Literature Reviews/Previous Studies

Recently, various machine learning algorithms were proposed for crop yield prediction. Most of them have focused on using either weather/climate data, satellite remote sensing products, or both, in a regression problem for predicting crop yield in the future (Klompenburg et. al. 2020; Kodimalar Palanivel 2019; Saeed Khaki and Lizhi Wang 2019; Cai et.al. 2019; Mu 2019).

However, only a few studies have been done on real-time crop yield estimation in a field based on object detection and counting. In a study done by Reza et al., (2019), an image processing method along with the K-means clustering algorithm with a graph-cut (KCG) algorithm is used on RGB images collected using a multi-rotor drone to estimate rice yield (Panday et al., 2020). This study produced a single image of the entire crop field by mosaicking many images with an overlap ratio of 80% to 85%. Four section images were cropped from the single mosaicked image, which was further cropped into 5x6 cell images, which was then cropped into 4x4 sub-cell images. These sub-cell images were used to estimate the rice yield, by estimating the area of grains in each sub-cell. This approach has many challenges with the preprocessing of the data and contains many computationally heavy steps for preparing the data for prediction. Moreover, this study does not investigate and utilize convolutional neural networks. In two other studies (Wang et al., 2013; Koirala et al., 2019), the number of fruits is estimated in an orchard. The first study (Wang et al., 2013) removes distortions from an image and then uses visual cues to detect red and green apple regions. Morphological methods are then used to convert these regions into counts. The significant challenge of counting apples on a tree or in an orchard is the fact that some apples are visible in multiple images and can be counted multiple times. To deal with this issue, the authors used block matching to triangulate the 3D positions of the apples. This study also relies on complicated and computationally expensive operations for obtaining its predictions. Moreover, they have failed to explore deep learning techniques for estimating crop yield. The second study (Koirala et al., 2019) compares the performance of deep learning models for detecting and counting fruits in an orchard. Their methodology consists of taking an image from each side of a tree and counting the number of fruits in them and multiplying it by a correction factor. The biggest challenge in these studies is the number of images that needs to be taken. For an orchard with tens of thousands of trees, it will take a long time to predict the number of fruits in all images that are necessary to be taken. For wheat yield estimation, the field can be thought of as a 2D plane, which eliminates many of the complications presented in these studies. Moreover, our method will not count all wheat heads in a field. We use only a few hundreds of images taken from sample spots in a field to estimate the yield of the entire field. This will be much faster than the methodology used in these studies and will be much more accurate than manual counting estimates using only five sampling spots per field. For our proposed method, increasing the number of images will result in a more accurate estimation.

A few recent studies have explored using object detection algorithms for detecting wheat heads; however, none of these studies attempt to estimate the total wheat yield in a real-world farm field. These studies used machine learning algorithms to detect wheat heads: Khaki et al. (2021) used MobileNetV2; Bhagat et al. (2021) used the MobiletNetV3 and Wheatnet Lite-Neck; Wang et al. (2021) improved EfficientDet-D0; and Li et al. (2021) compared the performance of Faster R-CNN and RetinaNet. Existing AI algorithms are difficult to scale to real-life phenotyping platforms due to the limited high-quality local datasets that they have been trained with, resulting in challenges when extrapolating to new situations. All these studies were trained only with the Global Wheat Head Detection (GWHD) database. Most images in the GWHD were collected in academic research fields from a number of countries. The major purpose of these studies and GWDH is to help breeders to select important wheat traits linked to yield potential, disease resistance, or adaptation to abiotic stress. Our AI algorithms will be trained with local wheat datasets that are collected in real-world farm fields in Saskatchewan and Alberta. Our database and algorithms are designed for real-world crop yield estimation purposes instead of plant-breeding purposes. However, these existing AI algorithms and methods may prove useful to this project. We will test all these algorithms and methods with our local wheat database. If performance is good, we will use these new methods and algorithms to improve and optimize our processes.

Moreover, many new deep learning algorithms have emerged in recent years for object detection, which have been pre-trained on very large datasets, such as COCO. These transfer learning models already have a deep understanding of the context and are highly capable of extracting high-level semantic information from an image. Our goal is to finetune these new algorithms and investigate their capabilities for the task of wheat head detection and counting. We will then use the results of these algorithms to estimate the crop yield of the entire field.

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