per sample) and reliable approach that may be extensively used for estimating yield attribute and kernel counting.

Keywords: maize, yield attributes, image-processing, estimation, correlation

1. Introduction
Prediction of crop yield in agriculture is a paramount snag as the yield essentially hangs on weather conditions, pesticides, and many more. Decision-making concomitant to agricultural risk management and future conjecture needs unerring counsel concerning crop yield's history (Hajir Almahdi, 2020). To meet the requirements of enormous population growth there is a requirement for field-level statistics as it is essential to plan at micro-level and crop insurance exceptionally (Anup, 2005). Accurate and timely assessment of crop yield is an essential process to ensure the adequacy of the food supply. In the past, estimates of crop yield were done, in general, from the expertise of farmers or, as claimed by Geipel, Link and Claupein, (2014) "better estimations can be drawn from destructive sampling procedures in representative areas".
For yield estimation, basic mathematical or statistical relationships based on agronomic and meteorological data were established (Dadhwal & Ray, 2000), as well as crop development models (Thorp, De Jonge, Kaleita, Batchelor, and Paz, 2008); Later remote sensing techniques evolved as an effective tool for assessing and monitoring crop yield at a lower cost than other methods providing a spatial and periodic, comprehensive view of real crop state (Geipel *et al*., 2014). But these methods are expensive, time-consuming, and laboriousand require trained personnel and expertise. So it is mandatory to identify crop growth monitoring and prior estimation of yield using unbiased, systematized, and quicker methods like image processing than going for traditional methods.
Maize or corn (*Zea mays* L.) is an important annual cereal crop of the world belonging to the family Poaceae. It is the third leading crop of the world after rice and wheat (Sandhu, Singh, & Malhi, 2007). The world production of maize was 967 million metric tons (MMT) and in India, its production was 23 MMT in 2013–14 (India maize summit, 2014). It is considered a staple food in many parts of the world. The measurement of kernel traits is important for maize breeding and the evaluation of its yield (Lovemore Chipindu, 2020) [2].
Ears are a primary agricultural product of maize, which has led the majority of previous phenotyping efforts to focus on aspects of yield, such as ear size, kernel row number, and kernel structure and dimensions.

Additional information about the crop might be obtained and farmers could make projected kernel weight could be quantified fast and precisely. Recently, image processing, machine learning, and deep learning have shown great potential in progressing the digital capabilities needed for the future of agriculture. These techniques have shown to be reliable in high-throughput phenotyping and in enabling farmers to make a real-time decision, something that was previously not possible. (Saeed Khaki, 2020) [1].

Few method sallow the extraction of ear and kernel features through image processing.In the perspective of breeding, research has indicated that yield components have a higher heritability than overall yield. [23, 24]; allowing for independent selection for these qualities and then combining the responsible genetic loci to generate a genotype with higher performance or developing a selection index through trait combinations [24]. According to Miller *et al*. [6], more could be learned about the genetic underpinnings of yield components and how to improve those utilizing current and future maize genetic resources if its ear and kernel traits could be automatically evaluated with higher objectivity and precision. Using ear digital imaging, this study presents a simple, high-throughput, and robust approach for collecting yield components (ear and kernel properties) from harvested maize ears (EDI).

2. Materials and Methodology

Maize Hybrid Co (MH) – 6 was chosen for the research. The experiment was carried out at the Eastern block (75) in Tamil Nadu Agricultural University, Coimbatore [11.0087° N, 76.9404° E and altitude 300m]. For analysis 100 plants were randomly selected from the field and the data on cob attributes and their related plant characters were recorded for each selected plant using the standard method of measurements.

2.1 Photo acquisition

Harvested ears of randomly selected plants were collected from the field, numbered accordingly, and were dried upto 12-18% moisture content. First, the weight of cobs with and without sheath was recorded using Infra Digi precision balance with a resolution of 0.01gm. Then manual measurements of sheath length, sheath weight, cob length, cob width, and number of rows per ear, number of kernels per row, kernel length, kernel width, and kernel weight were taken.

First, the images were acquired by placing each selected cob one by one on a black chart using a mobile camera (16 MP rear camera) mounted on an Arm Stand Holder at a height of 60 cm from the mobile camera to the table at which maize is placed and positioned at nadir. The process of photo acquisition under diffused lighting conditions was setup in our computer lab. At the same height as cobs, an image of a ruler was taken to convert pixel values to known measurements. The images were numbered according to cob number and saved in a single folder as raw RGB images without any conversion for batch processing. To validate kernel counting, based on image versus manually counted kernels the kernels of selected ears were shelled using Mini hand corn thresher, winnowed, kept separately in plastic bags, and were numbered respectively to the ears. The number of kernels per cob was counted manually and the kernel weight of each cob was measured separately using Electronic Compact Digital Kitchen SF-400A Weighing Scale. The kernels of each cob were then imaged separately under the same setup as cobs and saved in a single folder by their cob number which is then batch processed.

2.2 Image Processing

Image analysis was conducted in Fiji [an extension of ImageJ software-which has a collection of plugins that make scientific picture analysis easier]. It is open-source software that will help us to extract yield component parameters (i.e. ear and kernel attributes) using a series of steps as per Makanza R. *et al.* (2018) [16].

The following steps were performed using built-in ImageJ plugins and the process was recorded as a macro to run subsequent images of cob. The images were pre-processed at first to obtain an even dark background using the background subtraction method with a threshold of 100. Then for segmenting individual kernels, CLAHE (Contrast Limited Adaptive Histogram Equalization) process is selected which helps in overcoming the noise problem by reducing noise by setting the parameters of the CLAHE plugin as (I) Block Size to 29 (II) No. of histogram bins to 250 and (III) Maximum slope to 5.

After this using the edge enhancement process the images were sharpened with an unsharp mask plugin with a radius of 15 and mask as 0.70 followed by conversion of images to 8-bit format. The images of low contrast were dealt with an auto local threshold method called Phansalkar whose parameters 1 & 2 were kept to default values as an increase in their default values proved to be of no effect while the radius of the local domain was set to 15 and the option of a white object on black background was selected to threshold the image.

The images were then binarized using convert to binary plugin and fill holes option was selected to avoid kernel split during adjustable watershed step followed later with a tolerance of 3. After the successful segmentation of kernels, the measurement of yield attributes was initialized.

The threshold is calculated using the equation

$$T(x,y) = m(x,y)\left[1 + pe^{-qm(x,y)}\right] + k\left(\frac{s(x,y)}{R}\right) - 1 \ (1)$$

Where, m = mean,

p & q = Phansalkar’s exponential constants,

k = constant in the range of 0.2-0.5,

s = standard deviation of pixel intensities,

R = dynamic range of standard deviation which is 0.5 for normalized images.

2.3 Kernel counts and attributes

The segmented images were then analyzed using analyze particles plugin after setting its size to 0.03-1.00 pixels^2 and the circularity to 0.05-1.00 which helps in identifying the kernels visible on the image. Then the kernel length and width of the cob image were measured as the distance between two points along the major and minor axis of ear and kernel which requires setting the scale to a known distance at first. The particle analysis plugin also helps us in measuring the total kernel area, average kernel area, and average perimeter of the ear in addition to kernel count, kernel weight, and total kernel number.

2.4 Ear count and attributes

The analysis can be done not only on single cob images but we can also analyze several cobs on a single image. To find the number of cobs in an image, the images were filtered out via a Gaussian blur filter with the sigma set to 10 for smoothing. Then they were binarized followed by the fill holes plugin and watershed process and analyze particles plugin was selected to count the number of cobs on a particular image. Ear length and width were measured as the distance between two points along the major and minor axis of a single ear.

2.5 Modeling of Kernel weight and Kernel Count

To count kernels via image the shelled kernels of each cob were spread to an area of 60 cm wide and 40 cm long on a black chart and images was taken as the same setup as cobs and the following steps were carried out through ImageJ built-in plugins to count kernels and were recorded as a macro for subsequent analysis. The color threshold of the image was first adjusted, then binarized, and was processed using the watershed plugin to split individual kernels from others. Then to get kernel count, analyze particles plugin is selected and the size and circularity of objects are adjusted to get an absolute count.

From the number of visible kernels on the image (kn) **(**Eq. 2, r=0.98*****)**, a linear regression model for predicting the total kernel number on each ear was constructed. The association between estimated and measured kernel parameters was evaluated using Pearson's correlation coefficient r.

Total Kernel Number = 2.4051 * kn – 6.7334 (2)

Where kn = number of visible kernels on the image.

The kernel weight model was created using a linear regression model between average kernel length ($\overline{kl}$) and average kernel weight (total kernel weight divided by the total number of kernels), both of which were physically measured using a digital balance with a precision of 0.01 g. Kernel weight was recorded at moisture content levels ranging from 11 to 13%. This was done with 100 ears of different kernel sizes. The visible region of the segmented ear was used to calculate the average kernel length. To build a model that correlates kernel length into kernel weight, ($\overline{kl}$) was plotted against the average measured kernel weight for each ear measured manually (Fig. 6a). The model was then tested, and it appeared to be correct in estimating the kernel weight (Fig. 6b).

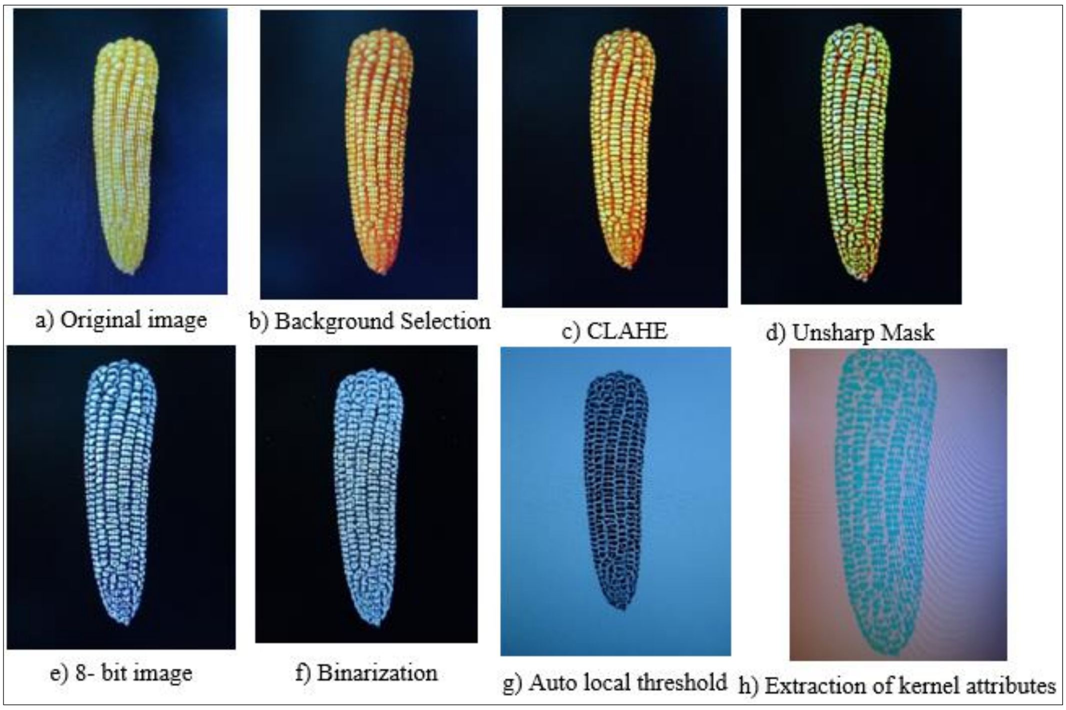
Average Kernel Weight (g) = ($\overline{kl} * 0.7435 – 0.155$) (3)

2.6 Estimation of Kernel Weight

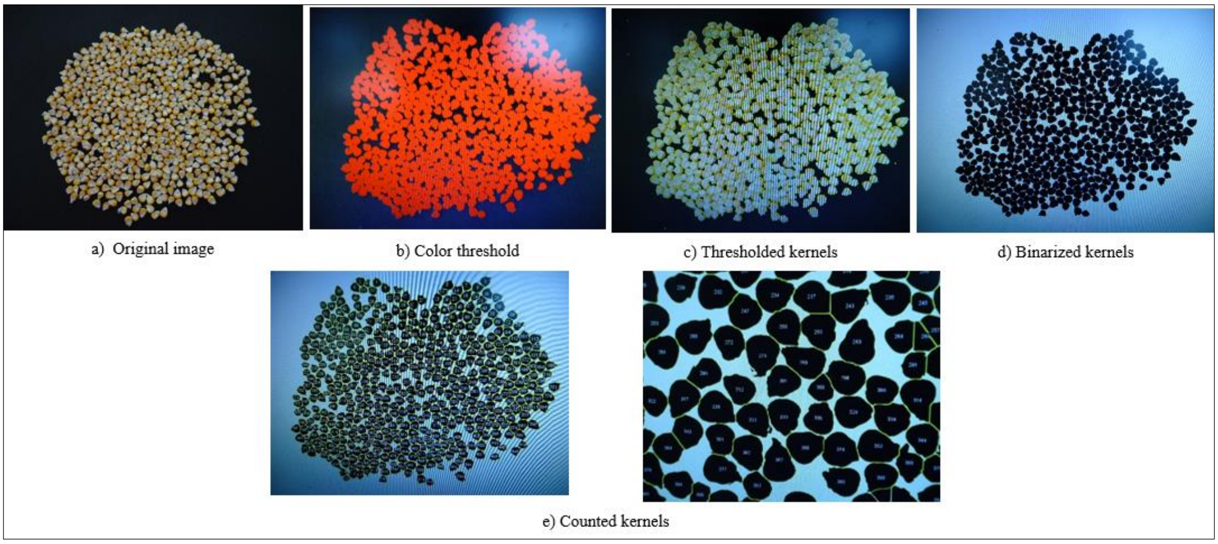
Given that Eq. 2 gives the total kernel number and Eq. 3 gives the average kernel weight, the total kernel weight (Eq. 4) is calculated by multiplying the two equations:

Total Kernel Weight (g) = (2.4051 * kn – 6.7334) * ($\overline{kl} * 0.7435 – 0.155$) (4)

The predicted total kernel weight was confirmed using 100 cob images taken under controlled lighting conditions.



Graph 1: Steps involved in cob image processing and mining of data



Graph 1: Steps associated with image processing of kernel

Table 1: Correlation between Actual and Estimated maize yield attributes

Variables	Correlation Coefficient (ρ)	R^2	Regression Equation
Image-based Kernel Count Vs Manual Kernel Count	0.9906	0.9815	y = 0.9794x + 0.0019
Estimated Ear Length (cm) Vs Measured Ear length (cm)	0.9553	0.9127	y = 0.9698x + 1.0451
Estimated Ear Width (cm) Vs Measured Ear Width (cm)	0.9535	0.9092	y = 0.8989x + 0.3615
Kernel Weight (g) Vs Kernel Length (cm)	0.9997	0.9995	y = 1.4194x + 0.2359
Estimated Kernel Weight (g) Vs Measured Kernel Weight(g)	0.9906	0.9815	y = 0.9794x + 0.0019

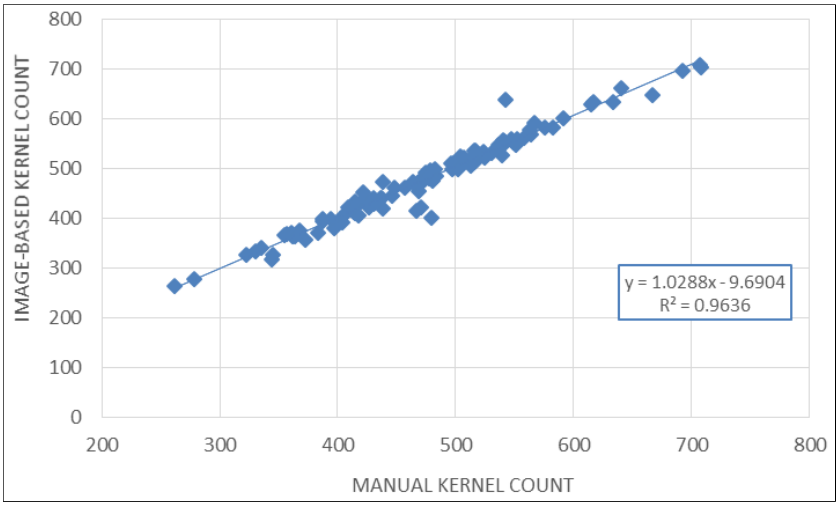


Fig 1: Regression modeling and Correlation between image-based Kernel Count and manual Kernel Count

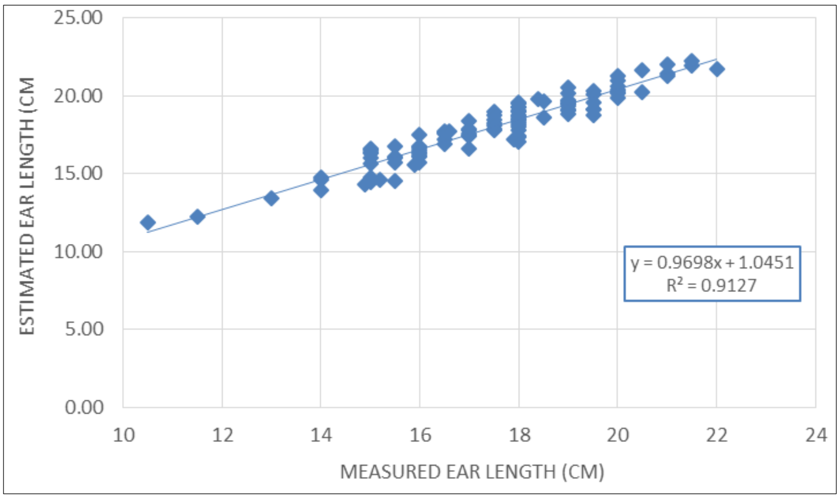


Fig 2: Regression modeling and Correlation between measured and estimated Ear Length

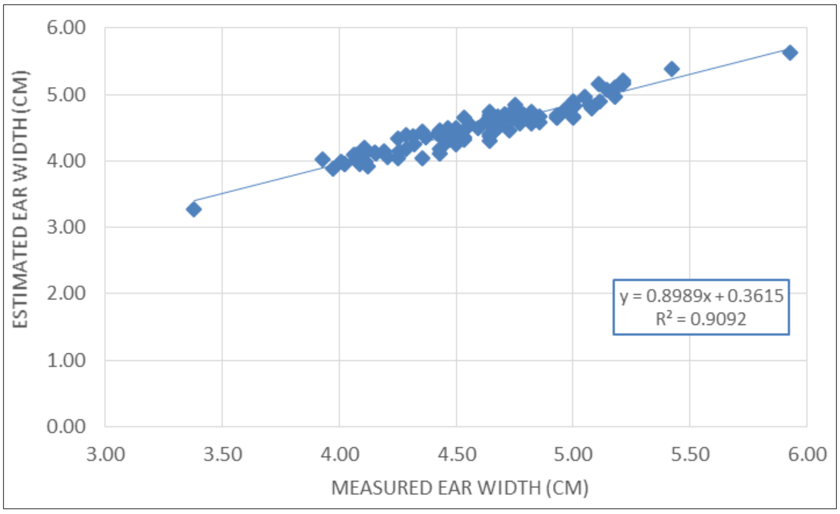


Fig 3: Regression modeling and Correlation between measured and estimated Ear Width

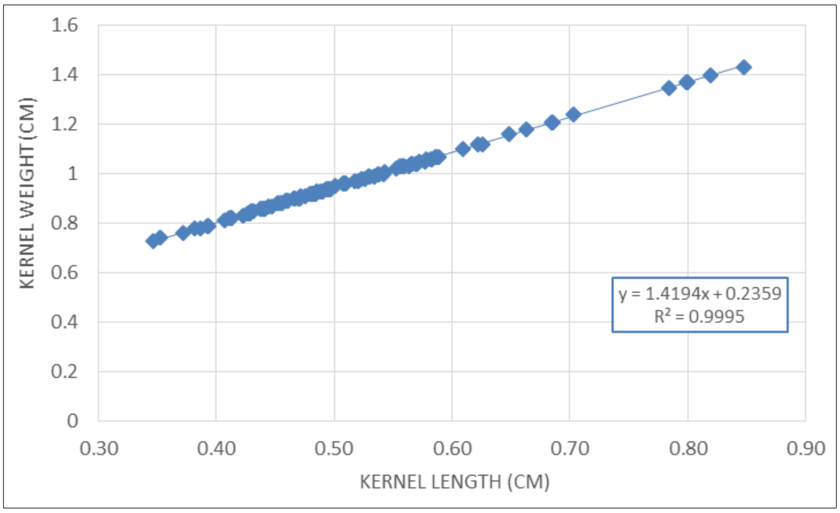


Fig 4: Regression model for predicting Kernel Weight from Kernel Length

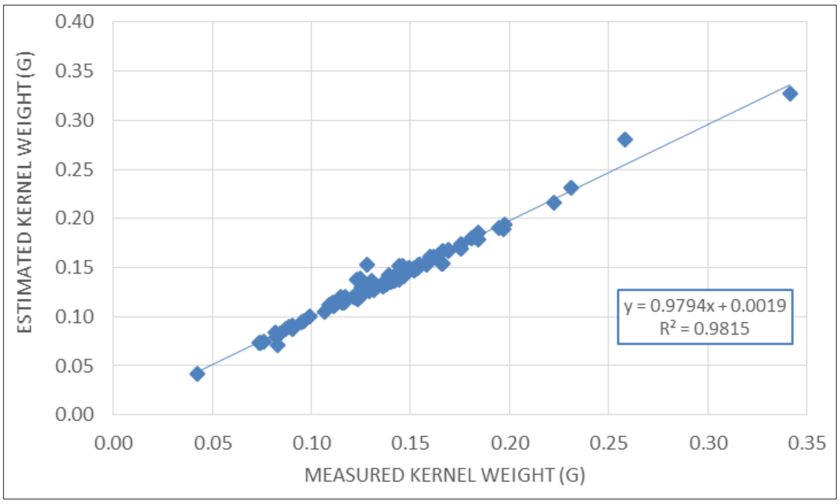


Fig 5: Regression modeling and Correlation between measured and estimated Kernel Weight

3. Result & Discussion

3.1 Kernel Count and Ear attributes

As indicated in the methodology section, the kernel count model was evaluated using 100 ears collected from randomly selected plants in the field. The calculated kernel count from entire ears using the model and the actual count of detached kernels exhibited a linear connection (ρ=0.98, p<0.001) in the data. The identical ears that were utilized for kernel count validation were used to compare manual ear length and width measurements to those generated by the image processing method. For both attributes, the analysis shows a linear correlation of (r > 0.95, p0.001) between the two procedures.

3.2 Kernel Weight Estimation

Data were obtained from 100 ears (as detailed in the procedure) to validate the kernel weight estimate approach. The weight of the measured kernels was then compared to the weight of the estimated kernels. The results show that, on average, the calculated kernel weight and the measured kernel weight are in relatively excellent agreement, with a correlation of r = 0.99.

The number of harvestable kernels with their weight can be used to predict maize grain yield. Kernel number, out of such two yield factors, typically explains the most variation and is highly connected to ear size. Kernel qualities, despite their importance, are difficult to assess quickly and correctly, mainly because of the necessity for ear threshing before they can be measured. The number of rows in one length of the ear can be counted manually and multiplied by the number of kernels in one length of the ear to get the total kernel count of cobs. These manual yield component measurements have shown to be effective and were utilized in a divergent selection study of the connection between ear length and yield, for example.

The issue with these approaches is the lack of consistency inherent in the way data is gathered (which is dependent on the training and appreciation of the people committed to that work), as well as the time and related expense, which makes them most appropriate for very small trials. According to a preliminary evaluation, depending on the intended measurement, the suggested EDI technique can be twice (example: ear count) to five-fold (example: ear dimensions) quicker than manual methods. Manual techniques are labor demanding, making them more expensive than the EDI approach. Because of differences in labor costs, the cost difference would vary depending on the location/country. Automated measures that are more reliable, quick, and low-cost might be used in yield component research and crop improvement choices.

Miller *et al*. [6] presented a kernel counting imaging technique based on individual kernel areas. The technique assesses kernel size (width and depth) on separated kernels alone. While this procedure is quite accurate, it necessitates the removal of the kernels from the ears, which may be inconvenient when dealing with a large number of ears. Similarly, Liang *et al*. [4] have developed a technique for scoring maize kernel characteristics based on line-scan imaging, which is not appropriate for field evaluation due to time and cost constraints.

The suggested EDI technique has the benefit of generating ear and kernel characteristics data from intact ear pictures. Grift *et al*. [19] created a machine vision-based method to count maize kernels on the ear inside a quasi-cylindrical mid-section and ear maps, which is comparable to our methodology. While their approach is intriguing to some extent, the imaging is performed in a soft box with a light reflector and a high-quality diffused lighting environment. The throughput of this sort of imaging setup is its constraint. In the case of ear size, the EDI technique revealed excellent agreement between humanly measured ear measurements and automated image processing findings (Fig. 8). Miller *et al*. [21] observed similar findings. The primary difference between the two systems is that the one described by Miller *et al*. [21] acquires ear pictures using flatbed document scanners, whereas the EDI method employs an RGB image acquired by the camera in our work, it is the mobile camera. Furthermore, while the flatbed scanner has the advantage of being able to control lighting conditions in the field, the logistics of using it in the field (i.e. the need for a computer) and the limited number of ears (3–5) that can be scanned at one time make it unsuitable for evaluating thousands of ears in a breeding trial.

The EDI technique also predicts kernel weight based on kernel size, allowing for a low-cost yield performance evaluation, especially in cases where ear shelling and kernel weighing are too expensive or when the necessary equipment is unavailable. It's worth noting that this technique doesn't account for kernel moisture (as the kernel weight model was designed for a range of kernel moisture between 11 and 13 percent), which can have a big impact on the final weight if it's not taken into account. Furthermore, the EDI technique does not account for kernel depth when estimating weight, which may result in a minor underestimate of the real kernel weight in some situations.

4. Conclusion

The EDI technique has been demonstrated to be a viable alternative to standard ear phenotyping methods in this study. Hand measures, which generally use calipers and manual counting, are more reliable, especially for large numbers of ears that are routinely assessed in breeding experiments. The accuracy of this approach is primarily dependent on the camera's resolution; however, this is no longer a serious problem due to recent considerable improvements in the resolution of all camera types, including smartphone and tablet cameras. As the results show a good correlation with the images taken using a mobile camera. The technique will be especially beneficial to breeding operations with limited operating resources. The ability to combine ear and kernel characteristics might aid in the development of cultivars with desired farmer qualities such as ear or kernel size.

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