

Furrow Mapping of Sugarcane Billet Density Using Deep Learning and Object Detection

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III. METHODOLOGY

A. Data Collection

A machine vision system had been created for the purpose of data capture but was not implemented due to travel restrictions. A GoPro® Hero8 was attached beneath the planter looking into the open furrow in two orientations, forward- and rear-facing. Data was captured over two days of planting using 60 frames per second (fps) and 240 fps video. In total, 9 videos were collected with around 100 minutes of footage in varying natural lighting conditions.

B. Constructing the Dataset

The data collected was of poor quality due to dust and lighting issues caused by the planter moving at an average speed of 12km/hr through freshly formed beds. The best 240fps video was split into frames and every 60th frame used in order to increase the variability of the dataset. The images were then cropped to a Region of Interest (ROI). Each billet in the image was labelled using a bounding box technique as a single class. High quality annotated lab data was added to provide finer grained detail of a billet. In total, 1500 annotated images were used in the final iteration.

C. Training the YOLOv3 Model

A YOLOv3 model was trained initially with 500 images and transfer learning using 2 different models and weights, YOLOv3-spp and YOLOv3-tiny. 500 high quality lab images were then added and transfer learning again used to create models. Each model used 80% training data from one source and 20% test data from another. A batch size of 4 increased the throughput and variability in each training iteration and allowed training on a NVIDIA® 1050 GPU. Mosaic tiling and HSV augmentation were also applied [18]. Another 500 images were added to the final training set and a final YOLOv3-spp model trained. Each model was trained for 300 epochs and the epoch with the best results was used for comparison.

D. Performance evaluation

In order to determine the performance of each model, the precision, recall, mean Average Precision (mAP) and F1 scores were used and compared to determine the best performance, Table I.

TABLE I
MODEL PERFORMANCE INDICATORS

Model	Precision	Recall	mAP	F1
YOLOv3-spp	0.686	0.851	0.793	0.76
YOLOv3-tiny	0.647	0.728	0.714	0.685
YOLOv3-spp	0.700	0.741	0.743	0.720
YOLOv3-tiny	0.686	0.733	0.726	0.709
Final model	0.745	0.888	0.852	0.810

IV. RESULTS AND DISCUSSION

The YOLOv3-spp model trained using transfer learning out-performed the others and was used to detect billets in an unseen test video. This model detected billets with a reasonably high accuracy as seen in Figure 2a in some images but experience false negatives and false positives in others, Figure 2b. These results were used in the following sections.

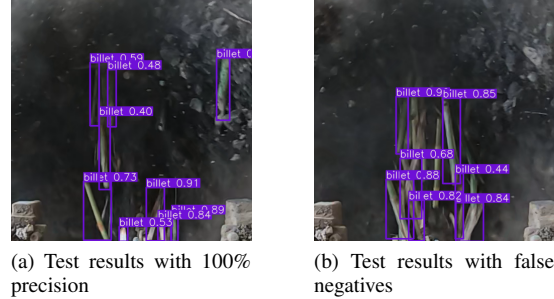


Fig. 2. Sugarcane Billet detection using YOLOv3 detector

A. Seed Density Mapping in the Furrow

The results of each image was output to a text file with the class and bounding box co-ordinates for each object. A python script was written to open each output and count the number of billets per image. This was stored in an array and used to plot a furrow map of seed density as seen Figure 3. A map across the field of seed density will allow for improvements to be made to existing planters and results recorded. This will add the most value to the sugarcane industry as it should determine where underlying issues exist with current planting processes. Each detection run on the NVIDIA® 1050 took around 0.06 seconds, which would provide an accurate indication of billets per meter in real-time to a planter operator.

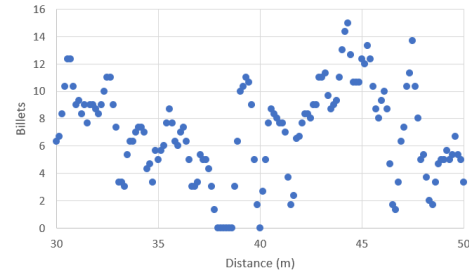


Fig. 3. Furrow seed density mapped over a 20m section

V. CONCLUSION

The GoPro® data demonstrates the feasibility of using machine learning and object detection to provide furrow mapping of sugarcane billet and useful real-time metrics. Data quality is key to improving the existing model and this experiment proves the need for a higher quality machine vision system to be implemented. A system will be implemented using controlled lighting, a high quality machine vision camera and positive pressure to remove dust from the ROI for future tests.

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