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RESEARCH ARTICLE

Sugar Beet Seed Classification for Production Quality Improvement by Using YOLO and NVIDIA Artificial Intelligence Boards

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Abstract

All inputs are required for excellent and proper crop production, especially seed quality. In this way fewer disease and insect issues, increased seedling germination, uniform plant population and maturity, and better responsiveness to fertilizers and nutrients, leading to higher returns per unit area and profitability, and low labor costs could be possible. Because of this reason, NVIDIA Jetson Nano and TX2 artificial intelligence boards were used to test the efficiency of the YOLOv4 and YOLOv4-tiny models for sugar beet monogerm and multigerm seed classification for better production. YOLOv4-tiny outscored the other model based on FPS with 8.25–8.37 at NVIDIA Jetson Nano, 12.11–12.36 at NVIDIA TX2 artificial intelligence boards with accuracy 81–99% for monogerm seeds, and 89–99% for multigerm seeds at NVIDIA Jetson Nano, 88–99% for monogerm seeds, and 90–99% for multigerm at NVIDIA TX2 accuracy, respectively, implying that the YOLOv4 is more accurate but slow with based on FPS with 1.10–1.21 at NVIDIA Jetson Nano, 2.41–2.43 at NVIDIA TX2 artificial intelligence boards with 95–99% for monogerm seeds and 95–100% for multigerm seeds at NVIDIA Jetson Nano, 92–99% for monogerm seeds and 98–100% for multigerm seeds at NVIDIA TX2, respectively. As a result of the evaluations, NVIDIA Artificial Intelligence cards and YOLO deep learning model will be used effectively in classifying monogerm and multigerm sugar beet seeds, thus reducing seed loss with the help of NVIDIA Artificial Intelligence cards classification.

Keywords Sugar beet · NVIDIA Jetson Nano · NVIDIA Jetson TX2 · Real-time seed detection · YOLOv4-tiny

Introduction

The sugar beet (*Beta vulgaris* L.) is the second-most important raw material after sugarcane, in addition to being a good source of sugar. It is vital to initially choose the appropriate seeds and the ideal place for growing crops to yield high-quality seeds (Mall et al. 2020). Crop yield and amount are heavily influenced by seed quality. Seed quality influences 20–25% of the amount, according to Kanwar and Pawar (2017) physical, physiological, genetic, and storage features all have a part in determining seed quality.

In the previous few years, machine vision has been the most popular artificial intelligence trend based on YOLO for seed producers. Redmon et al. (2016) introduced the first regression-based one-step method, YOLO. The network structure is more intricate, and there were more parameters in the network when employing YOLO serial methods or their updated methods. Detecting objects in real-time requires a large amount of GPU (graphics processing unit) computing power. In real-world applications, several mobiles, and embedded devices require real-time object detection, yet these devices have limited computing capacity and memory (Mao et al. 2019). For real-time inference on smartphones and embedded video surveillance, a mix of low-power embedded GPUs or even embedded CPUs with limited memory is necessary. This means that detecting objects in embedded and mobile devices is difficult. Several researchers have proposed lightweight object detection systems as a solution to this challenge.

The use of GPUs in neural network calculations ushered in a new era in machine vision, allowing a wider spectrum of researchers to employ neural networks. Because of CUDA, CuDNN may now be used by single-board computers in real-time operations (Chen et al. 2021). CUDA is

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a software and hardware parallel computing paradigm that uses NVIDIA GPUs to dramatically boost computing speed. As a result, NVIDIA's single-board computers can be used in more challenging machine vision jobs. Zhao et al. (2021), for example, used the Jetson Nano board to develop a system that uses deep learning to recognize flaws on the full surface of soybean seeds in real time.

The preceding examples demonstrate that machine vision has practical applications; as a result, implementing this technology necessitates special hardware conditions, the most important issue is low-cost equipment and computing power. The scope of single-board computer implementation is vast, and its use is limited only by the fact that the depth of neural networks is increasing faster than the cost of the hardware component is decreasing. However, frameworks and libraries, as well as a variety of additional tools, are available to help single-board computers work more quickly. Machine vision frameworks and libraries are updated at a rate that no other field of research can match. As a result, knowing all the options for increasing FPS (Frames Per Second) on the single-board computer is extremely tough. In terms of subjects, Mittal (2019) delivered a work that was as near to ours as possible. On the Jetson platform, they evaluated and optimized neural network applications.

So, considering the literature, this research focused on sugar beet seed detection as monogerm and multigerm necessitates intelligence and automation, as well as accurate and real-time detection. Because current sugar beet detection approaches need some new applications not to lose monogerm seeds while separating from the multigerm seeds, different from physical sorting systems. Multigerm seed is an undesirable factor that increases labor and production costs in sugar beet farming. In the sugar beet seed processing technique, air separation and sieve methods are used for multigerm seed separation. With these methods, the processing time is prolonged in separation and some monogerm seed wastage occurs. For this reason, it is important to provide a more sensitive method for multigerm seed separation that will reduce monogerm seed loss. For this aim, a hardware design for real-time image capture and processing of sugar beet seeds is created. YOLOv4 and YOLOv4-tiny models, which are based on the images taken, were subsequently used to identify sugar beet samples. Experiments are then used to validate the efficiency of the sugar beet seed determination system. The outlines of our proposal introduce the ideas and methods of the YOLOv4 and YOLOv4-tiny object detection methods. At last, display and discuss evaluated outcomes.

Material and Methods

During 2012, there are a lot of deep learning-based object detection frameworks developed like AlexNet, OverFeet, VGGNet, R-CNN, Fast R-CNN, GoogleNet, Faster R-CNN, ResNet, FPN, Hourglass, SSD, ResNet v2, R-FCN, ResNeXt, DenseNet, DCN, DPN, RetinaNet, MobileNet, Mask R-CNN, RefineDet, SENet, Cascade RCNN, CornerNet, NASNet, FSAF, ExtreNet, EfficientNet, NAS-FPN, FCOS, CenterNet, Detnas, respectively. One-stage detectors, such as YOLO and its variants, and two-stage detectors, like region-based CNN (R-CNN), are the two main categories now used in deep learning-based object detection frameworks. In the first stage of two-stage detectors, a proposal generator generates a small number of proposals from which features are extracted; the features are then used by region classifiers to make predictions about the category of the suggested region. Instead of using a cascading method to classify regions, one-stage detectors use feature maps to produce a direct categorical prediction of items at each point (Fig. 1). Although one-stage detectors are far more time-efficient and applicable to real-time object identification, two-stage detectors typically achieve better detection performance and report state-of-the-art scores on public benchmarks (Wu et al. 2020). Additionally, between two deep learning-based object detection methods YOLO gives more accurate results,

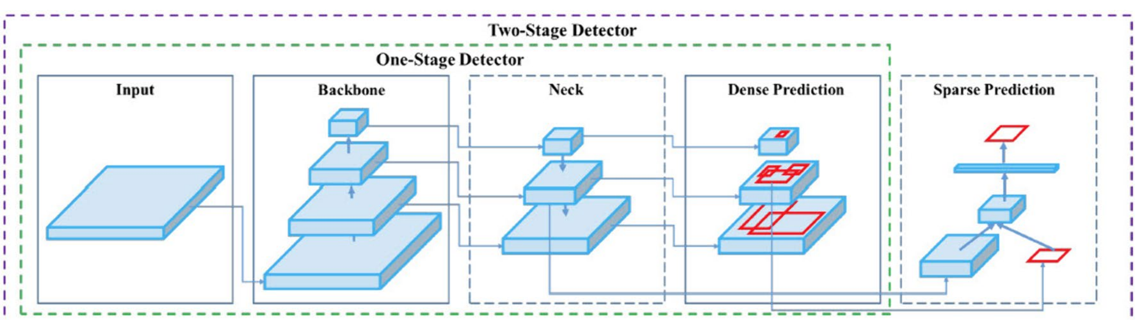


Fig. 1 YOLO architecture as input (image), backbone (feature extractor), neck (prediction layers), dense prediction (predict bounding boxes and class probabilities in a single pass), sparse prediction (propose potential bounding boxes then classify the objects and refine the bounding box coordinates) (Bochkovskiy et al. 2020)

on the other hand, YOLO-tiny gives more FPS performance at the application stage. This condition is also related and changes with artificial board properties and capacities.

Because of this reason, YOLO was selected as a suitable deep learning-based object detection framework. So, in this research, we examined the most current advances in object detection, and these are the models of the YOLOv4 and YOLOv4-tiny object detection methods. The material and methods section explains that the outlines of our proposed method focused on sugar beet seed detection based on YOLO.

Sugar Beet Seeds

The beta genus of central florists collects beets of all types. The most cultivated species in this breed is *Beta vulgaris* L. Sugar beet is a 2-year-old plant for seed production that is utilized for both food and different chemical materials. The root body develops beneath the earth during the first year, allowing for sugar generation, while the above-ground parts develop during the second year, allowing for seed production.

Sugar beet seeds come in both monogerm and multigerm seeds. Low amounts of multigerm seeds (multi-ruched (embryo) beets) can be seen in monogerm seeds, whereas monogerm seeds are produced by single-ruched beets. The sugar beet plant seeds, which are brown and hard-shelled, are a wonderful source of cellulose. Figure 2 depicts genetic monogerm seeds in their monogerm and multigerm forms. Figure 3 also shows embryos of monogerm and multigerm seeds.

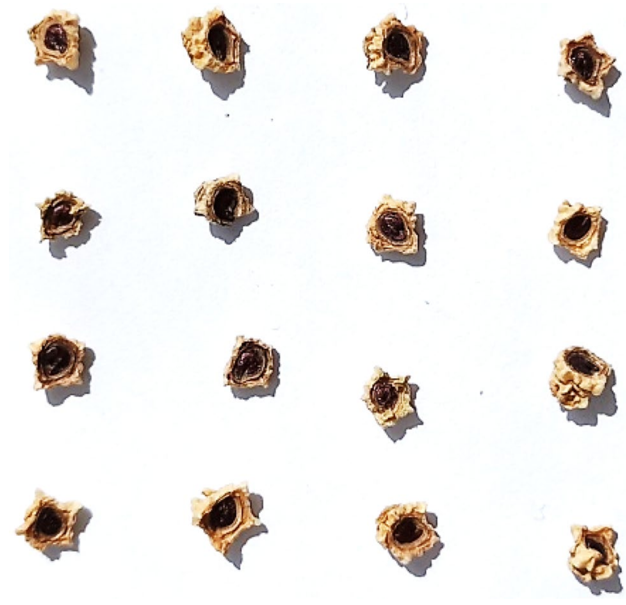
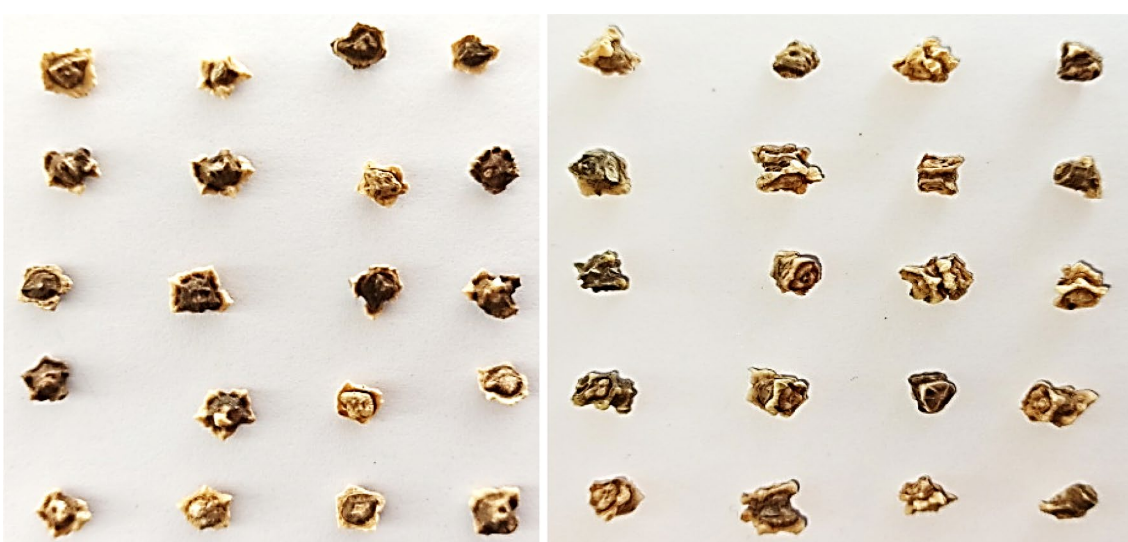


Fig. 3 Embryos of sugar beet seeds

A typical multigerm seed contains multi-ruched (embryo) between 2 and 3 seeds, depending on the variety (Fig. 4).

A multigerm seed is generated when two or more blooms in section Beta form clusters of two or more, each with its genuine seed. Sowing the resulting monogerm seed with precision machinery is useful, but if at the same time, multigerm seeds are sowed, it increases the payments of the sugar beet production for farmers. Gravity separations, routinely utilized in seed processing, were found to be inadequate in



(a) (b)

Fig. 2 The sugar beet seeds are shown in two forms: **a** monogerm and **b** multigerm

Fig. 4 Double and triple-ruch sugar beet seed sections (Saripinar 2011)

eliminating all multigerm seeds. In this research, Terranova sugar beet variety seeds were used for evaluation. The selection reason for the Terranova variety is that it is a resistant variety to Rhizomania because it has several dominant and resistance genes that come from its genetic pool.

General Principles of Seed Processing

A good seeding procedure is critical for enhancing yield and end-product quality. As a result, the finished product must be distinguished from those with seed traits. The process of enhancing seeds through pre-treatment, cleaning, size separation, and seed size limitation is referred to as seed preparation. The seeds can be cleaned and categorized in several ways based on their physicomechanical qualities. This is what distinguishes it: the dimensions of an object, aerodynamic qualities, surface properties, shape features, flexibility features, mechanical friction, weight, and electrical properties. With the help of seed processing, multigerm seeds can be separated from monogerm ones. The reason for selecting monogerm seeds is that the multigerm seeds do not have good body development.

Image Acquisition System

The experimental focus of this study is sugar beet seeds obtained from the Ankara Sugar Institute in Turkey. The sugar beet seeds images, shown in Fig. 1, were shot on February 20, 2022, in the image processing laboratory, Celestron Microdirect 1080p HDMI handheld digital microscope, computer. The Celestron Microdirect 1080p HDMI handheld digital microscope has 10 × to 220 × power magnification with a focal length of 5 cm. A total of 500 high-resolution photos are saved in the 'JPG' file format. 250 photos of YOLOv4 and YOLOv4-tiny models were utilized for all applications, and sugar beet seeds were positioned at random degrees for image enhancement. Sugar beet seeds, on the other hand, were positioned at random degrees. LabelImg was used to label and annotate the sugar beet shoots and seeds in a 'txt' standard format to determine their orientation and ensure that the label box is closely next to the desired border of each label (Anonymous 2021).

YOLO Model Architecture and Training

It will be released in April 2020, YOLOv4 is a real-time object detection model that performs at the highest level in the COCO dataset. YOLO uses regression to define object positioning through bounding boxes and classification to determine the object's class. In the event of a crisis, YOLOv4 can be used to implement many of the previous research contributions in the YOLO family, including new features such as WRC, CSP, and CmBN as well as SAT, Mish activation, Mosaic data magnification, and CmBN editing. Improved network architecture and new data magnification techniques can be employed by YOLOv4 (Bochkovskiy et al. 2020).

In this investigation, four metrics were used to evaluate the model's performance: precision, recall, mAP, accuracy, and detection speed. The mAP is the average value of the AP (Average Precision) when detecting a sugar beet seed; the greater the value the better the sugar beet seed detection result.

Google Colab Pro was used as a training platform. Deep learning models take a long time to train on a computer's CPU. These models can be trained in a matter of minutes or seconds on GPUs and TPUs, however. Experts always prefer a GPU over any other CPU because of its sheer computational power and speed of execution in data science hackathons and deep learning projects. The NVIDIA Tesla P100-PCI-E-16 GB was utilized in this study to test Colab Pro YOLOv4 and YOLOv4-tiny models using CUDA-version: 11, cuDNN: 7.6.5, and OpenCV version: 3.2.0.

NVIDIA Artificial Intelligence Boards

NVIDIA Jetson Nano and NVIDIA Jetson TX2 devices were utilized to recognize a single sugar beet seed with YOLO models. In both devices, a Logitech C920 Full-HD webcam

Table 1 Comparison of different YOLO models with the parameters true positives (TP), false positives (FP), false negatives (FN), precision, recall, and intersection over union (IoU)

Model	Precision	Recall	$F1$-score	TP	FP	FN	IoU (%)
YOLOv4-tiny	0.98	1.00	0.99	50	1	0	76.19
Y0L0v4	1.00	1.00	1.00	50	0	0	95.52

Table 2 Comparison of different YOLOv4-tiny model results for each sugar beet seed with the parameters average precision (ap), true positives (TP), and false positives (FP)

Class Id	Name	ap (%)	TP	FP
0	*Monogerm*	100	21	0
1	*Multigerm*	100	29	1

Table 3 Comparison of different YOLOv4 model results for each sugar beet seed with the parameters average precision (ap), true positives (TP), and false positives (FP)

Class Id	Name	ap (%)	TP	FP
0	*Monogerm*	100	25	0
1	*Multigerm*	100	25	0

was employed for recognition by YOLO models at 640 × 480 pixel resolution.

FPS Optimizing Method

We used the Jetson Nano and TX2 single-board computers to put the recommended approaches to the test. To develop the neural network, we used YOLOv4 and YOLOv4-tiny models to search for one item in real-time video with a resolution of 640 × 480 pixels from a Logitech C920 Full-HD webcam. YOLO was chosen because it has several benefits that have been explicitly highlighted by Bochkovskiy et al. (2020). Darknet is developed in C and runs on CUDA with cuDNN support. cuDNN is a basic library for ultra-precise neural networks that run on the GPU.

Results

The train was made after 1 h of work time for YOLOv4-tiny using the NVIDIA Tesla P100-PCI-E-16 GB graphic card with Cuda GPU support. Furthermore, the YOLOv4 model was trained in 6 h using the NVIDIA Tesla P100-PCI-E-16 GB graphic card with Cuda GPU support.

In Table 1, true positives, false positives, false negatives, precision, recall, and intersection over union are referred to as TP, FP, FN, Precision, Recall, and IoU values of YOLO models, respectively.

Tables 2 and 3 also show the outcomes of various YOLOv4-tiny and YOLOv4 model findings for each sugar beet seed type. Whole ap (average precision) (%) values for sugar beet seed model results are 100%.

Table 4 also includes a comparison of various YOLO models in FPS and mAP (mean average precision). According to Table 4, the YOLOv4-tiny model is 22.980 Mb in size and supports 8.31 FPS in NVIDIA Jetson Nano GPU, while the YOLOv4-tiny model is 22.980 Mb in size and provides 12.20 FPS in NVIDIA Jetson TX2 GPU.

The NVIDIA Jetson Nano and TX2 devices were used to assess the detection speed for a single sugar beet seed as a real-world application using only the YOLOv4 and tiny models, and the results are presented in Tables 5, 6, 7 and 8.

Additionally, Figs. 5 and 6 show accuracy and FPS samples of sugar beet seed detection using YOLOv4-tiny and YOLOv4 models in NVIDIA Jetson Nano and TX2 GPU.

According to Table 5, the accuracy of the YOLOv4-tiny model application for sugar beet recognition in NVIDIA Jetson Nano AI Board varies between 81–99% for monogerm seeds and 89–99% for multigerm seeds.

The YOLOv4-tiny model application for sugar beet seed recognition accuracy in NVIDIA Jetson TX2 AI Board GPU varies between 88–99% for monogerm seeds, and 90–99% for multigerm seeds according to Table 6.

Table 7 demonstrates that the YOLOv4 model application for sugar beet recognition accuracy ranges from 95–99% for monogerm seeds and 95–100% for multigerm seeds.

At last, according to Table 8, the YOLOv4 model application for sugar beet recognition accuracy in NVIDIA Jetson TX2 AI Board GPU ranges from 92–99% for monogerm seeds and 98–100% for multigerm seeds.

Discussion

In the literature, on this subject, Jiang et al. (2020) produced an enhanced version of the YOLOv4-tiny system that could detect objects in real-time, with confidence scores of trains ranging from 0.92–2.90 in their sample Fig.s with YOLOv4-tiny to 0.94–0.90 in their suggested technique.

Fang et al. (2021) employed deep learning-based channel and network layer pruning to recognize ginger photos in real time. According to the findings of their tests, the trimmed

Table 4 Comparison of different YOLO models and platforms in frame per second (FPS) and mean average precision (mAP)

Method	Model size (KB)	FPS	mAP
YOLOv4-tiny (NVIDIA Jetson Nano GPU)	22.980	**8.31**	0.50
Y0L0v4 (NVIDIA Jetson Nano GPU)	250.037	1.17	0.50
YOLOv4-tiny (NVIDIA Jetson TX2 GPU)	22.980	**12.20**	0.50
Y0L0v4 (NVIDIA Jetson TX2 GPU)	250.037	2.42	0.50

Bold definitions are significant

Table 5 YOLOv4-tiny model application with accuracy, frame per second (FPS) and mean average precision (mAP) values for sugar beet seed detection in NVIDIA Jetson Nano AI board

Material	Accuracy (%)	Model	FPS	mAP
Monogerm seed	99	YOLOv4-tiny	8.35	0.5
Monogerm seed	97	YOLOv4-tiny	8.37	0.5
Monogerm seed	98	YOLOv4-tiny	8.35	0.5
Monogerm seed	81	YOLOv4-tiny	8.33	0.5
Monogerm seed	95	YOLOv4-tiny	8.31	0.5
Multigerm seed	98	YOLOv4-tiny	8.30	0.5
Multigerm seed	99	YOLOv4-tiny	8.29	0.5
Multigerm seed	99	YOLOv4-tiny	8.27	0.5
Multigerm seed	89	YOLOv4-tiny	8.25	0.5
Multigerm seed	89	YOLOv4-tiny	8.24	0.5

Table 7 YOLOv4 model application with accuracy, frame per second (FPS) and mean average precision (mAP) values for sugar beet seed detection in NVIDIA Jetson Nano AI board

Material	Accuracy (%)	Model	FPS	mAP
Monogerm seed	95	YOLOv4	1.20	0.5
Monogerm seed	98	YOLOv4	1.21	0.5
Monogerm seed	99	YOLOv4	1.21	0.5
Monogerm seed	97	YOLOv4	1.21	0.5
Monogerm seed	99	YOLOv4	1.21	0.5
Multigerm seed	98	YOLOv4	1.1	0.5
Multigerm seed	100	YOLOv4	1.13	0.5
Multigerm seed	100	YOLOv4	1.14	0.5
Multigerm seed	95	YOLOv4	1.15	0.5
Multigerm seed	100	YOLOv4	1.18	0.5

Table 6 YOLOv4-tiny model application with accuracy, frame per second (FPS) and mean average precision (mAP) values for sugar beet seed detection in NVIDIA Jetson TX2 AI board

Material	Accuracy (%)	Model	FPS	mAP
Monogerm seed	96	YOLOv4-tiny	12.36	0.5
Monogerm seed	88	YOLOv4-tiny	12.26	0.5
Monogerm seed	95	YOLOv4-tiny	12.25	0.5
Monogerm seed	91	YOLOv4-tiny	12.23	0.5
Monogerm seed	99	YOLOv4-tiny	12.21	0.5
Multigerm seed	99	YOLOv4-tiny	12.21	0.5
Multigerm seed	94	YOLOv4-tiny	12.14	0.5
Multigerm seed	98	YOLOv4-tiny	12.14	0.5
Multigerm seed	99	YOLOv4-tiny	12.13	0.5
Multigerm seed	90	YOLOv4-tiny	12.11	0.5

Table 8 YOLOv4 model application with accuracy, frame per second (FPS) and mean average precision (mAP) values for sugar beet seed detection in NVIDIA Jetson TX2 AI board

Material	Accuracy (%)	Model	FPS	mAP
Monogerm seed	93	YOLOv4	2.42	0.5
Monogerm seed	98	YOLOv4	2.42	0.5
Monogerm seed	99	YOLOv4	2.41	0.5
Monogerm seed	97	YOLOv4	2.41	0.5
Monogerm seed	92	YOLOv4	2.41	0.5
Multigerm seed	99	YOLOv4	2.44	0.5
Multigerm seed	100	YOLOv4	2.44	0.5
Multigerm seed	98	YOLOv4	2.43	0.5
Multigerm seed	100	YOLOv4	2.42	0.5
Multigerm seed	99	YOLOv4	2.42	0.5

model lowered model size by 87.2% while increasing detection speed by 85%. It had a mean average precision (mAP) of 98.0 for ginger shoots and seeds, which was only 0.1% worse than the model before pruning, which had an mAP of 98.0. Using this model on a Jetson Nano, the results showed that its mAP was 97.94%, recognition accuracy was 96.7%, and detection speed was 20 frames^{-1}. The proposed method enabled accurate and real-time picture recognition of ginger, laying the framework for autonomous and accurate ginger seeding.

Li et al. (2021) concentrated on creating and testing a YOLOv4-based cracked corn kernel detection device. The YOLOv4-tiny model was found to be 93.5% correct for intact kernels and 90.0% correct for broken kernels, with precision, recall, and $F1$ score values of 92.8, 93.5, and 93.11%, respectively.

Guo et al. (2021) created a novel YOLOv4-tiny network for real-time electrical component detection. The accuracy of the original algorithm has increased from 93.74 to 98.6%. When compared to current standard algorithms such as

Fig. 5 Accuracy and FPS samples of sugar beet seeds detection with YOLOv4 and YOLOv4-tiny models at Jetson Nano

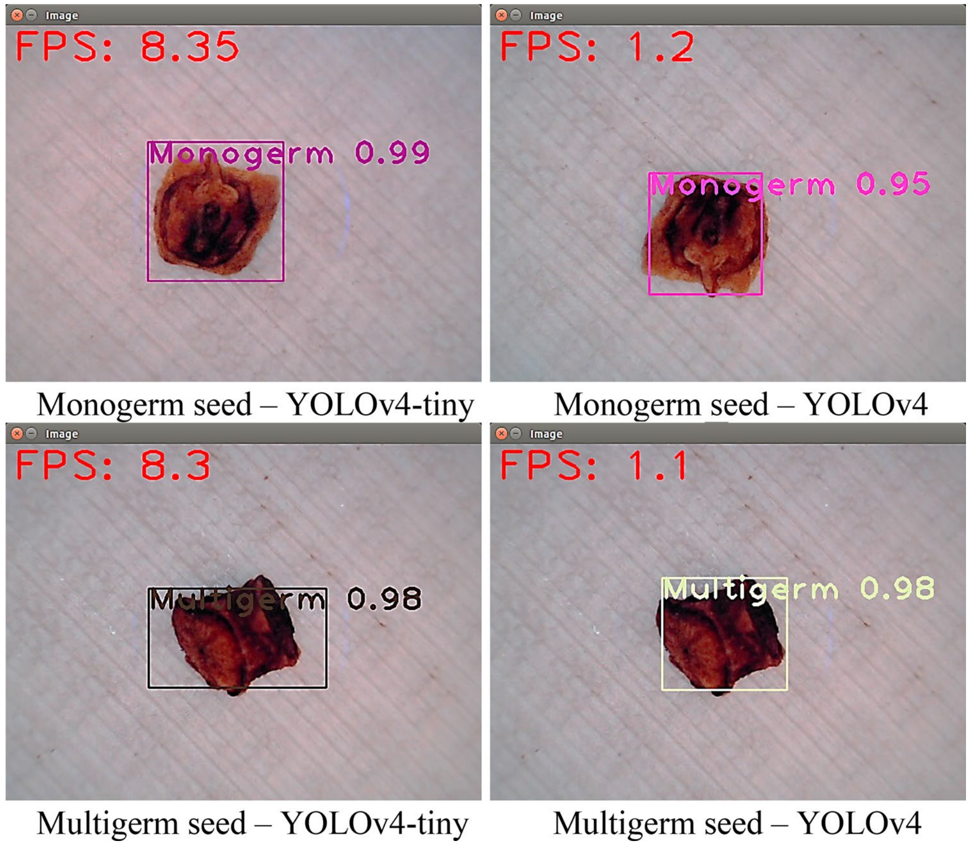
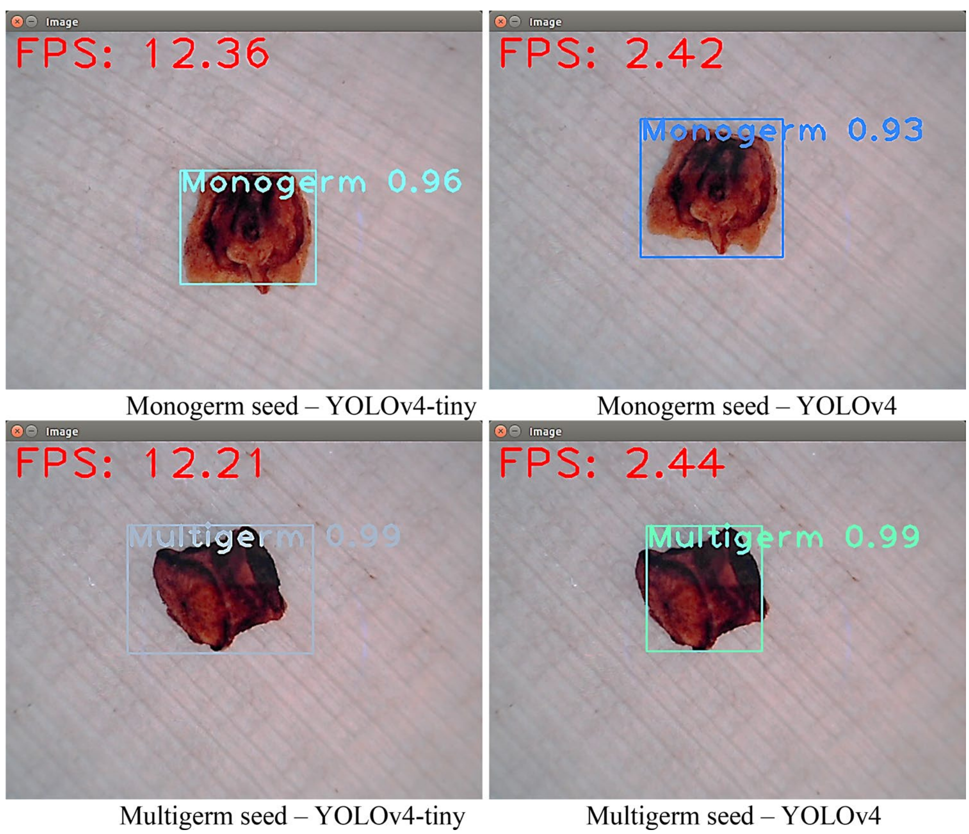


Fig. 6 Accuracy and FPS samples of sugar beet seeds detection with YOLOv4-tiny model at TX2



Faster RCNN, SSD, RefineDet, EfficientDet, and YOLOv4, the approach is the fastest and most accurate. It is also hinted that the method can be utilized as a technical reference to construct production robots for the electronics industry.

According to our research, the accuracy of the YOLOv4-tiny model application for sugar beet seed detection in the NVIDIA Jetson Nano AI Board ranges from 81–99% for monogerm seeds and 89–99% for multigerm seeds. Also, the YOLOv4-tiny model application for sugar beet recognition accuracy ranges from 88–99% for monogerm seeds, to 90–99% for multigerm seeds in NVIDIA Jetson TX2 AI Board GPU.

The YOLOv4 model application for sugar beet recognition accuracy ranges from 95 to 99% for monogerm seeds and 95–100% for multigerm seeds on the NVIDIA Jetson Nano AI Board. Furthermore, the YOLOv4 model application for sugar beet recognition accuracy ranges from 92–99% for monogerm seeds, to 98–100% for multigerm seeds on NVIDIA Jetson TX2 AI Board GPU.

It is a well-known reality for mobile artificial intelligence boards that compact models of artificial intelligence libraries such as TensorFlow, Keras, Coffee, and YOLO have the best performance in real-world applications such as in this research, and 8.30–12.20 frames per second were obtained from NVIDIA Artificial Intelligence Boards. On the other hand, dataset constructions with a small number of images always have the risk of model overfitting.

Conclusion

We have examined the most popular and proven way of improving FPS on NVIDIA single-board computers in this research. We can conclude that thanks to the usage of the described tools, deep neural networks run on NVIDIA Jetson Nano and TX2 boards with an acceptable FPS (FPS—8.31, YoloV4-tiny, Jetson Nano, and FPS—12.20 Jetson TX2). We evaluated FPS in this article because it is the most significant criterion in practice, and we did not consider difficulties like energy consumption, size, or other factors that can be solved using financial approaches if necessary. As a result, specialists who utilize machine vision in their projects find it challenging to keep up with all the new frameworks for the single-board computer industry. Also, this study applies a YOLOv4-tiny network structure to determine sugar beet seeds and demonstrates good detection accuracy without adding massive calculations. When compared to YOLOv4 and YOLOv4-tiny, YOLOv4-tiny has a faster detection rate and approximately comparable average precision.

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Declarations

Conflict of interest The authors declare no conflict of interest.

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