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Araştırma Makalesi/Reserach Article

Counting and Classification of Seed Using Machine Learning Methods

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Abstract

Deep learning, machine learning and image processing techniques have become important tools used in facilitating agricultural work and developing solutions to different problems in the production phase. In this study, a seed number and type detection algorithm was developed using YOLO deep learning architecture, a real-time object detection algorithm employing the CNN structure in AugeLab Studio sofware. With the developed model average loss factor of 0.417 was achieved after 3000 iterations. As a result of the analysis, it has been determined that the bean classification accuracy varies between 97% and 100%, while the chickpea classification accuracy varies between 91% and 100%. In addition, the total number of 11 beans and 10 chickpea seeds in a single image was determined with 100% accuracy. The results demonstrated that AugeLab, a software employing artificial inteligence based image processing techniques, can be used by seed production companies, agricultural biotechnology laboratories and seed certification institutions in counting and classification of seeds. It can also be used in variety and/or species separation, separating and detecting germinated seeds, or detecting and proportioning foreign mixtures in seed certification processes within shorter time and less costs.
Keywords: Artificial intelligence, Deep learning, Machine learning, Seed counting, Classification, AugeLab

Makine Öğrenmesi Yöntemleri Kullanarak Tohum Sayısının Tespiti ve Sınıflandırılması

Öz

Derin öğrenme, makine öğrenmesi ve görüntü işleme teknikleri tarımsal işlerin kolaylaştırılmasında ve üretim aşamsındaki farklı problemlere çözümler geliştirilmesinde kullanılan önemli birer araç haline gelmişlerdir. Bu çalışma kapsamında AugeLab Studio'da derin öğrenme mimarilerinden CNN kullanılarak, eş zamanlı nesne tespiti için genelde tercih edilen YOLO algoritmasıyla bir tohum sayısı ve türünün tespit uygulaması geliştirilmiştir. Çalışma sonucunda 3000 iterasyonla ortalama kayıp 0.417 civarına düşürülmüştür. Analizler sonucunda fasulye sınıflandırma başarı oranı %97-%100 arasında değişiklik gösterirken nohut sınıflandırma oranının %91 ile %100 arasında değişmekte olduğu tespit edilmiştir. Buna ek olarak tek görseldeki toplam 11 adet fasulye ve 10 adet nohut tohumunun sayısı %100 doğrulukla tespit edilmiştir. Sonuç olarak yapay zeka görüntü işleme tekniklerinin kullanılarak tohumluk üretim firmaları, tarımsal biyoteknoloji laboratuvarları ve tohum sertifikasyon kuruluşlarının tohum sayma, çeşit ve/veya tür ayrımı yapma, çimlenen tohumların ayrıştırılması ve tespiti veya tohum sertifikasyon süreçlerindeki yabancı karışımların tespit edilip oranlanması gibi tarımın bir çok alanında iş yükünün ve maliyetin azaltılırken zamandan kazanç sağlanabileceğini göstermiştir.
Anahtar Kelimeler: Yapay zeka, Derin öğrenme, Makine öğrenmesi, Tohum sayımı, Sınıflandırma, AugeLab

Introduction

Artificial intelligence (AI) is a combination of hardware and software components allowing features of human intelligence to be converted into computer models. Artificial intelligence applications are systems that analyze complex data using different methods and are able to update itself based on the experience gained as a result of previous runs (Hosny *et al*., 2018). Image processing method is used to convert an image into digital form and then process the image to reveal the desired information (Balaji *et al*., 2017). In this method, the image is passed through various stages. Hence, image preprocessing sofware affects both performance and quality (Deng *et al*., 2016). The errors, called noise, is reduced by using different image processing techniques (Mohan & Poobal, 2018; Michalak & Okarma, 2019). Number of computer vision and artificial intelligence based image processing applications have increased significantly in recent years offering new generation solutions

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to problems. Artificial intelligence techniques have been widely used in agriculture, medicine, engineering, biomedical and military fields, in the development of security systems, robotics, geographic information systems and many other areas. Machine learning, a method of (AI), builds statistics-based logical prediction algorithms to make decisions, even though they are not specifically designed to perform a given task. To establish this logic, it is necessary to create a mathematical model based on a dataset created by the user known as "Training Data" (Koza *et al*., 1996). Object detection is one of the most well-known and used applications of machine learning. In order for the object to be learned by the machine, many different pictures of it must be introduced in trainin phase. In this way, similar shapes, patterns, colors and pixels are learned for definition of images. As a result of machine learning, different images can be distinguished, common or different points of similar images can be identified (Pathak *et al*., 2018).

In deep learning, another artificial inteligence method, feature extraction and transformation is performed using many nonlinear processing layers. It learns by taking both the successive layer and the outputs from the previous layer as input (Deng & Yu, 2014). Deep learning algorithms including supervised or unsupervised classification are based on more than one feature level or representation of data. Low-level features are derived using high-level features to create a hierarchical representation (Bengio, 2009). In general, this network detects the objects by scanning the entire picture in a sliding window structure or by running it on selected spots on the picture, depending on the chosen method.

To meet the global food and nutrition needs of increasing population, it is necessary to use the resources effectively and to obtain the highest yield. Today, it is possible to encounter image processing techniques or artificial intelligence-based methods at every stage of agricultural activities (Latha *et al*., 2014; Ağın & Melaslı, 2016). For instance; artificial intelligence is frequently used in sustainable agriculture for the evaluation of waste, efficient use of resources, efficiency in product processing and increasing the diversity of agricultural activities (Hof & Wolf, 2014). In particular, it helps to increase efficiency in agricultural activities such as pesticides and fertilizer applications, and land/water use. It is also widely used in aquaculture, proper soil preparation, detection and use of quality seed, and post-cultivation applications such as product processing and storage. For this reason, the use of machine learning in sustainable agriculture has become an important tool (Sofu *et al*., 2013; Hof & Wolf, 2014; Latha *et al*., 2014; Ağın & Melaslı, 2016). Up to now, fruit and vegetables classification in terms of size or quality using image processing techniques have been used (Balcı *et al*., 2016). Different methods such as effective and fast object detection studies using simple features of objects (Viola & Jones, 2011), pattern matching, shape, color, corner and edge recognition (Sonka *et al*., 2014) and complex background extraction (Hussin *et al*., 2012) are used. In determining the properties of the object; by using methods such as classification, clustering, and digital image analysis, related objects are classified in terms of different parameters such as type, quality, size or number. As a result of the widespread use of computer vision in agriculture, studies such as irrigation (Hof & Wolf, 2014), plant growth and product quality monitoring (Wu & Sun, 2013), spraying, harvesting, and product classification are carried out (Latha *et al*., 2014). In addition, machine learning techniques are used in, wheat (Demirbaş and Dursun, 2010), apple (Sofu *et al*., 2013), cherry (Balcı *et al*., 2016), peach (Sert *et al*., 2010; Kurtulmuş *et al*., 2013), walnuts (Ercisli *et al*., 2012), almonds (Antonucci *et al*., 2012), hazelnuts (Bayrakdar *et al*., 2015) classification and yield estimation. Artificial intelligence based image processing and object detection methods are based on algorithms such as You Only Look Once (YOLO) and Single Shot Detector (SSD). The YOLO algorithm (Redmon *et al*., 2016) aims to process the image faster by considering it completely convolutional. In a study conducted on the COCO database (Lin *et al.,* 2017), it was determined that the YOLO algorithm was 98% successful in large objects, but this rate decreased to 60% as the objects got smaller. When Convolutional Neural Network (CNN), SSD and YOLO are compared; it was noticed that CNN had the highest accuracy at lowest speed. Also, YOLO has demonstrated better performance in large objects comparing to smaller objects. In terms of speed, its performance is better than others (Redmon *et al*., 2016).

AugeLab Studio, an image processing application, employs Python as programming language, and in image processing methods such as Open GL, Open CV and YOLO. It also uses libraries such as Tensorflow, Scikit-Learn and Keras. AugeLab Studio provides a no-code programming environment in artificial intelligence and image processing.

This study was carried out using AugeLab Studio to evaluate its performance in counting and classification of seeds which is a time consuming task that should be performed with minimal errors.

Material and Method

Data Set Creation and Data Labeling

In this study, the EN-1887 variety of chickpea (*Cicer arietium*) belonging to the Legumes (*Fabaceae*) family and the bean variety (*Phaseolus vulgaris*) obtained from Konya-Akşehir were used. A data library was prepared by using a total of 104 images, with 10 chickpeas and 11 beans in each. Images were acquired from a height of approximately 30 cm over a blue background. The 5000×4000 resolution images were reduced to 500×400 using the FastStone Photo Resizer application. Studies in deep learning and object detection focus on two basic structures including CNN and YOLO. The flowchart of the model is given in Figure 1.

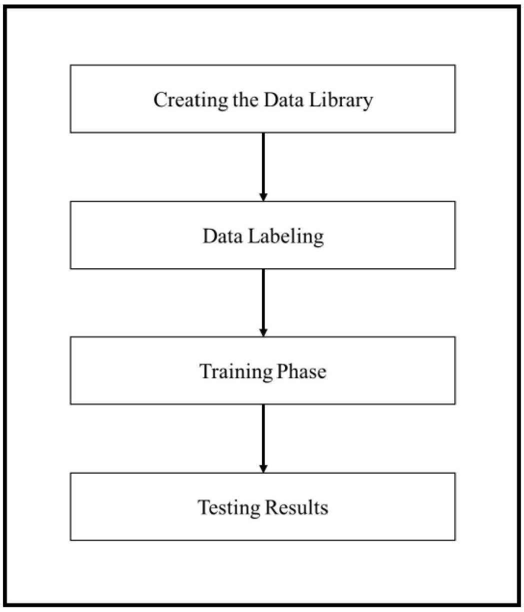

Figure 1. Application flowchart

In regional-based CNN similar regions are combined. The goal in this algorithm is to define required amount of spots employing a selective search method and to find the right object instead of searching through the whole picture. However, in YOLO algorithm it is aimed to provide a proper structure for real-time processing. Here, the image is completely processed convolutionally, rather than processing it spot-by-spot approach. The entire image is divided into grids based on its size, and a distinction is made according to their similarity. In this study, it is aimed to count seeds faster, enhance the accuracy and to accurately classify both objects. Therefore, the YOLO algorithm embedded in the AugeLab Studio function blocks is preferred for fast detection.

The labeled images are uploaded to the software from the computer. Then, as in Figure 2, two different classes (beans, chickpeas) are created and the seeds in each photo are labeled one by one. Upon completion of the labeling process, the “class file” file (class.names) is automatically created by AugeLab Studio.

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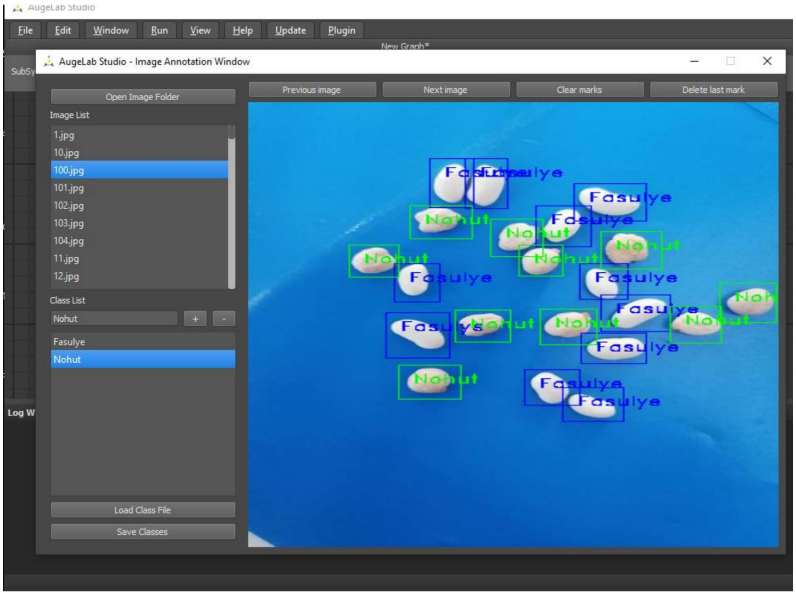

Figure 2. Preparation of the data set to be used in the study

Development and Training of the Object Detection Model

The main purpose in object detection is to identify the object's instance and approximate the object position. If an object's single class is detected it is called single class object detection while it is called multi class detection if the classes of all objects are detected (Figure 3). The major challenges that needed to be addressed in object detection are occlusion, varying light, positions, and scale (Pathak *et al*., 2018).

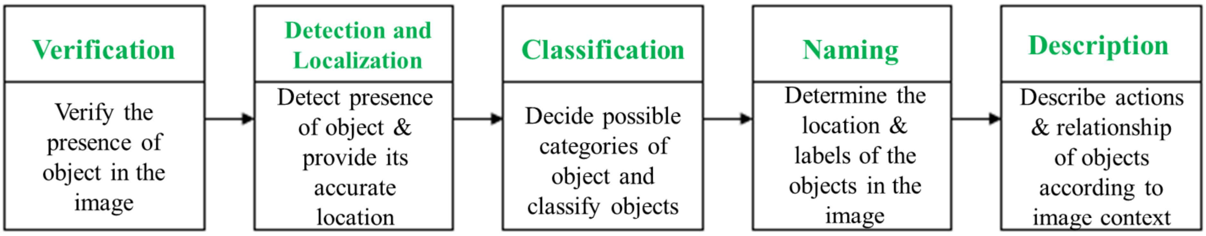

Figure 3. Object detection steps

The CNN employs a convolutional operator used in the extraction of the image properties. By learning the display properties of the input data the relationship among the pixels are maintained by the convolutional operator**.** After each convolutional operation, classification was made using the ReLU activation function.

Result and Discussions

YOLO provides the user sample weight matrices and configuration files in its own structure. Weight matrices are structures that the algorithm extracts as a result of learning process. Users share sample weight matrices in order to make simple determinations and shorten YOLO's learning process. Weight matrices emerge from the testing and validation process of configuration files. In order for YOLO to have a good learning process, the configuration files must be well-structured.

In this study, the seed sets labeling process is performed together for a faster convolutional and YOLO algorithms. Labeling and learning processes are performed 3000 iterations in total, and the average loss is reduced to 0.417 after 7 hours and 23 minutes. Since the progress after this process oscillates between 0.417 and 0.480, the learning phase was terminated. The YOLO learning curve is given in Figure 4.

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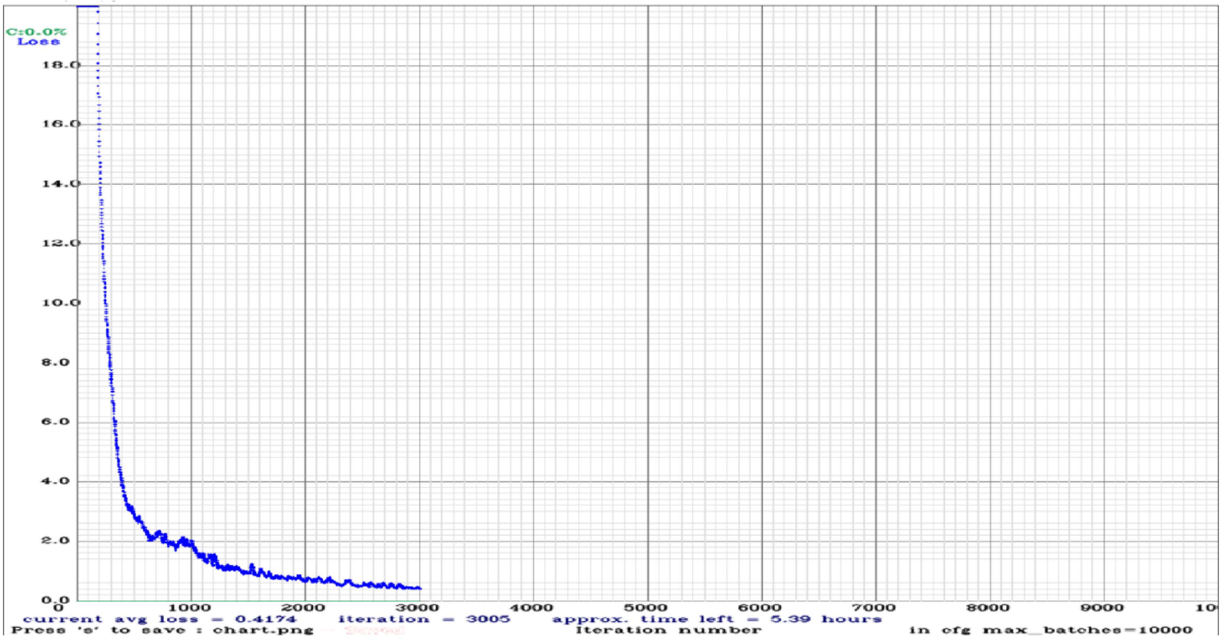

Figure 4. YOLO learning curve

In this study the AugeLab Studio, CNN and YOLO algorithms are run on a computer with an Intel i5 processor with Nvidia GeForce GTX 4GB 1060 GPU Graphics card and 16GB Ram, which has optimum system conditions.

The “Object Detection – Custom” function block from the AugeLab block is used to test the Object detection model (Figure 5).

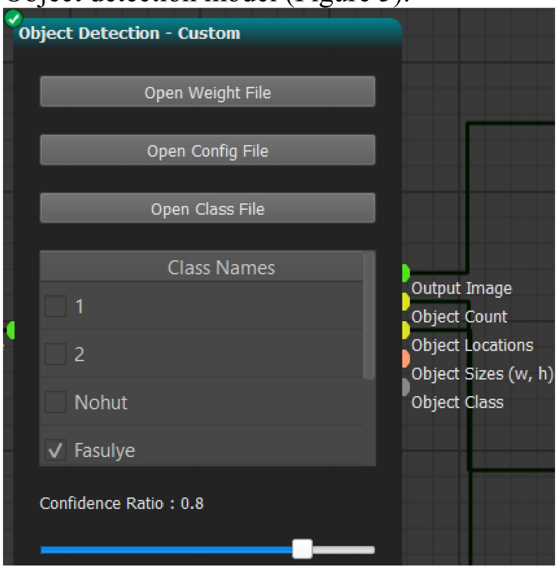

Figure 5. AugeLab Studio object detection custom function block

The model created is made ready for use by loading the “.weight, .cfg and .names” files, respectively. Then, the model is run with “Run One Step” by making connections of the "Load Image/Load Video" block necessary for uploading the pictures to be detected, the "Show Image" block necessary for the visualization of the results, and the "output" block to convert the results into numerical data, with the object detection custom block. Detailed information about the AugeLab Studio function blocks (Figure 6) and analysis results used in the study are given in Figure 7a and Figure 7b.

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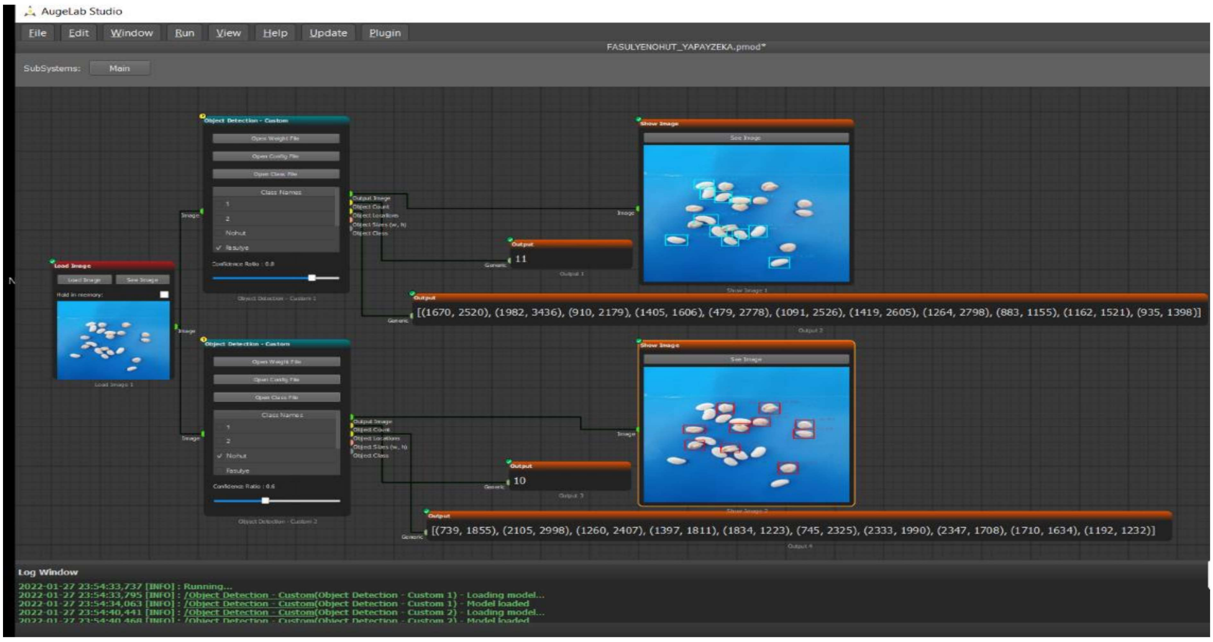

Figure 6. AugeLab Studio function blocks and analysis results used in artificial intelligence image processing

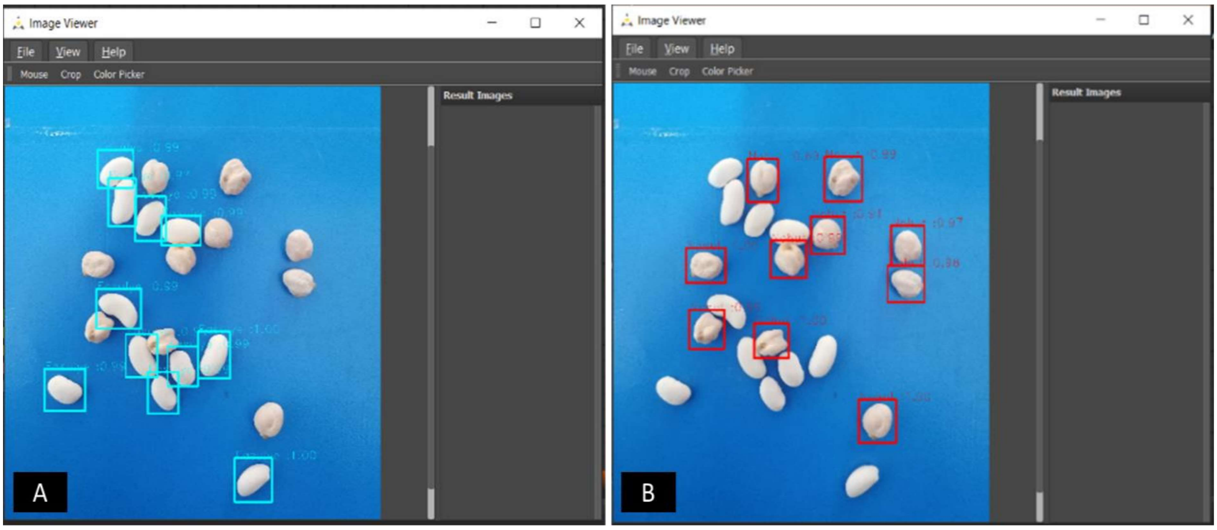

Figure 7. Detection and accuracy of seeds, A. Bean, B. Chickpea

As a result of the analyzes, it is determined that the bean classification accuracy varied between 97% and 100% (Figure 7a), while the chickpea classification accuracy varied between 91% and 100% (Figure 7b). In addition, the total number of 11 beans and 10 chickpea seeds (Figure 6) is distinguished with 100% accuracy. It is determined that image processing techniques can be used in seed counting/classification in addition to irrigation (Hof & Wolf, 2014), spraying, harvesting, product classification, and product development, studies that classify fruits such as apple, wheat, hazelnut and almond have been carried out by different researchers (Latha *et al*., 2014). In this sense, it has been observed that the seed classification and counting process with the block coding method provides a useful tool in agricultural applications.

Conclusions

In this study it is aimed to develop a fast, real time seed classification and counting application using AugeLab Studio elmploying machine learning algorithms. A data set containing bean and chickpea seed images is created using a standard protocol. The model created, trained and tested using the dataset. A model employing ReLu as activation function along with YOLO algorithm is able to count the numbers of bean and chickpea in a mixed population.

It is noted that major factors affecting the classification accuracy are number of images used in the database and variations in the image composition including different background and light conditions. Another issue that should be considered is the computer used in the classification. The ram, processor and graphics card affects the data processing speed.

As a result, performance of a software developed for industrial applications based on block-coding logic is tested in real-time seed counting and variety/species classification. It is observed that time can be saved while reducing the workload and cost in many different sectors of agriculture such as seed production companies, agricultural biotechnology laboratories and seed certification bodies. In the light of the experience obtained from this study, models related to the classification of larger amounts and relatively smaller seeds will be conducted. In addition, this software will be used to identify plant diseases in field scale using images acquired by drones.

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Authors' Contributions

Selçuk Çetin and Hakan Nar developed and performered machine learning analysis, Ünal Kızıl planned the study wrote the manuscript and evaluated the model performance.

Conflicts of Interest Statement

The authors declare that they have no conflicts of interest.

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