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YOLOv4 and Tiny YOLOv4 Based Forage Crop Detection with an Artificial Intelligence Board

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HIGHLIGHTS

- Farmers try to make maximum use of the existing agricultural areas.
- One of these ways is mixed sowing systems.
- It is very difficult to sow species with different grain sizes in mixtures.
- Special sowing machines are needed for this aim.
- So, the article aims to be a guide for artificial intelligence capable mixed sowing in forage crops.

Abstract: The decrease in the possibilities of increasing the arable agricultural areas in the world and the continuous increase in the population have led those who are engaged in plant production to seek ways to make maximum use of the existing agricultural areas. One of these ways is mixed sowing systems. It is very difficult to sow species with different grain sizes in mixtures. Special sowing machines are needed for this aim. Because of this reason, the article aims to be a guide for artificial intelligence capable of mixed sowing in forage crops. In the research, it is found that there are some differences between YOLOv4-tiny and Y0L0v4 models as Precision, Recall, F1-score, TP, FP, FN scores. For the YOLOv4-tiny model, these scores were found as 0.99, 1.00, 0.99, 90, 1, 0, respectively and the scores for the Y0L0v4 model were 1.00, 1.00, 1.00, 90, 0, 0. According to the YOLOv4-tiny and YOLOv4 tests in the lab, suggesting that the YOLOv4-tiny is faster, and the YOLOv4 is more reliable in terms of all these factors combined. This research establishes a standard for real-time recognition of forage crops based on current technology at NVIDIA Jetson TX2 due to its high performance and low power consumption and a high-performance computer with CUDA support.

Keywords: forage crops; smart agriculture; real-time object detection; yolov4-tiny; yolov4.

INTRODUCTION

One of the world's primary importance problems is providing sufficient and safe food to the increasing population [1-2]. Therefore, plant and animal production must be increased. However, due to the increasing input costs and the decrease in yield growth, it becomes difficult to produce the needed food [3-4]. Since opening new cultivated areas to overcome this difficulty is impossible, increasing productivity per unit area has become necessary [5]. To increase agricultural production, superior varieties suitable for ecology [6] and mixed growing systems such as annual or perennial legume-grass/cereal mixtures must be used to produce high yield and quality roughage required in animal production [7]. In addition, taking advantage of artificial intelligence applications to reduce the increasing input costs and use resources effectively has become necessary.

Legumes have been grown all over the world for a very long time, either as pure or mixed with cereals [8]. Also, leguminous forage crops are one-year forage plants that have an important place as nutrition of ruminant animals in livestock with the high protein, minerals, vitamins they contain [9-12]. Including legumes in rotation by sowing them pure or mixing them with grass/grains provides many advantages, such as preventing soil and water erosion, improving the physical properties of the soil, fixing the free nitrogen of the air to the soil, and simplification of weed and pest control [13-18]. In America, when alfalfa is sowed in the fall, it is sowed with sorghum to protect it from cold damage. The dead leaves of Sorghum protect from the cold by covering the alfalfa seedlings [19]. Although there is no such problem in perennial legume cultivation, the most important problem in pure sown annual legume cultivation is the decrease of forage yield and quality, and the difficulty of harvesting caused by the lying stem [20,21]. Due to the lying problem in legume seed production, flowering, and fruit set decrease, so grain yield decreases. The most practical way to solve this problem is to use mixed sowing methods, in which two or more plant species are grown together in the same period. [22,23]. In addition to all these, the most important advantage is that the yields of legume-grass/cereal mixtures are superior in yield and quality compared to pure sowing [24,25]. However, to benefit from the advantages of mixed cultivation, the proportions of the species in the mixture must be precisely adjusted [26].

Traditional seed drills are widely used around the world to produce high-quality roughage in forage crops, especially for the sowing of annual legume-cereal mixtures. However, it is practically impossible to sow the species with different sizes and weights in the mixtures with conventional sowing machines at the desired proportions. Since the main purpose of the drills specially designed for forage crops is pure sowing, it is very difficult to sow the mixtures at the desired proportions even with these machines. This is another important problem that hinders the expected benefits of legume-grass/grain mixtures. Because the proportions of legumes and cereals in the mixtures are among the most affecting yield and quality factors [27,29]. For this reason, it is necessary to change the point of view of forage seed drills and develop seed drills that can sow at desired proportions using modern technologies such as artificial intelligence or machine learning.

Intelligence and automation used in forage crops need to detect seeds accurately and in real-time. Since current detection methods for forage crop seeds are lacking in accuracy and reliability, this study examines the YOLOv4 and tiny models for forage crop detection in a complex and changing sowing environment. A new YOLO (YOLOv1) network was suggested in 2016 by Joseph Redmon and coauthors [30] that does not require images to go through tedious processing steps to recognize objects in real-time. There are several advantages to using the YOLO network additional advantages make YOLO a better choice than other object identification techniques. One of them is the advantage of training and testing with a full-image view is that it implicitly encodes contextual information about the item classes and their look. To put it simply, the YOLO network can learn universally applicable images and so beats other detection algorithms when trained with natural images and evaluated with the artwork. This means that the YOLO algorithm retains a high average detection accuracy even detecting the fastest speeds. When using YOLO serial methods or their upgraded methods, the network structure is more complicated and there are more parameters in the network. They need a lot of GPU (graphics processing unit) processing power to detect objects in real-time. Some mobile and embedded devices in real-world applications require real-time object identification, but these devices have limited computing power and memory [31]. A combination of low-power embedded GPUs or even embedded CPUs with limited memory is required for real-time inference on embedded video surveillance. This means that embedded and mobile device object detection is a significant challenge. As a solution to this problem, several researchers have developed lightweight object detection methods. The network topology and number of parameters are both simplified in lightweight approaches. So, they consume less processing power and memory and perform detection tasks more quickly than their predecessors. Mobile and embedded devices are better suited for their use. Even though they have a lower detection rate, they meet the requirements of the needed applications, such as seed detection, identification, and classification. Because of these reasons, a new lightweight YOLO series approach based on YOLOv4-tiny has been developed [32].

In this research, the number of forage crop seeds used for YOLO-based seed determination can be used in mixed sowing which is an important parameter for farmers. Therefore, the classification of forage crop seeds is a challenging task for farmers and the agro-industry. There is a need to automate seed rates. If production is continued with sowing machines that do not automatically adjust the seed rate, the sowing rate desired by the producer will not be kept and seed loss will continue. Because in a mixed sowing, seeds vary in size, specific gravity, etc. Since their characteristics are different from each other, seed detection became more important. The reason why YOLO was chosen is that it has three advantages over other object detection methods. First and foremost, the YOLO network is extremely fast. Second, because the YOLO network sees the entire image during training and testing, contextual details about the object classes and their appearance are implicitly encoded. Third, the YOLO network learns generalizable representations of objects; thus, when trained with natural images and tested on the artwork, the YOLO algorithm outperforms other detection methods. As a result, the YOLO algorithm maintains high average detection accuracy while providing the fastest detection speed [33]. So, in section 1, we looked at the most recent developments in object detection. Section 2 explains our proposed method and introduces the YOLOv4-tiny and YOLOv4 object detection method's principles and procedures with different hardware support for real-time applications. YOLO model results are shown and discussed in Sections 3-4.

MATERIAL AND METHODS

Material

The materials of the research consisted of fodder pea, triticale, oat, sorghum, and vetch seeds, which are generally mixed at different rates in the production of forage crops. Each of the seeds can be sowed pure or mixed. Of these seeds, vetch and fodder pea are in the legumes group, while the others are in the grasses group. It has been reported in many studies that there is an increase in yield and quality when mixed planting compared to plain planting of legumes and grasses.

In the research, Vicia sp. and Pisum sp. seeds were selected as legume varieties and *Sorghum sudanense (Piper) Stapf*, *Triticosecale sp*., and *Avena sp*. seeds were selected as grass forage plant varieties obtained from Kırşehir, Turkey is the experimental application in this research. The *Vicia pannonica* (called in the research *Vicia sp.*) is a plant with a high adaptation to cold and dry climate conditions. The herb, which is very high in efficiency and quality, is very nutritious for animals [34]. Sown mied *Vicia pannonica* is wrapped in cereals, making harvesting of the growing plant easier and at the same time, productivity losses are significantly reduced. *Pisum Sativum L*. (called in the research *Pisum sp*.) is a good forefront plant, as it connects free nitrogen in the air to the ground. Therefore, the proliferation of plantation areas will be useful in both animal feeding and the development of planting watch systems [35]. *Sorghum sudanense (Piper) Stapf* (*called in the research Sorghum*) is a hot-climate annual forage crop that has a good ability to adapt to difficult terrain conditions. Green and dry herbage are used in the production of silage feed to provide essential nutrients for milk production, it is a highly prolific forage plant. Triticale (called in the research *Triticosecale sp.)* has a good tolerance of biotic and abiotic stress conditions, it is a more suitable plant for marginal areas [36]. Triticale has a high yield compared to other cereals, as well as wide adaptation capability and high nutritional value [37]. It is more recent than *Avena sativa L.* (*called in the research Avena sp*.), which is an agricultural plant that is used in various industries.

Method

Data preparation for training

As depicted in Figure 1, the forage crop photographs were taken on Feb 20, 2022, using a studio, DSLR camera, computer, fill light, and camera stand (5). This is a Nikon D800 with a 135 mm zoom lens and a 45 cm focal length. The 'JPG' file format is used to save a total of 2000 high-resolution images. 1000 images were used for all applications of each of the YOLOv4, and YOLOv4-tiny models, and for the aim of image enhancement forage crop seeds were positioned at random degrees. Also, five seeds were used from each forage crop seed species, so a total 100 evaluations were done. Some of the forage crop seeds have a circular shape. But in any way, forage crops were positioned at random degrees.

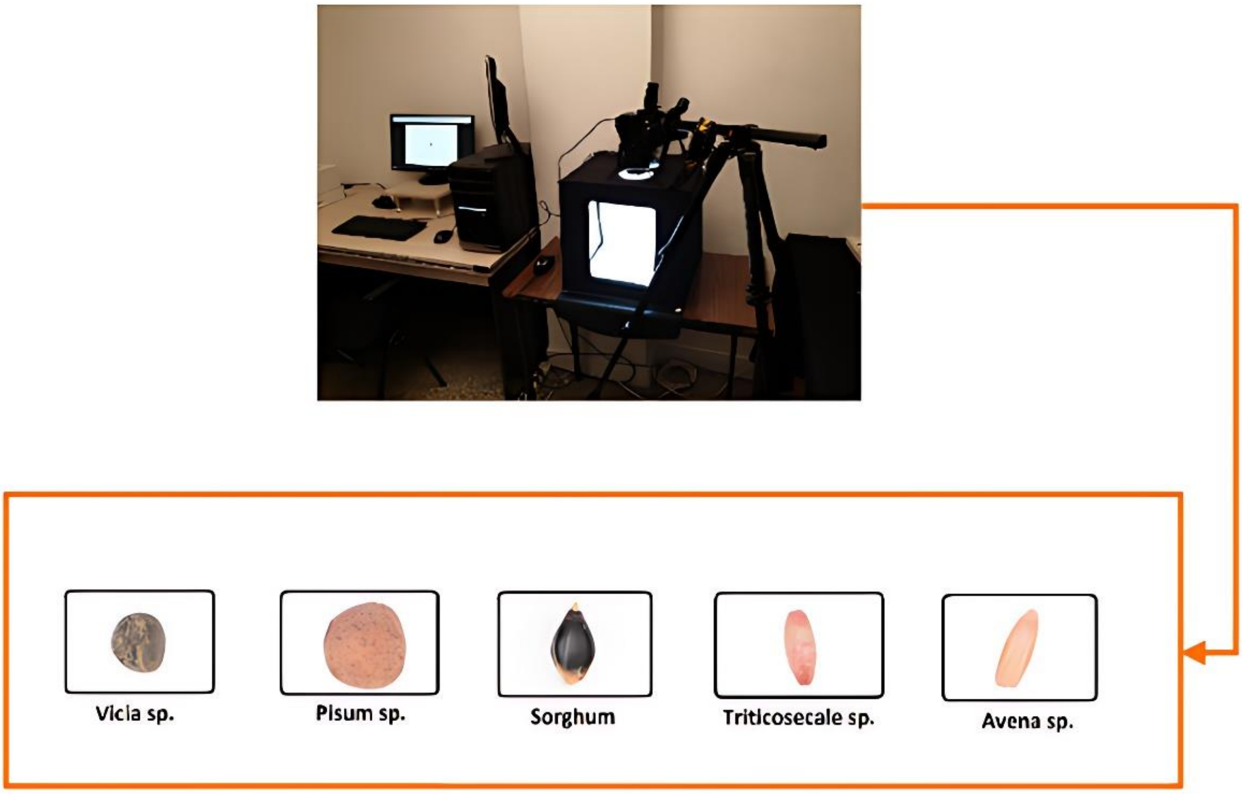

Figure 1. Forage crop seed imaging system.

Forage crop images are processed as follows LabelImg has been used to tag the images, and the forage crop seeds are divided into five test sets. In this way, LabelImg was used to label and annotate the forage crop seed shoots and seeds in a YOLO format standard txt file to establish their orientation to ensure that the label box is tightly next to the target boundary of each label for the YOLOv4 train and validation needs [38]. Each variety was identified by its taxonomical name for labeling. Labeled data was stored as 'txt' files. The text file contains all crop coordinates and tag information. System training is involved in the following steps. Before tagging and processing, a set of photos is sorted into three sets: training, validation, and detection sets. Convoluting images from the training set through the feature extraction network is used to create a texture feature map, which is then normalized in batches. During the model step, the network training parameters are adjusted based on the difference in recognition result and tag. When the loss rate falls within the set range or reaches the maximum number of iterations, the training is complete.

Dataset training

Google Colab Pro was used during the training process. Google Colab Pro has powerful GPUs and TPUs machine learning applications and creating models for this aim. In this research, Nvidia Tesla P100-PCI-E-16GB was used to test Colab Pro YOLOv4 and tiny deep neural network models with the help of CUDA-version: 11, cuDNN: 7.6.5, OpenCV version: 3.2.0. There are two separate sets of forage crops in the image set, one for training and one for validation, according to the 90% and %10 ratios respectively. The research examines a model's performance in terms of five different metrics, including the F1-score, an average precision value, recall, and detection speed (mAP) [39].

Implementation of GPU-based systems

In the research, to show the efficiency of the YOLOv4 and tiny models in real-time applications on different hardware platforms was used. These are a high-performance computer and NVIDIA Corporation Jeston TX2 Artificial Intelligence Board. The reason for the selection of these platforms is to make a comparison between mobility and process power. Also, mobility is important for making good quality seed process machines for agricultural mechanization. Additionally, the Nvidia Jetson TX2 device is cheap and more powerful when comparing the other artificial intelligence boards. The high-performance computer configuration is i7 4.5 GHz Cpu, 32 GB ram, Nvidia Geforce GTX 1660 Ti graphics card with 6 Gb ram, 1 TB

SSD disk with the support of CUDA-version: 10.2, cuDNN: 7.6.5, OpenCV version: 4.5.1 with the support of Python 3.7, also Colab Pro support and Nvidia Jetson TX2 device was used to detection of a single forage crop seed. All platforms used Logitech Brio 4K webcam for forage crop seed detection by YOLO models in both devices at 640x480 px resolution.

Overarching steps of the applied approach

At first, a hardware design is created to capture and process images of forage crops in real-time. Forage crop samples were then identified by training with the YOLOv4 and tiny models, which are based on the photographs taken. After that, the effectiveness of the forage crop detection system was then validated through experiments (Figure 2).

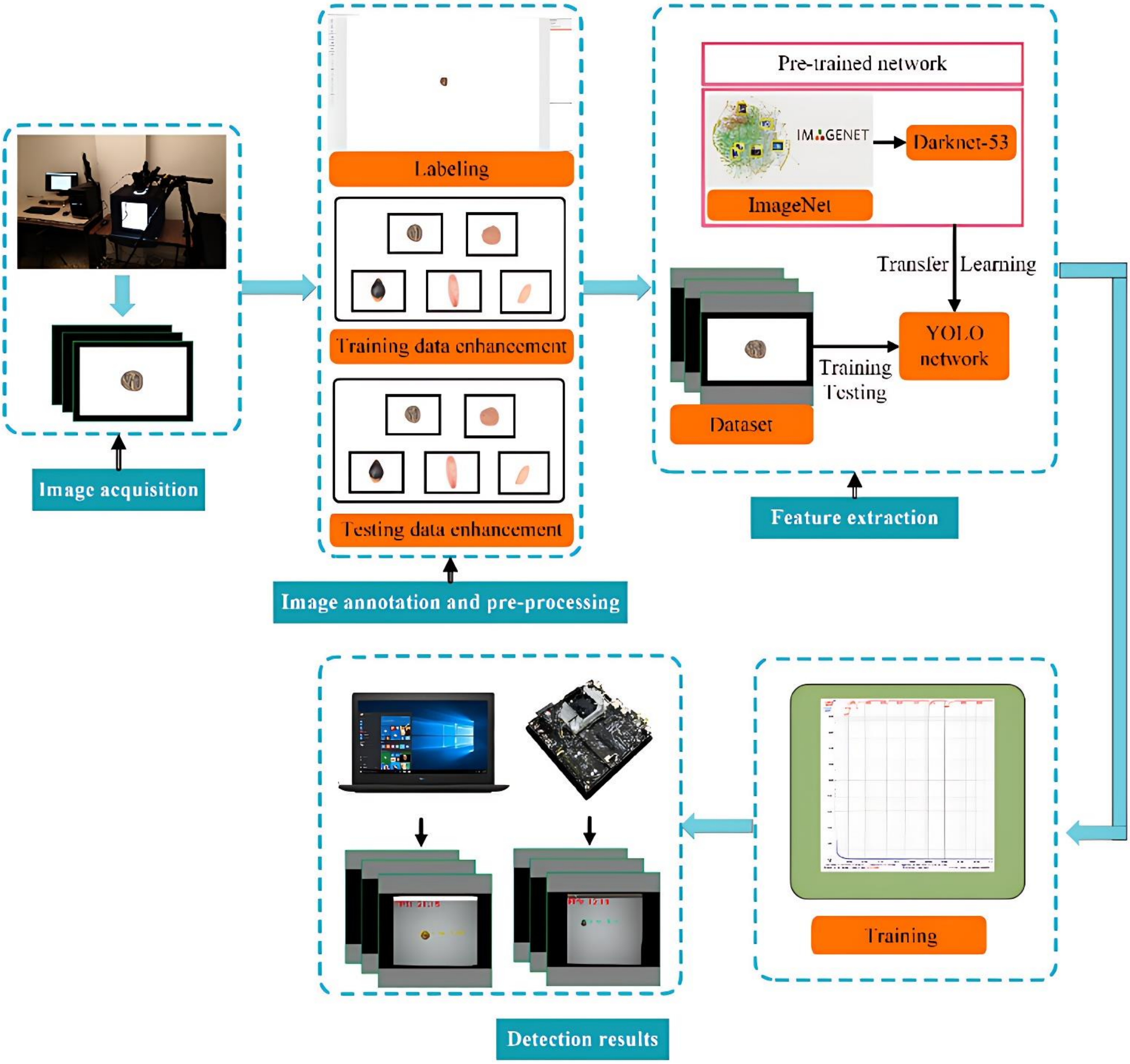

Figure 2. Overarching steps of the applied approach.

RESULTS

YOLOv4-tiny model train graph can be seen in Figure. 3. Train graph created after 7h work time of Nvidia Tesla P100-PCI-E-16GB graphic card and its Cuda GPU support. Also, the YOLOv4 model was trained in 21h work time of Nvidia Tesla P100-PCI-E-16GB graphic card and its Cuda GPU support.

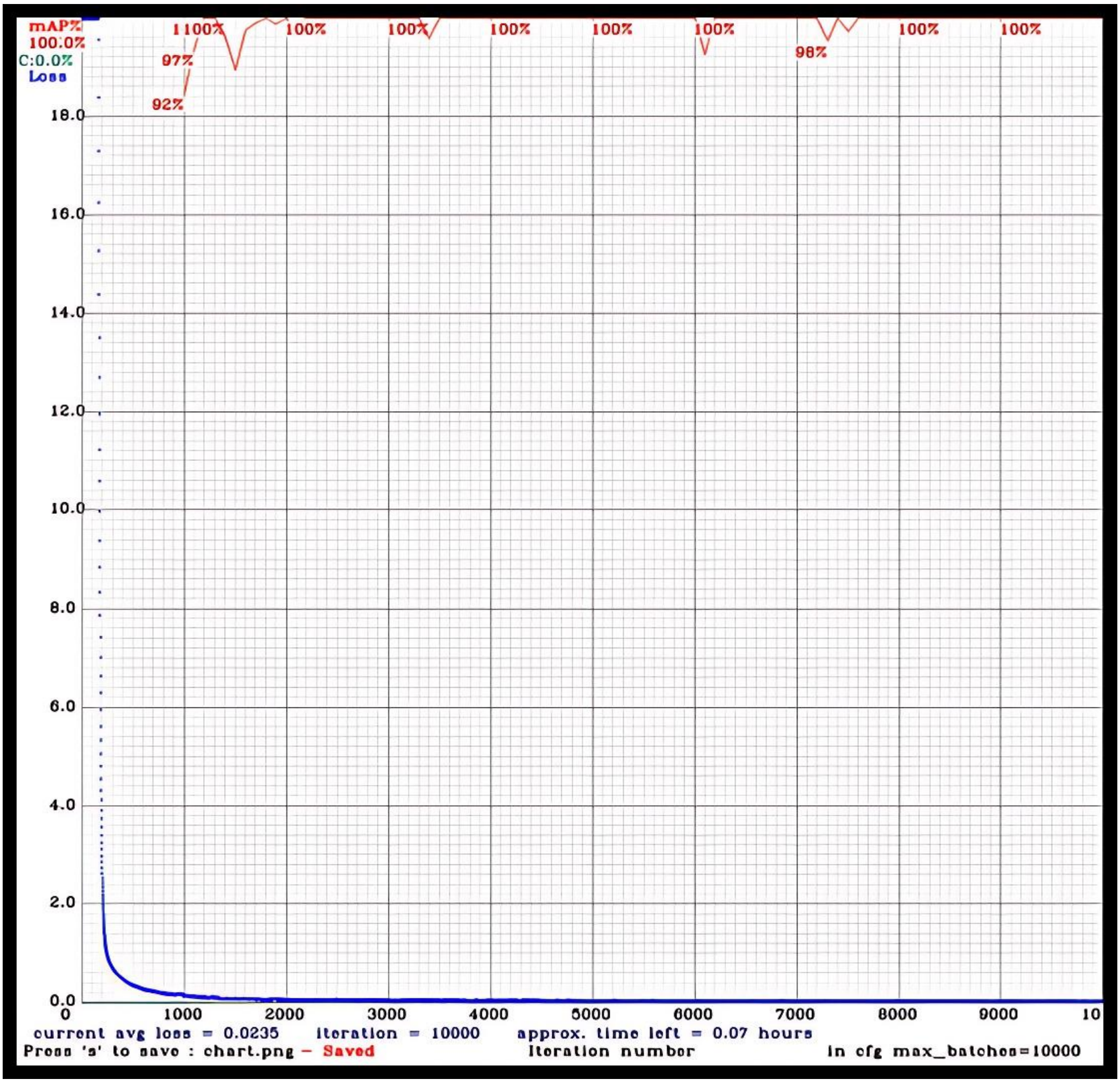

Figure 3. YOLOv4-tiny model train graph.

As for performance metrics, true positives, false positives, and false negatives, precision and recall are referred to as TP, FP, and FN, Precision and Recall, respectively in Table 1.

Table 1. Comparison of different YOLO models in parameters.

Model	Precision	Recall	F1-score	TP	FP	FN
YOLOv4-tiny	0.99	1.00	0.99	90	1	0
Y0L0v4	1.00	1.00	1.00	90	0	0

Also, results of different YOLOv4-tiny and YOLOv4 model results for each forage crop species can be seen in Tables 2 and 3. According to Tables 2 and 3 whole ap (%) values are 100 % for forage crop seed model results.

Table 2. Comparison of different YOLOv4-tiny model results for each of forage crop species

Class Id	Name	ap (%)	TP	FP
0	*Avena sp.*	100	24	0
1	*Pisum sp.*	100	14	0
2	*Sorghum*	100	18	0
3	*Triticosecale sp.*	100	14	0
4	*Vicia sp.*	100	20	0

Table 3. Comparison of different YOLOv4 model results for each of forage crop species

Class Id	Name	ap (%)	TP	FP
0	*Avena sp.*	100	18	0
1	*Pisum sp.*	100	18	0
2	*Sorghum*	100	18	0
3	*Triticosecale sp.*	100	18	0
4	*Vicia sp.*	100	18	0

Additionally, a comparison of different YOLO models in FPS and mAP was presented in table 4. According to table 4, the YOLOv4-tiny model size is 23 Mb, and it supports 12.3 FPS in Nvidia Jetson TX2 GPU, also YOLOv4-tiny model size is 250 Mb, and it supports 21 FPS in High-Performance Computer GPU. The YOLOv4-tiny method is lighter and faster to run than the original YOLOV4, but its diagnostic accuracy is less accurate as well. With the YOLOv4-tiny method, objects can be detected quicker than using the YOLOv4 method. It significantly increases the number of embedded systems and mobile devices that can make use of an object detection approach [40].

Table 4. Comparison of different YOLO models and platforms in FPS and mAP.

Method	Model Size (KB)	FPS	mAP(%)
YOLOv4-tiny (Nvidia Jetson TX2 GPU)	23.007	**12.3**	0.5
Y0L0v4 (Nvidia Jetson TX2 GPU)	250.100	2.3	0.5
YOLOv4-tiny (Computer GPU)	23.007	**21**	0.5
Y0L0v4 (Computer GPU)	250.100	10	0.5

For mobile artificial intelligence boards, it is a well-known reality that tiny models of artificial intelligence libraries like TensorFlow, Keras, Coffee, and YOLO have the best performance in real-world applications like in this research. NVIDIA Jetson TX2 device and a high-performance computer were used to measure the detection speed for a single forage crop as a real-world application only with the YOLOv4 and tiny models then results were presented in table 5 - 8.

Additionally, accuracy and FPS samples of forage crop seeds detection with YOLOv4-tiny and YOLOv4 models inTX2 and High-Performance Computer GPU can be seen in Figure 4 – 7. The ranges between 0.00-1.00 in Figure 4 – 7 are equal to the ranges between 0-100% accuracy.

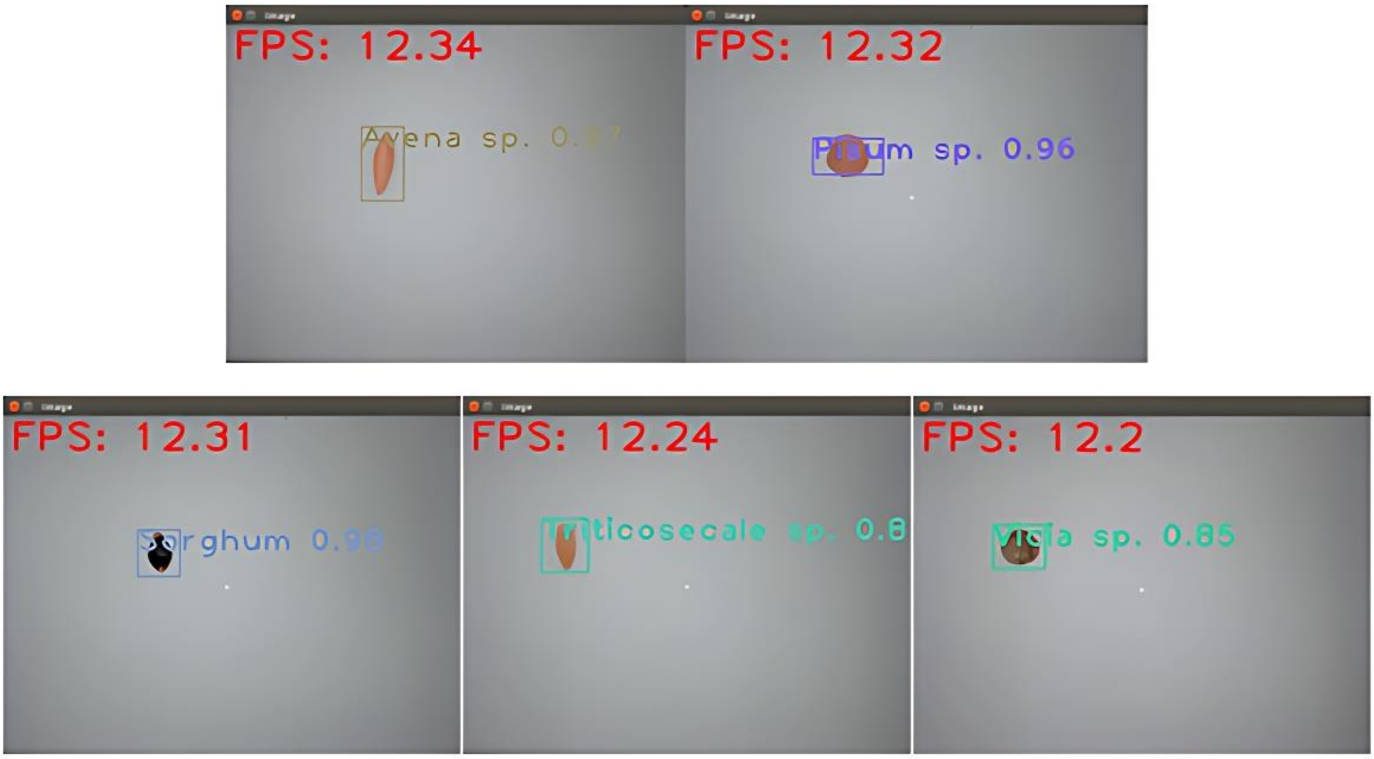

Figure 4. Accuracy and FPS samples of forage crop seeds detection with YOLOv4-tiny model at TX2.

Figure 5. Accuracy and FPS samples of forage crop seeds detection with YOLOv4-tiny model at High-Performance Computer GPU.

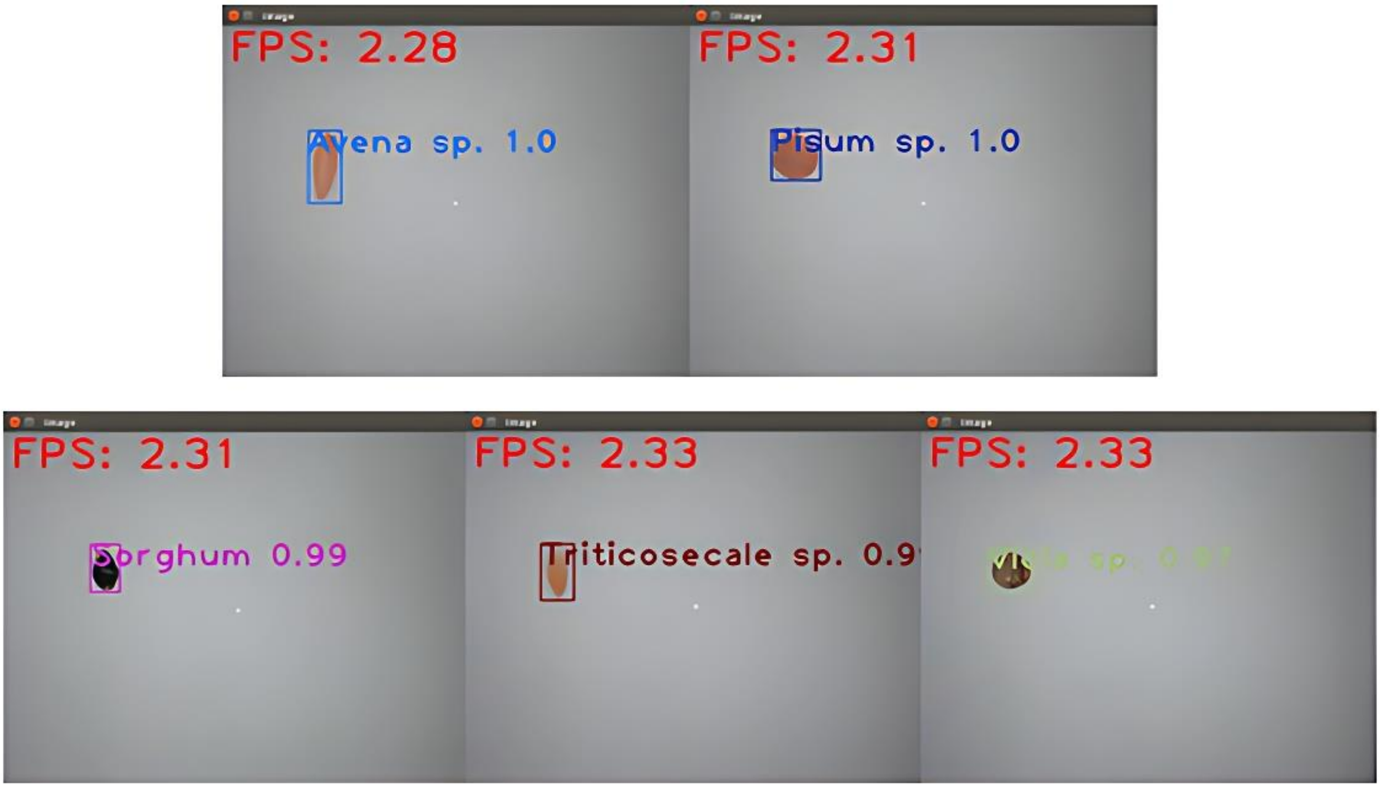

Figure 6. Accuracy and FPS samples of forage crop seeds detection with YOLOv4 model at TX2.

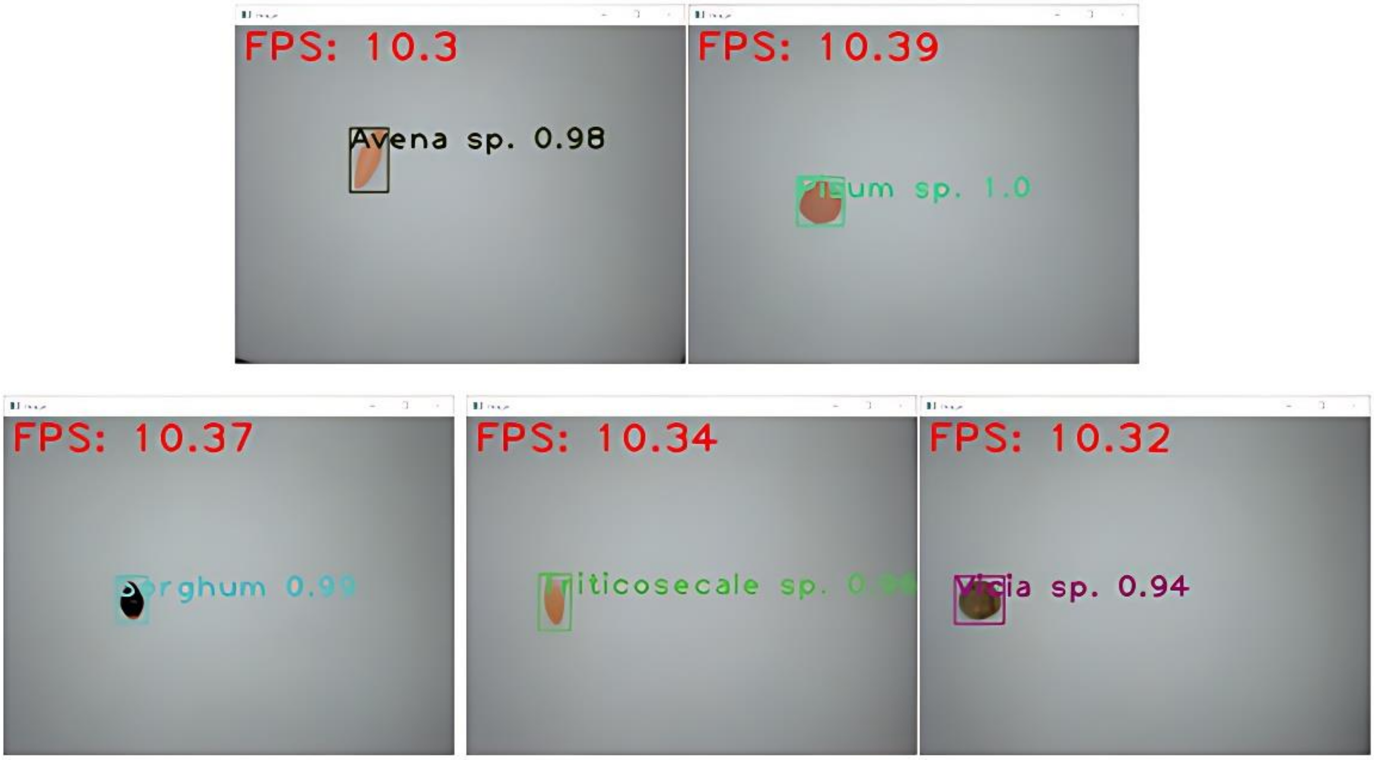

Figure 7. Accuracy and FPS samples of forage crop seeds detection with YOLOv4 model at High-Performance Computer GPU.

According to table 5, YOLOv4-tiny model application for forage crop detection accuracy ranges between 85-96 % for *Vicia sp.*, 98-100 % for *Pisum sp.*, 93-98 % for *Sorghum*, 82-90 % for *Triticosecale sp.*, and 92-99 % for *Avena sp.* in NVIDIA Jetson TX2 AI Board.

Table 5. YOLOv4-tiny model application for forage crop detection in NVIDIA Jetson TX2 AI Board

Material	Accuracy (%)	Model	FPS	mAP(%)
Vicia sp.	93	YOLOv4-tiny	12.18	0.5
Vicia sp.	85	YOLOv4-tiny	12.20	0.5
Vicia sp.	96	YOLOv4-tiny	12.19	0.5
Vicia sp.	95	YOLOv4-tiny	12.18	0.5
Vicia sp.	93	YOLOv4-tiny	12.18	0.5
Pisum sp.	99	YOLOv4-tiny	12.33	0.5
Pisum sp.	96	YOLOv4-tiny	12.32	0.5
Pisum sp.	100	YOLOv4-tiny	12.32	0.5
Pisum sp.	100	YOLOv4-tiny	12.32	0.5
Pisum sp.	98	YOLOv4-tiny	12.32	0.5
Sorghum	94	YOLOv4-tiny	12.32	0.5
Sorghum	98	YOLOv4-tiny	12.31	0.5
Sorghum	98	YOLOv4-tiny	12.31	0.5
Sorghum	93	YOLOv4-tiny	12.31	0.5
Sorghum	98	YOLOv4-tiny	12.31	0.5
Triticosecale sp.	90	YOLOv4-tiny	12.29	0.5
Triticosecale sp.	82	YOLOv4-tiny	12.24	0.5
Triticosecale sp.	91	YOLOv4-tiny	12.23	0.5
Triticosecale sp.	82	YOLOv4-tiny	12.22	0.5
Triticosecale sp.	83	YOLOv4-tiny	12.14	0.5
Avena sp.	99	YOLOv4-tiny	12.34	0.5
Avena sp.	97	YOLOv4-tiny	12.34	0.5
Avena sp.	99	YOLOv4-tiny	12.34	0.5
Avena sp.	92	YOLOv4-tiny	12.33	0.5
Avena sp.	94	YOLOv4-tiny	12.33	0.5

According to table 6, the YOLOv4-tiny model application for forage crop detection accuracy in High-Performance Computer GPU ranges between 81-90 % for *Vicia sp.*, 92-100 % for *Pisum sp.*, 91-99 % for *Sorghum*, 84-99 % for *Triticosecale sp.*, and 82-98 % for *Avena sp*.

Table 6. YOLOv4-tiny model application for forage crop detection in High-Performance Computer GPU

Material	Accuracy (%)	Model	FPS	mAP(%)
Vicia sp.	81	YOLOv4-tiny	21.14	0.5
Vicia sp.	88	YOLOv4-tiny	21.15	0.5
Vicia sp.	97	YOLOv4-tiny	21.16	0.5
Vicia sp.	95	YOLOv4-tiny	21.21	0.5
Vicia sp.	90	YOLOv4-tiny	21.18	0.5
Pisum sp.	100	YOLOv4-tiny	20.86	0.5
Pisum sp.	92	YOLOv4-tiny	20.91	0.5
Pisum sp.	100	YOLOv4-tiny	20.97	0.5
Pisum sp.	97	YOLOv4-tiny	21.00	0.5
Pisum sp.	99	YOLOv4-tiny	21.05	0.5

Cont. Table 6

Sorghum	96	YOLOv4-tiny	21.1	0.5
Sorghum	98	YOLOv4-tiny	21.15	0.5
Sorghum	91	YOLOv4-tiny	21.20	0.5
Sorghum	99	YOLOv4-tiny	21.25	0.5
Sorghum	98	YOLOv4-tiny	21.30	0.5
Triticosecale sp.	99	YOLOv4-tiny	21.26	0.5
Triticosecale sp.	93	YOLOv4-tiny	21.31	0.5
Triticosecale sp.	84	YOLOv4-tiny	21.33	0.5
Triticosecale sp.	98	YOLOv4-tiny	21.37	0.5
Triticosecale sp.	97	YOLOv4-tiny	21.4	0.5
Avena sp.	87	YOLOv4-tiny	20.54	0.5
Avena sp.	98	YOLOv4-tiny	20.62	0.5
Avena sp.	92	YOLOv4-tiny	20.70	0.5
Avena sp.	83	YOLOv4-tiny	20.76	0.5
Avena sp.	82	YOLOv4-tiny	20.81	0.5

Table 7 shows that in the NVIDIA Jetson TX2 AI Board, the YOLOv4 model application for forage crop detection accuracy ranges from 93-99 % for *Vicia sp.*, 100 % for *Pisum sp.*, 99-100 % for *Sorghum*, 83-99 % for *Triticosecale sp.*, and 100 % for *Avena sp*.

Table 7. YOLOv4 model application for forage crop detection in NVIDIA Jetson TX2 AI Board

Material	Accuracy (%)	Model	FPS	mAP(%)
Vicia sp.	99	YOLOv4	2.32	0.5
Vicia sp.	97	YOLOv4	2.33	0.5
Vicia sp.	96	YOLOv4	2.33	0.5
Vicia sp.	98	YOLOv4	2.33	0.5
Vicia sp.	93	YOLOv4	2.33	0.5
Pisum sp.	100	YOLOv4	2.31	0.5
Pisum sp.	100	YOLOv4	2.31	0.5
Pisum sp.	100	YOLOv4	2.31	0.5
Pisum sp.	100	YOLOv4	2.30	0.5
Pisum sp.	100	YOLOv4	2.31	0.5
Sorghum	99	YOLOv4	2.31	0.5
Sorghum	99	YOLOv4	2.31	0.5
Sorghum	100	YOLOv4	2.31	0.5
Sorghum	100	YOLOv4	2.31	0.5
Sorghum	99	YOLOv4	2.31	0.5
Triticosecale sp.	98	YOLOv4	2.33	0.5
Triticosecale sp.	99	YOLOv4	2.33	0.5
Triticosecale sp.	83	YOLOv4	2.33	0.5
Triticosecale sp.	97	YOLOv4	2.33	0.5
Triticosecale sp.	94	YOLOv4	2.33	0.5
Avena sp.	100	YOLOv4	2.21	0.5
Avena sp.	100	YOLOv4	2.28	0.5
Avena sp.	100	YOLOv4	2.29	0.5
Avena sp.	100	YOLOv4	2.29	0.5
Avena sp.	100	YOLOv4	2.30	0.5

In High-Performance Computer GPU, the YOLOv4 model application for forage crop detection accuracy ranges from 94-99 % for Vicia sp., 100 % for *Pisum sp.*, 99-100 % for *Sorghum*, 95-98 % for *Triticosecale sp.*, and 97-100 % for *Avena sp.*, according to Table 8.

Table 8. YOLOv4 model application for forage crop detection in High-Performance Computer GPU

Material	Accuracy (%)	Model	FPS	mAP(%)
Vicia sp.	96	YOLOv4	10.32	0.5
Vicia sp.	94	YOLOv4	10.32	0.5
Vicia sp.	98	YOLOv4	10.32	0.5
Vicia sp.	96	YOLOv4	10.31	0.5
Vicia sp.	99	YOLOv4	10.31	0.5
Pisum sp.	100	YOLOv4	10.39	0.5
Pisum sp.	100	YOLOv4	10.39	0.5
Pisum sp.	100	YOLOv4	10.38	0.5
Pisum sp.	100	YOLOv4	10.38	0.5
Pisum sp.	100	YOLOv4	10.38	0.5
Sorghum	98	YOLOv4	10.38	0.5
Sorghum	99	YOLOv4	10.37	0.5
Sorghum	100	YOLOv4	10.37	0.5
Sorghum	100	YOLOv4	10.36	0.5
Sorghum	99	YOLOv4	10.35	0.5
Triticosecale sp.	97	YOLOv4	10.35	0.5
Triticosecale sp.	96	YOLOv4	10.34	0.5
Triticosecale sp.	98	YOLOv4	10.34	0.5
Triticosecale sp.	98	YOLOv4	10.33	0.5
Triticosecale sp.	95	YOLOv4	10.32	0.5
Avena sp.	100	YOLOv4	10.10	0.5
Avena sp.	98	YOLOv4	10.30	0.5
Avena sp.	97	YOLOv4	10.37	0.5
Avena sp.	99	YOLOv4	10.38	0.5
Avena sp.	100	YOLOv4	10.39	0.5

DISCUSSION

In many studies, deep learning algorithms have been used in seed analysis applications in agriculture. According to Uzal and coauthors [41] used deep learning algorithms, and convolutional neural networks (CNN) to predict seeds per pod for plant breeding. On the other hand, Altuntas and coauthors [42] stated that they were able to identify haploid and diploid maize seeds using convolutional neural networks and a transfer learning approach. Zhao and coauthors [43] reported that they developed a deep learning-based real-time recognition system for exact surface defects in soybean seeds. According to Koklu and coauthors [44] created models using artificial neural network (ANN) and deep neural network (DNN) algorithms and convolutional neural network (CNN) algorithm to classify rice varieties. The classification successes obtained from the models were reported as 99.87% for ANN, 99.95% for DNN, and 100% for CNN. Additionally, Khanal and coauthors [45] stated that they used deep learning for counting and external quality classification of maize seeds.

An improved version of the YOLOv4-tiny system developed by Jiang and coauthors [40] was able to detect objects in real-time, with confidence scores of trains that ranged from 90-92 % in their sample figures with YOLOv4-tiny to 90-94 % in their proposed method.

Li and coauthors [46] focused on developing and testing a YOLOv4-tiny algorithm-based broken corn kernel detection device. The YOLOv4-tiny model was found to be 93.5 % accurate for intact kernels and %90.0 accurate for broken kernels, with precision, recall, and F1 score values of 92.8 %, 93.5 %, and 93.11 %, respectively.

For real-time electronic component detection, Guo and coauthors [47] developed a new YOLOv4-tiny network. From 93.74 % to 98.6 %, the original algorithm's accuracy has been improved. The method is the fastest and most accurate when compared to current mainstream algorithms, such as Faster RCNN, SSD, RefineDet, EfficientDet, and YOLOv4. It's also implied that the method can be used to develop manufacturing robots for the electronics industry as a technical reference.

CONCLUSION

This research employs a YOLOv4-tiny network structure to determine forage crop seeds and shows the detection accuracy without increasing enormous calculations. As compared to YOLOv4 and YOLOv4-tiny has a faster detection rate and a nearly similar average precision.

Efficiency and quality in mixed crops may vary depending on the types of plants used, the blend ratios, and the harvest times [48]. Because in the seed mix, the competitiveness of the legumes is lower than the grain. Therefore, the quality of the grass in the blends is reduced as the proportion of the legumes decreases [49]. This means that in mixed crops, the percentage of seeds to be applied is very important. There are no machines capable of planting this type of mixed crop. It's a blow-by-blow for the design of machines that can plant this kind of mixed crop, later control and optimization of the systems can be done by real-time YOLOv4-tiny models.

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