Liang Zhao, S.M. Rafizul Haque and Ruojing Wang (2022).
Seed Science and Technology, **50**, 1, **Suppl.**, 75-102.
https://doi.org/10.15258/sst.2022.50.1.s.05

Invited Review

Automated seed identification with computer vision: challenges and opportunities

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(Submitted January 2022; Accepted June 2022; Published online August 2022)

Abstract

Applying advanced technologies such as computer vision is highly desirable in seed testing. Among testing needs, computer vision is a feasible technology for conducting seed and seedling classification used in purity analysis and in germination tests. This review focuses on seed identification that currently encounters extreme challenges due to a shortage of expertise, time-consuming training and operation, and the need for large numbers of reference specimens. The reviewed computer vision techniques and application strategies also apply to other methods in seed testing. The review describes the development of machine learning-based computer vision in automating seed identification and their limitations in feature extraction and accuracy. As a subset of machine learning techniques, deep learning has been applied successfully in many agricultural domains, which presents potential opportunities for its application in seed identification and seed testing. To facilitate application in seed testing, the challenges of deep learning-based computer vision systems are summarised through analysing their application in other agricultural domains. It is recommended to accelerate the application in seed testing by optimising procedures or approaches in image acquisition technologies, dataset construction and model development. A concept flow chart for using computer vision systems is proposed to advance computer-assisted seed identification.

Keywords: artificial intelligence, computer vision, dataset construction, deep learning, image analysis, machine learning, seed identification, seed testing

Introduction

It is highly desirable in seed testing to apply advanced technologies, such as computer vision, to meet seed certification needs and to get fast and accurate testing results with less training demands. Artificial Intelligence (AI) and computer vision are promising technologies for seed testing. Among tests or analyses, seed identification is one of the most appropriate tests that could adopt AI and computer vision without changing standard methods or seed testing rules. The specific and focused discussion of AI or computer vision in seed identification can also promote other applications in seed testing, such as seedling evaluation.

Seed identification is to determine plant taxonomic identities, i.e., taxon, through the examinations of plant dispersal units, such as seeds or dry fruits with or without fruit accessories (hereafter dispersal units referred to as seeds). Currently, seed identification is conducted in seed testing laboratories worldwide, mainly based on seed morphological features and by trained seed analysts. The identification of seed taxon is achieved by comparing the seeds under analysis with a mental image or awareness of what something should be, specimens in a reference collection, illustrations of seeds in literature, online references and/or identification keys. Seed identification is an essential diagnosis used in seed percent purity analysis, noxious weed seed search, other seed determination and other examinations for seed certification (AOSA, 2021; ISTA, 2022). Seed identification is also used in weed or quarantine species analysis in phytosanitary certification of grain import and export (Njoroge, 2018), genotype or phenotype screening in crop breeding (Lin *et al*., 2019; Toda *et al*., 2020), and commodity labeling for agricultural commodities (Vansickle *et al*., 2003; Countryman and Bonanno, 2019). Through trade activities across regions and continents, seeds are the main agent for the long-distance dispersal of invasive plants and noxious weeds into new areas (Huelma *et al*., 1996; Wilson *et al*., 2016). Preventing unwanted plant species from spreading is usually achieved through plant protection-related regulations and quarantine requirements (FAO, 2017) such as phytosanitary certification for possible weed seed contaminants. Therefore, seed identification is a scientific application for regulatory enforcement, surveillance and monitoring. As components of pharmaceutical products, seeds also possess important medicinal properties and have been widely used. In recent years, along with the increasing popularity and accessibility of seeds as medicinal products, numerous substitutes and adulterants have shown up on the market (Xiong *et al*., 2018). The accurate identification of seed herbal medicines (Xiong *et al*., 2018) or food allergens such as wheat kernel or peanut contamination is also essential for their safe use.

Although the morphological examination of seeds by seed analysts, specialists or experts is effective, seed identification is an acquired skill, demanding practice time, reference resources, and taxonomy expertise to maintain. A certified seed analyst requires at least 1500 hours of training to identify seeds from about 300 species based on typical features (CFIA, 2015). The situation becomes worse when considering natural variation in seeds, significant expansion of trading areas and the expanded quarantine list of plant species over the years. There is also a shortage of trained seed analysts in the job market. Seed identification based on chemistry or molecular methods such as quantitative PCR (Johnson *et al*., 2013) and amplified fragment length polymorphism (Krauss and He, 2006) have also been developed to identify targeted plant species, cultivars or breeding lines. While proving to be effective, such methods are criticised as being destructive, labour-intensive and costly (reviewed by ElMasry *et al*., 2019). More importantly, these destructive methods use milled samples and thus cannot tell if the detected chemical fingerprint is from seeds or other non-reproducible plant materials such as debris, pollen or broken seeds unless the sample is pre-cleaned.

Computer vision, a field of computer science, enables computers to emulate human vision by acquiring a high-level understanding of digital images or videos and being able to make inferences and take actions. Computer vision applications comprise digital systems equipped with technologies for image acquisition, followed by image processing and analysis (Wagner *et al*., 2011; Sabanci *et al*., 2017). Different imaging systems (or camera systems) can be used to generate different types of images, such as visual light images, i.e., RGB (Red, Green and Blue) images (Yi, 2017), multi- or hyperspectral images (ElMasry *et al*., 2019; Liao *et al*., 2019) and x-ray images (Musaev *et al*., 2021). Object features can be extracted from the generated images and are combined with machine learning (ML) classifiers to classify or identify objects from the images (Sabanci *et al*., 2017). In recent years, computer vision studies have been conducted to meet the growing demand for fast and accurate seed classification and identification using ML algorithms (reviewed by Du and Sun, 2006; Zareiforoush *et al*., 2015).

Computer vision applications for seed identification may use different ML algorithms, which have been broadly categorised into two types. One is the traditional ML algorithms, which includes Naïve Bayes, k-nearest neighbour (KNN), support vector machine (SVM), decision tree, random forest, Adaboost, principal component analysis (PCA) and linear discriminant analysis (LDA). The other group includes deep learning (DL) algorithms such as convolutional neural networks (CNNs), which is one of the latest ML algorithms and recognised for its superb performance in a wide range of computer vision applications.

Traditional ML algorithms have to manually define a set of features to classify objects. This approach is less desirable within the increasing weed species on the phytosanitary list. This feature of traditional ML limits the fast and wide application of computer vision systems in seed identification. In contrast, DL does not involve hand-crafted feature engineering; it can learn and abstract the important features itself through the training process. This feature of DL could speed up the development of classifiers when dealing with a long list of objects and help the wide application of computer vision in seed identification tasks. The DL-based computer vision system has been studied and applied widely in various object classification tasks in agriculture domains such as crop disease diagnosis, pest recognition (Cheng *et al*., 2017; Ren *et al*., 2019), weed detection (Asad and Bais, 2019), fruit and flower counting (Sa *et al*., 2016; Bargoti and Underwood, 2017a; Dias *et al*., 2018; Bresilla *et al*., 2019; Farjon *et al*., 2019), and fruit sorting and grading (Hossain *et al*., 2018). However, compared to other areas of agriculture, the application of DL methods in seed identification has received much less attention and was limited to several specific areas such as cultivar identification (Zhu *et al*., 2019a) and phenotyping (Toda *et al*., 2020). Thus, it is essential to better understand the pros and cons of both ML and DL techniques to optimise computer vision systems in seed identification. Meanwhile, the experience in developing DL models in other agricultural domains can be used to facilitate DL application in seed identification.

In this review, we summarise the development of ML techniques in seed identification and DL techniques in other agricultural domains, with the aim to address the following questions:

(1) What are the features and the limitations of traditional ML in seed identification?

(2) What are the major characteristics and requirements of DL when applied to agricultural domains?

(3) What will be the major challenges, solutions and considerations when applying DL to seed identification?

(4) What will be the key strategies and steps in developing the DL-based computer vision system in seed identification?

Traditional ML algorithms in computer vision

The computer vision system, developed in recent years, has been used to meet the growing demand for fast and accurate seed identification. In a computer vision system, seed images can be generated by the integrated cameras at the first stage (Wagner *et al*., 2011; Sabanci *et al*., 2017). From the seed images, a large number of features can be extracted and used for seed identification. As summarised in table 1, these features can be roughly grouped into several categories, such as shape (Adjemout *et al*., 2007; Chen *et al*., 2010; Li *et al*., 2012; Silva and Sonnadara, 2013; Lo Bianco *et al*., 2015; Frigau *et al*., 2020), morphology (Granitto *et al*., 2000, 2003; Liu *et al*., 2005; Kambo and Yerpude, 2014a; Lo Bianco *et al*., 2015; Kuo *et al*., 2016; Terral *et al*., 2021), geometry (Chen *et al*., 2010; Zhao *et al*., 2011; Mebatsion *et al*., 2013; Huang and Chien, 2017; Cervantes *et al*., 2021; Terral *et al*., 2021), texture (Güneş *et al*., 2014; Lemanzyk *et al*., 2015; Lo Bianco *et al*., 2015; Chen *et al*., 2017b; Fayyazi *et al*., 2017; Frigau *et al*., 2020) and colour (Pazoki and Pazoki, 2011; Rad *et al*., 2011; Cao *et al*., 2012; Anami *et al*., 2013; Mebatsion *et al*., 2013b; Silva and Sonnadara, 2013; Kuo *et al*., 2016). The extracted features are usually combined with ML classifiers or algorithms such as SVM (Lemanzyk *et al*., 2015; Frigau *et al*., 2020), KNN (Pan *et al*., 2016; Frigau *et al*., 2020), Naïve Bayes (Granitto *et al*., 2000, 2003; Ajaz and Hussain, 2015; Frigau *et al*., 2020), PCA (Kambo and Yerpude, 2014a, b; Frigau *et al*., 2020), LDA (Sarigu *et al*., 2017, 2019; Frigau *et al*., 2020), random forest (Kong *et al*., 2013; Frigau *et al*., 2020) and artificial neural network (ANN) (Liu *et al*., 2005) to finally classify the images (table 1).

The applications and improvements of ML-based computer vision in the seed industry have been reported in the past. For example, Ebrahimi *et al.* (2014) exploited ANNs and an imperialist algorithm to analyse wheat seed classification. In this study, as the feature selection process is critical but non-intuitive, the Imperialist Competitive Algorithm was used to overcome the challenge of selecting seed features in classification by optimising the number of extracted features. Frigau *et al*. (2020) firstly pre-processed images by performing principal component analysis and Fourier analysis, and then classified 19 cultivars of Sardinian *Prunus domestica* L. and four cultivars of other *Prunus* species. The results indicated that data pre-processing is a useful tool for cultivar classification. Sarigu *et al*. (2017) applied LDA analysis based on 134 size, shape, colour and texture descriptors to study plum biodiversity. The ANNs were also used to construct a robust system for classifying wheat grains and impurity identification. For the system developed by Singh and Chaudhury (2016), the image-taking hardware consisted of two types

Table 1. List of seed identification studies that used traditional machine learning methods.

Seed classes	Model	Features	Accuracy	Reference
57 species	Naïve Bayes classifier and artificial neural networks	Morphological, colour and textural characteristics	95.3%~ 99.4%	Granitto *et al.* (2000)
57 weed species	Naïve Bayes and artificial neural network	Morphological and textural seed characteristics	73.0%~ 93.7%	Granitto *et al.* (2003)
Six rice varieties	Principal component analysis and neural network	Seven colour and 14 morphological features	74~90%	Liu *et al.* (2005)
Four species: corn, oat, barley and lentil	K-means algorithm	Shape and texture features	85, 75 and 78%	Adjemout *et al.* (2007)
Five Chinese corn varieties	Two-stage classifier combining distance discriminant and a back propagation neural network	17 geometric, 13 shape and 28 colour features	100, 94, 92, 88 and 100%	Chen *et al.* (2010)
Seven classes of individual grain kernels	Four-layer back propagation network	Seven colour and ten morphological features	90~ 100%	Lee *et al.* (2011)
Six wheat cultivars	Artificial neural network	Texture, morphology and colour features	87.22% overall	Pazoki and Pazoki (2011)
Five rice varieties	Back propagation neural networks	22 colour and texture features	96.67% overall	Rad *et al.* (2011)
Three varieties of corn seeds	Genetic algorithm and support vector machine	Colour,texture and shape features,	94.4% overall	Zhao *et al.* (2011)
Maize purity analysis	Back propagation neural network	Three colour values RGB	94.50% overall	Cao *et al.* (2012)
Three varieties of delinted cottonseeds	Back Propagation neural network	Colour and shape characteristic parameters	90% overall	Li *et al.* (2012)
Eight species: finger millet, mustard, soyabean, pigeon pea, aniseed, cumin, greengram and blackgram	Artificial neural network, support vector machine, back propagation neural network-based classifier	18 colours-Hue Saturation Value, and 42 wavelet based texture features	80~97%	Anami *et al.* (2013)
Four rice cultivars	K-nearest neighbor classifier, support vector machine, random forest	Spectra from 1,039 to 1,612 nm	80~100%	Kong *et al.* (2013)
Four species: barley, oat, rye and wheat	Least square classifier	Morphological and colour features	98.5, 99.9, 99.93, and 100%	Mebatsion *et al.* (2013)

Table 1. *cont'd*

Table 1. *Continued.* List of seed identification studies that used traditional machine learning methods.

Seed classes	Model	Features	Accuracy	Reference
Nine rice varieties	Artificial neural network	13 morphological features, 6 colour features and 15 texture features	92% overall	Silva and Sonnadara (2013)
Wheat purity: wheat and non-wheat seeds	Imperialist competitive algorithm and artificial neural networks	Total 52 colour, morphology, and texture characteristic parameters	96.25, 87.50, and 77.22%	Ebrahimi *et al.* (2014)
Four wheat varieties	K-nearest neighbor classifier	Textural features	45%~ 80%	Güneş *et al.* (2014)
Three rice varieties	K-nearest neighbor classifier	Area, major axis length, minor axis length, eccentricity, perimeter	79% overall	Kambo and Yerpude (2014a)
Three wheat varieties	Multilayer perceptron, Logistics, SMO, Naïve Bayes updateable, Naïve Bayes, Bayes Net, MultiClass classifier, Classification via regression and LWL	Area, perimeter, compactness, length of kernel, width of kernel, asymmetry coefficient and length of kernel groove	95.2% overall	Ajaz and Hussain (2015)
Three superordinated classes of incanut seeds	Support vector machines	227 contour, colour and texture attributes	97.0% overall	Lemanzyk *et al.* (2015)
67 Italian bean (*Phaseolus vulgaris* L.) accessions	Linear Discriminant Analysis	138 size, shape and texture descriptors	99.1% overall	Lo Bianco *et al*. (2015)
30 rice varieties	Sparse-representation-based classifier	Morphological, colour, and textural traits of the grain body, sterile lemmas, and brush were quantified.	89.1% overall	Kuo *et al.* (2016)
Four gramineous grass species	Nearest neighbor classifier	The difference of local fractal dimension	98.59% overall	Pan *et al.* (2016)
Four bulk rice varieties	Back propagation neural network	18 colour features, 27 texture features, 24 wavelet features and 45 combined features	96% overall	Singh and Chaudhury (2016)
12 gramineous grass species	Local similarity pattern and linear discriminant analysis	10 LSP histogram and four histogram statistics	91.07% overall	Chen *et al.* (2017b)

Table 1. *cont'd*

Table 1. *Continued.* List of seed identification studies that used traditional machine learning methods.

Seed classes	Model	Features	Accuracy	Reference
Three Iranian rice varieties	Principal component analysis and MLP neural network classifier	17 morphological and 41 textural features	55.93, 84.62 and 82.86%	Fayyazi *et al.* (2017)
Three rice seed varieties	Back propagation neural network	Seven geometric features	92.68, 97.35 and 96.57%	Huang and Chien (2017)
Common wheat and durum wheat	Artificial neural network	Main visual features of 4 dimensions, 3 colours and 5 texture	99.9% overall	Sabanci *et al.* (2017)
23 Prunus domestica cultivars	Linear Discriminant Analysis	134 size, shape, colour and texture descriptors	N/A	Sarigu *et al.* (2017)
41 accessions for a total of 3,317 seeds	Linear Discriminant Analysis	124 morpho-colorimetric quantitative and qualitative features	N/A	Sarigu *et al.* (2019)
19 cultivars of Sardinian *Prunus domestica* L. and four cultivars referable to other *Prunus* species.	k-Nearest Neighbour, Linear Discriminant Analysis, naïve Bayes, Support Vector Machines and Random Forest	Size, texture and shape	90.67%	Frigau *et al.* (2020)
Ten groups of the Vitaceae seeds	Geometric Models	Shape, geometric features	N/A	Cervantes *et al.* (2021)
Fossil seeds of ancient olive trees and domesticated forms	Geometrical morphometric analysis	shape	75% as threshold	Terral *et al.* (2021)

of cameras: cell phones with a resolution of 0.3 megapixels and a conventional point-and-shoot camera with a resolution of 12-megapixel. Images were then processed with three methods including colour attributes (RGB and HSI) extraction, GLCM method and wavelet-based decomposition for each colour channel (R, G and B). The extracted features were subject to a four-layer back-propagation neural network to complete the classification task. The authors also compared the proposed method with other classifiers including Naïve Bayes, KNN and SVM. Sabanci *et al.* (2017) improved a computer vision system with an adjusted camera position to obtain grain images at a perpendicular angle. The obtained images were first converted to grayscale and then binarised with the Otsu method which was followed by threshold-based segmentation. The seed features of colour, size and texture were extracted, and finally seven visual features including length, ratio of length to width, blue, green, green ratio, and feature variation were used as the data input for the ANN. The ANN consisted of three layers and could classify bread wheat and durum wheat with a high accuracy based on multi-layer perceptron.

These studies proved the ability of traditional methods in seed identification. The features or parameters extracted by traditional methods from images, such as seed shape (Chen *et al*., 2010), size (Adjemout *et al*., 2007; Lurstwut and Pornpanomchai, 2011), colour (HemaChitra and Suguna, 2018) and texture (Fayyazi *et al*., 2017), are easy to understand and the classifiers such as ANN (Lee *et al*., 2011), KNN (Pan *et al*., 2016) and SVM (Lemanzyk *et al*., 2015) are explained well mathematically. However, one has to manually design features for a specific application and to find a set of suitable features, which requires expert domain knowledge and is labour-intensive and time-consuming in itself (Wang *et al*., 2017). Although extracting features manually works well for relatively less complex classification tasks, it becomes less and less practical for humans to define a set of features to classify the increasing classes to be identified, which is the case for seed or weed identification. Further, a set of features suitable for distinguishing some seed classes may perform poorly when used to classify other seed species (Kamilaris and Prenafeta-Boldú, 2018). In other words, the feature extraction experience does not generalise well among different identification tasks (Amara *et al*., 2017). This limitation is more apparent in seeds because morphological features, such as size, shape or colour, have large natural variation, especially for wild species. These limitations restrain the wide application of computer vision systems in seed identification.

DL in computer vision

DL has proved to be very successful in many areas such as computer vision (Szegedy *et al*., 2015), bioinformatics (Min *et al*., 2017), natural language processing (Bordes *et al*., 2014), automatic driving (Chen *et al*., 2015), automatic safety control (Olmos *et al*., 2018) and machine translation (Vinyals *et al*., 2015). With the explosive advances in AI techniques, extensive studies have been conducted to apply DL in diverse agriculture domains. However, the application of this algorithm in routine seed testing is still limited. To advance DL in seed testing, it will be helpful to have a better understanding of DL principles, key elements and requirements with examples from well-studied agricultural domains.

DL is one of the most advanced ML algorithms and ANN makes up the DL backbone. In fact, it is the number of hidden layers (or depth) of neural networks that distinguishes a single neural network from a deep learning algorithm, which must have more than three. For this, DL is sometimes described as deep neural networks. DL realises AI with massive training data and a variety of additional hidden layers (Zhang *et al*., 2020).

Advantages of using DL

One important advantage of using DL over traditional ML methods in computer vision systems is the reduced requirement of feature engineering, it can learn and abstract the important features itself through the training process (Sladojevic *et al*., 2016). As aforementioned, traditional methods in image processing tasks had been based on hand-crafted feature engineering (Ngugi *et al*., 2020). Feature engineering is a time-consuming and expertise-requiring process that relies heavily on the features defined based on the human experience. Moreover, the defined features need to be altered or modified considerably when the task or the dataset changes (reviewed by Kamilaris and Prenafeta-Boldú, 2018). Although hand-crafted features engineering works reasonably well when handling a limited number of seed species, it becomes more and more difficult for humans to define a set of parameters to classify an increasing number of seed species. Thus, DL could have more potential for a large number of seed species for identification. DL could improve the robustness to intra-class variability, acquisition conditions, as well as background heterogeneity of the images under process (Boulent *et al*., 2019). Moreover, the method of DL in extracting features can be transferred among different tasks, improving the training efficiency and reducing the demand for expertise. However, one disadvantage of DL is that the learning process to extract these visual representations successfully requires large-scale training data as the input; and training a DL model requires a longer time and higher skills to optimise the model (Alom *et al*., 2018). Fortunately, once the DL models are developed, they can be as fast and efficient as traditional ML methods. Other disadvantages include overfitting when training with small datasets that lack representativeness, optimisation difficulty and hardware limitations (LeCun *et al*., 2015; Goodfellow *et al*., 2016).

DL Architectures

Deep learning is represented by a variety of architectures built for a range of problem areas. Layers of deep neural networks include convolution layers, batch normalisation layers, activation layers, pooling layers, fully connected layers, gates, memory cells, activation functions and encode/decode schemes (reviewed by Kamilaris and Prenafeta-Boldú, 2018). By combining these layers hierarchically or repeatedly into a model, DL can abstract complex features by learning simple features from the bottom layers and then stacking these simple features into complex features at the top layers (LeCun and Bengio, 1995; Schmidhuber, 2015). This way of feature abstraction in DL can improve classification accuracy and reduce errors in various regression tasks when adequately large datasets describing the problem are available. In general, the aforementioned DL attributes such as the large learning capacity with more hidden layers, the flexibility in building a DL model, and the hierarchical structure in feature extraction allow DL to perform predictions and classification in a wide variety of complex challenges with high accuracy, efficiency and adaptability (reviewed by Pan and Yang, 2009).

Convolutional Neural Network (CNN)

In the area of computer vision, CNNs are the main DL architectures (reviewed by Rawat and Wang, 2017). CNN models are kinds of ANN that contain at least one convolution layer (LeCun *et al*., 1998; Goodfellow *et al*., 2016). The convolution layers in CNNs can be viewed as matching filters that are derived directly from the images (Boulent *et al*., 2019). Convolution filters can be applied to many layers of the CNN model (Zhang *et al*., 2020; figure 1). At the shallower or beginning layers, more basic and low-level features can be learned, while the features learned become more specific and descriptive with the depth of the network. Usually, a huge number of filters will be used in each CNN layer, and thus the convolution layers altogether can be understood as banks of filters

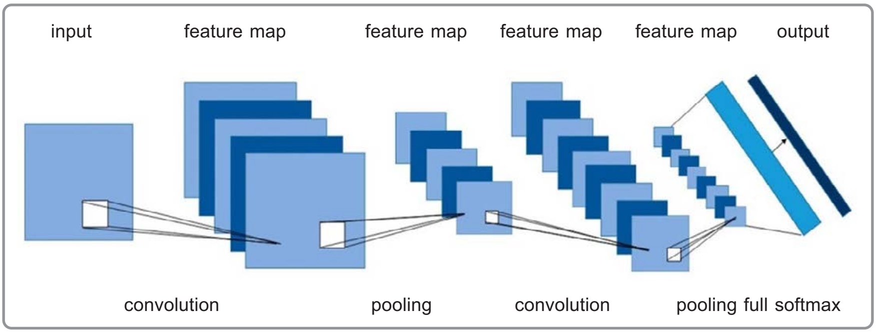

Figure 1. Illustration of the major architecture of Convolution Neural Networks. Source: Zhang *et al*., 2020.

that depict an input image with a huge number of specific patterns (Zhang *et al*., 2020). The convolutional layers thus act as automatic feature extractors from the input images. The pooling layers function to reduce the dimensionality of the images and increase the generality (Zhang *et al*., 2020). The fully connected layers, based on the learned high-level features, act as classifiers to make numerical predictions or classify the input images into predefined classes (Basha *et al*., 2020). The fully connected layers take a vector as input and generate another vector as output and they are commonly placed at the end of the model. Sladjevic *et al.* (2016) showed that the extracted features after each processing step of a CaffeNet CNN gradually identified a plant disease (figure 2). The specific components of the image that depict the indication of disease become more and more evident after the last processing of Pool5.

There are many popular and advanced backbones in CNN architectures. Although most CNN models are composed of a set of basic layers, each model has its own characteristics and contributions to the CNN development. VGGNet (Simonyan and Zisserman, 2014) improved the understanding of the balance between the number of CNN layers and performance of a CNN model. VGGNet inherits many features of AlexNet (Krizhevsky

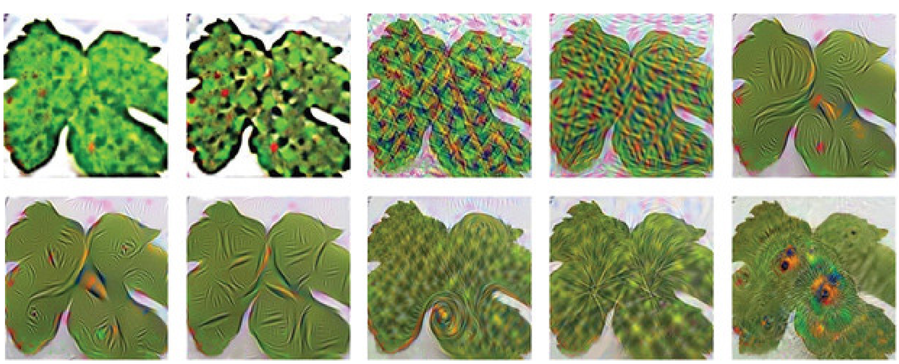

Figure 2. Visualisation of the output layer images after each processing step of the CaffeNet CNN (i.e. convolution, pooling, normalisation) for a plant disease identification problem based on leaf images. Source: (Sladojevic *et al*., 2016).

et al., 2012) and LeNet (LeCun *et al*., 1998), and it first explored the role of the smaller size of the convolution filter and the increased depth of the network in improving the performance of the model. To improve computing performance, GoogLeNet (Szegedy *et al*., 2015) was developed as a novel strategy. In GoogLeNet, multiple sizes of convolution filters are reassembled to extract the features of different scales which are accurately gathered with a strong correlation in advance, thus facilitating the network convergence. Based on GoogLeNet, DetectNet (Tao *et al*., 2016) consisting of two parts of a fully convolution neural network and clustering function was proposed. The full CNNs in the DetectNet are modified based on GoogLeNet by deleting the input layer, the internal product layer and the final pooling layer, which reduces training time and improves model accuracy. Residual Network (ResNet; He *et al*., 2016) was developed to cope with the problem of degradation which refers to the situation that, by adding more layers, the model performance first increases and reaches a plateau, but the performance drops if further layers are added. ResNet mitigated this problem significantly by adding parallel shortcut connections called residual blocks. The DenseNet introduced by Huang *et al*. (2017) borrowed the basic idea from ResNet and connected all the previous layers to the latter layers. While increasing the depth of layers enhances the classification performance of the network, increasing the width could perform similarly. Inception (Szegedy *et al*., 2016) enlarges the width through diversifying convolution kernel sizes such as 3×3, 5×5 and 1×1, which can learn various features and increase feature diversity.

Each of these aforementioned CNN backbones has its own advantages and appropriate application scenarios (Canziani *et al*., 2016). For example, the relatively less deep network of VGGNet is superior in extracting object features, as the network is more efficient to extract features when it is closer to the bottom. Thus, many models employ VGGNet as the basic backbone for image classification-related tasks. Meanwhile, ResNet has a higher capacity in extracting information through passing the image information to deeper layers, and it is widely used in the analysis of dense scenes. DenseNet has some significant advantages: it minimises the vanishing-gradient problem, enhances feature propagation, has better feature use efficiency and substantially reduces the number of parameters. DenseNet performs better than ResNet with fewer parameters (Zhang *et al*., 2021). Hence, for seed identification, DenseNet can be an ideal option as the CNN backbone.

CNN application requirement

Data collection

As a data-driven science, the very basis for CNN in object identification is image databases consisting of comprehensive images for each object class. The quality and quantity of training data often determine the depth of the network and the effects of the model. Indeed, it has been noted that whenever a sufficient image dataset is available, CNN models can be well trained and suitable for plant disease recognition tasks (Barbedo, 2018, 2019). To improve the performance of CNNs, the database needs to contain a variety of object categories and a sufficient sample size for each category. Large datasets containing thousands of images, either real or simulated with computer program (Rahnemoonfar and Sheppard, 2017), collected under various conditions were essential to train a CNN model. Some example datasets used in agricultural domains are listed in table 2.

Table 2. Examples of datasets used to train deep learning models in agricultural domains.

Dataset	Number of images	Number of classes	Reference
Flowers 102	40-258 images consisting of different scale, pose, as well as lighting variations for each of the 102 flower categories	102 common flowers in the United Kingdom	Nilsback and Zisserman (2006)
PlantVillage	50,000 images	38 classes based on plant species and disease	Hughes and Salathé (2015)
UEC-FOOD100	12,905 food images	100 classes	Kawano *et al*. (2015)
Xie1	60 images per species	24 classes of crop insects	Xie *et al*. (2015)
Self-collected dataset	575 images for avocado, orange, apple, mango, strawberry, rockmelon and capsicum fruits	Fruit and non-fruit classes	Sa *et al*. (2016)
Urban Trees datasets	14,000 urban street and park trees	171 distinct species	Wegner *et al*. (2016)
VegFru	160,000 fruit and vegetable images that associate with our daily life closely	25 upper-level categories and 292 subordinate classes	Hou *et al*. (2017)
Synthetic images	24,000 synthetic tomato images	Tomato and non-tomato classes	Rahnemoonfar and Sheppard (2017)
PestDisPlace	18,000 banana images with 30,952 annotations	Leaves, fruits and stems that infected by specific pathogens at different infection stages	Cuellar *et al*. (2018)
Fruit360	90,380 images of fruit and vegetables	131 classes of fruits and vegetables	Mureşan and Oltean (2018)
Xie2	4,500 images	40 classes of crop insects	Xie *et al*. (2018)
Apple-NDDA and NDDAW	1,110 apple images	Defective and non-defective classes	Ismail *et al.* (2019)
MangoNet semantic dataset	11,096 image patches from 40 daytime mango fruit on canopy images	Mango and non-mango classes	Kestur *et al*. (2019)
MangoYOLO	1,730 mango fruit on canopy images collected at night	Mango and non-mango classes	Koirala *et al*. (2019)
DeepWeeds	17,509 labelled images	Eight nationally significant weed species native to eight locations across northern Australia	Olsen *et al.* (2019)
CropDeep	31,147 images with over 49,000 annotated instances	31 categories according to the agricultural biological taxonomy	Zheng *et al.* (2019)
Synthetic images	400 images	20 barley cultivars	Toda *et al.* (2020)
Plant Photo Bank of China	5,256,659 plant photos	493 families, 5,048 genera, and 33,249 species	http://plantphoto.cn

Image variation among classes is also a must to effectively classify objects (Yalcin, 2017). As commented by Mohanty *et al*. (2016) and Sa *et al*. (2016), a dataset without diversity among classes could reduce the accuracy of the trained models. For example, a confusion between plants of maize and soya bean crops (Kussul *et al*. 2017) or seeds of triticale, wheat and rye (Rußwurm and Körner, 2017) illustrates how feature similarity among crops could be high. It was reported high colour similarity between fruit or foliage presented a big challenge in fruit counting (Chen *et al*., 2017a; Bargoti and Underwood, 2017a). Weed recognition tasks were also challenged by similar appearance between weed species and crops in terms of texture, colour and their overlapping (Dyrmann *et al*., 2016a, 2017). Ienco *et al*. (2017) found that tree crops, summer crops and truck farming crops were highly mixed classes. This low variation or high similarity has affected classification accuracy significantly. To improve the diversity of the training dataset, data augmentation technique has been adopted by many studies (Li *et al*., 2019; Zheng *et al*., 2020). The data augmentation can be achieved through geometric transformation and intensity transformation. While the geometric transformation includes sample tailoring, size adjustment, inversion, rotation, etc., the intensity transformation can be the transformation of contrast, brightness, colour and noise. Applying data augmentation can expand the image dataset rapidly to support the training of CNN networks when the sample images are not sufficient, such as representing the uncertainty of illumination and the object placement angle and position.

Samples in the dataset need to be annotated accurately to be used as the reference or ground-truth to which the outputs from the CNN model are compared. However, the annotation is relatively more subjective, time-consuming, expertise-requiring and labour-intensive, which is susceptible to considerable inconsistencies (reviewed by Barbedo, 2016). Annotation results may vary substantially among different human experts depending on their knowledge and experience. Therefore, the subject expert input, such as image annotation and peer-evaluation or review, is important for dataset quality, which will directly impact the performance of a developed computer vision system. The performance of the trained model can be varied depending on which expert's annotation was being relied on as the ground truth annotation (Dyrmann *et al*., 2017; Sørensen *et al*., 2017). In seed identification, the same challenge exists and high level seed analysts are crucial to sample preparation and seed image annotation.

Model training

There are two ways to train a CNN model. While the first strategy is transfer learning, the second is training from scratch, meaning the model is not pre-trained. Transfer learning is a network pre-trained on a large set of images and adapted to another task. Transfer learning is supported by the fact that the beginning convolutional layers extract low-level generic features that are not task specific (Zeiler and Fergus, 2014). As these weights extract the very basic features in common objects, such as shape, colour, lines and edges, it can be easily transferred to another project. Sometimes it is impossible to train a network from scratch due to having a small training dataset or having a complex multi-task network, and the network must be at least partially initialised with weights from another pre-trained model. Thus, transfer learning, benefiting from the low data requirements (Venkateswara *et al*., 2017), is getting more attention to facilitate application of DL in less popular domains with a small dataset. This would be a good method to use when there are only a few seed specimens, for example of a weedy or wild species, to use to build a dataset. Transfer learning with VGG16, DenseNet, AlexNet or GoogleNet was adapted to the many particular challenges and datasets, for example by Lee *et al*. (2015), Reyes *et al*. (2015), Christiansen *et al*. (2016), Mohanty *et al*. (2016), Sa *et al*. (2016), Steen *et al*. (2016), Bargoti and Underwood (2017b), Lu *et al*. (2017) and Sørensen *et al*. (2017). Transfer learning can be used in seed identification as seed datasets are usually, currently, small.

Besides transfer leaning, the architectures can be further customised with training from scratch. Training from scratch is to train a model with randomly initialised parameters rather than inherited parameters from a previous model. Training from scratch usually has a higher risk of overfitting as the network has no experience from previous training sessions. As the network can only learn features from the input data, it requires large training datasets. However, this strategy enables researchers to construct a task-specific model which can be adjusted flexibly. For example, to exploit the colour information, a three channel convolutional neural network was proposed by Zhang *et al*. (2019). To detect diseased lesions, a three-stage process based on the training of several CNNs to compute heat maps was proposed by DeChant *et al*. (2017). A strategy of training from scratch can also be used in training models for seed identification when sufficient images are provided.

Selecting a training strategy needs to consider both thematic (availability of suitable architecture or compatibility of pre-trained parameters with the on-hand dataset) and technical (image dataset and computing capability) factors. The most straightforward way to determine a training strategy is to conduct a comparison. For example, Brahimi *et al*. (2018) compared three training strategies of feature extraction, complete fine-tuning and training from scratch on six CNN models (AlexNet, DenseNet-169, Inception v3, ResNet-34, SqueezeNet-1.1 and VGG13) using the PlantVillage dataset.

Application of DL in seed identification

Deep learning-based computer vision systems have been studied and applied widely in various object classification tasks in agricultural science. However, advancement in seed identification is much slower, although several pioneering studies have been conducted (Wang *et al*., 2018; Huang *et al*., 2019; Zhu *et al*., 2019a; Toda *et al*., 2020). The experience in developing DL-based computer vision systems from other agricultural domains can guide computer vision development in seed identification. A good understanding of the difficulties and challenges should help in developing effective solutions in the application for seed identification.

Challenges and solutions in constructing seed image datasets

As a data-driven science, the key factor preventing DL application in seed identification is a shortage of large scale and comprehensive datasets. DL studies in agricultural domains were summarised in table 2, which have built task-specific datasets consisting of mega scale images to train their models. However, to the best of our knowledge, there is no computer vision specific dataset that is open access, although a few datasets containing hand-crafted features for several species can be found (e.g. seven features of three wheat cultivars can be found at https://archive.ics.uci.edu/ml/datasets/seeds). A few seed image datasets are available publically e.g. GEVES I. D. Seed (https://www.geves.fr/tools/i-d-seed/), but the purpose is mainly to assist analysts to identify seeds. The number and diversity of the images are not sufficient for DL development. At the same time, DL studies in seed identification (Qiu *et al*., 2018; Zhu *et al*., 2019a) have only focused on a few species. Therefore, building a comprehensive seed database with a large number of plant species is critical for DL application in seed identification at a required or acceptable level of accuracy defined by organisations such as ISTA. Unfortunately, unlike other plant organs, such as leaves and flowers (table 2), acquiring large seed image datasets is not easy because of the accessibility of verified seed specimens and micro-imaging equipment. Unlike identifying cultivars or varieties in a few limited species, acquiring seed specimens and their images covering full variation of a taxon for a long accreditation or phytosanitary list of species is not always possible for AI developers. In this regard, data sharing for commercially important seeds as a crop or weed among seed laboratories, research institutes, botanical gardens, gene banks and herbaria, to construct a mega scale image dataset could be an effective solution for accelerating dataset construction. At the same time, the dataset construction also requires inputs of testing experts to solve specimen preparation challenges such as feature similarities among plant taxa, the intra-specific or natural variation of wild plant species and closely similar species. Thus, well trained seed analysts or botanists are required in seed specimen verification, feature acquisition, image annotation and selection of similar seed species during dataset construction. A close collaboration is a must for building quality datasets among seed laboratories, seed herbaria, seed analysts or botanists, and AI developers. Constructing a shared, comprehensive and mega-scaled database for seed images could benefit greatly in the advancement of AI application in seed identification.

Detecting minute differences of limited seed features among species on the small objects like seeds presents another challenge in dataset construction. The similarity of seed features such as colour and shape can sometimes present challenges to seed analysts (figure 3). The employment of high resolution RGB images (Yi *et al.*, 2017), or expanded light spectrum such as near infrared (NIR) or multispectral techniques may be an effective solution for seeds that are morphologically very similar. For example, Zhu *et al*. (2019a) employed near-infrared hyperspectral imaging to classify three soybean varieties, reaching 90% classification accuracy. To identify four rice seed varieties, Qiu *et al*. (2018) employed hyperspectral images to acquire different seed information at two different spectral ranges. The results suggested that spectral data can be analysed efficiently with the CNN. Meanwhile, to conduct defect classification of maize seeds, Huang *et al.* (2019) trained the CNN models with RGB images, but recommended the usage of multispectral or hyperspectral images to recognise not only the phenotypic characteristics but also the variety information of seeds, expanding the capability of the model. This may also indicate the possible solution for species that have similarities in seed morphology.

(A)

Bromus hordeaceus

(B)

Bromus japonicus

(C)

Bromus secalinus

(D)

Lolium temelentum

Figure 3. Similarity of morphological features among different species. (**A**) *Bromus hordeaceus*; (**B**) *Bromus japonicus*; (**C**) *Bromus secalinus*; (**D**) *Lolium temulentum*.

The heterogeneity or variation in seed morphology presents a challenge for completing information for datasets. Seeds have natural variations depending on the species genetics related to its adaptation history, seed development conditions and position on the plant or within the fruit. Sometimes, dimorphic seeds exist in wild species, with a species producing seeds that differ in shape, colour or size (figure 4). When collecting seed specimens and constructing seed data profiles for a species, these variations need to be considered and included. For example, seed specimens of the same species will be intrinsically connected to the specific geographical region where the data was collected (Barbedo and Castro, 2019). The data acquisition is the most resource demanding process, but is the foundation for advancing AI application and limiting its outcome for seed identification. When a dataset is generated from diverse sources (e.g., different production areas or distribution locations), it could potentially include more complete data to train DL models. This could be more reliable in real seed identification results (Barbedo, 2020). Collaboration in data construction and building a collective dataset are critical for the model training and AI application, particularly for seed identification due to localised distribution of species for international trades. Reference species of wild species could be rare in one place but abundant somewhere else.

Figure 4. Heterogeneity of morphological features within a species. (**A**) *Ambrosia artemisiifolia*; (**B**) *Ambrosia psilostachya*; (**C**) *Ambrosia trifida*.

Challenge and solutions in training DL models

Seed identification with DL, unlike traditional ML techniques, has not received sufficient study. Thus the related DL development experience is limited. Prior to DL model development, several considerations are worth attention.

The first consideration is to compare the performance of DL and traditional ML methods. In the field of seed identification, many computer vision systems can extract pre-defined characters and classify seeds with traditional ML methods. As the performance of these ML methods was reported to be very good at tasks such as seed classification (Ebrahimi *et al*., 2014), these methods were commonly compared when developing DL models. For example, to classify defects of maize seeds, Huang *et al*. (2019) employed both DL and ML methods; they found that the performance of ML algorithms was lower than DL (95% and 79.2% accuracy for DL and traditional ML respectively). The comparison was also conducted in other DL development studies in identifying seed cultivars of cotton (Zhu *et al*., 2019b), maize (Altuntaş *et al*., 2019; Liao *et al*., 2019) and soya bean (Zhu *et al*., 2019a). The results indicated that different models perform differently, and an appropriate model selected for a specific task will depend on the acceptable levels and application goals. However, for long-term and wider application, DL models will be more promising and more compatible for tasks involving a long list of species.

It is also worth noting that image features extracted by CNN and hand-crafted features by ML do not have to exclude each other. Many studies tried to improve classifier performance by combining both strategies in feature extraction. For example, Cruz *et al*. (2017) and Çuğu *et al*. (2017) combined a hand-crafted feature vector with a CNN feature vector at the fully connected layer, and a higher accuracy was achieved. Specifically, in detecting olive quick decline syndrome (Cruz *et al*., 2017), an additional hand-crafted vector containing order statistics, geometric, shape and texture were integrated with the fully connected layers in their DL model. It was suggested that hand-crafted features could guide the network to converge faster and to generalise better which could benefit the model training with small datasets. Also, Kaya *et al*. (2019) proved that a DL network with pre-trained weights could be deployed as feature extractors in conjunction with traditional ML classifiers such as LDA and SVM. In some cases, these combinations achieved better performance compared to either independent DL or ML approaches. As introduced above, ML has been studied broadly in seed identification. The experiences in feature extraction can be adapted in developing better models.

During model development, in the case of dataset shortage, some techniques such as artificial images, transfer learning and/or model re-training hold a lot of potential and can be used. Creating new images with computer programs based on available images is a common method to enrich a dataset (reviewed by Arsenovic *et al*., 2019). For example, to classify 20 different barley cultivars, 1,200 sets of synthetic images were generated and divided into training, validation and testing datasets by Toda *et al*. (2020). The trained DL model achieved 95% accuracy and a 96% recall rate when tested on a real-world dataset. Other results in this study showed that cultivars of other crops such as wheat, lettuce, oat and rice can also be classified effectively with this method. With the synthetic images, the challenges of limited seed samples and laborious data annotation can be alleviated in applying DL. However, in most cases, the synthesised image may not perform as effective as the real images; the strategy of employing synthesised images for model training while using real images for model testing was used by Dyrmann *et al*. (2016b) and Rahnemoonfar and Sheppard (2017). Besides synthetic images, data augmentation can also be used to enrich image dataset. Transfer learning could help to improve generalisability of models trained with insufficient images.

Challenges and solutions in method evaluation and standardisation

In seed testing, there are standard methods or testing rules to follow (AOSA, 2021; ISTA, 2022). When applying any new techniques, such as computer vision, it needs to be evaluated or accepted as a standard method or testing rule, and meet accreditation requirements in some cases. In the stage of application, testing industries and their standardisation organizations will play a role in facilitating the adoption and then future adaptation of new technologies. For example, a standard validation or verification procedure can be developed to compare the new technology assisted systems against the current proficiency performance standard. Computer vision performance in identifying seeds have been demonstrated with a remarkable accuracy in previous studies (Granitto *et al*., 2000; Chen *et al*., 2010; Yi, 2017; Huang and Chien, 2017). However, most of these published studies were a proof of concept study with limited plant species, and the developed method has not been evaluated using a standard, agreed or accepted approach. In other words, the application remains unofficial or unverified. Without a general guidance from seed testing institutes or laboratories, it is still hard for developers to evaluate their models to meet the requirement of seed testing standards or rules. To accelerate the adaptation of the advanced technologies, the involvement and outreach of the testing industry and method standardisation organizations, such as ISTA and AOSA, are highly recommended to guide technology developers.

Developing an in real-world scenario computer vision system for seed identification

Application of computer vision in seed testing and seed identification is in high demand but there is limited operational application based on a recent survey of testing laboratories (Zhao *et al*., 2021). This could be an opportunity to develop functional computer vision systems and to coordinate strategically inter-disciplinary and cross-field collaborations in constructing shared and open access data infrastructures and contributing to quality control points. A conception flow chart and its associated control points are proposed and illustrated in figure 5. The most important practical activities in developing this system are to construct a comprehensive, accurate, open to all users, and large-scale dataset for the development of specific applications.

The practical activities of the system contains:

(1) Identify the initial or targeted weeds and commonly cultivated species.

(2) Use verified reference specimens as an important quality control point for data accuracy and feature collections.

(3) Establish a sharable data infrastructure for image data storage and use.

(4) Build datasets among collaborators with the guidance of AI developers and the consideration of the end-user needs such as acceptable accuracy and application specifications. The dataset could also be constructed separately considering a particular test application such as classification of seeds or seedlings, and different types of imaging techniques for image acquisition, such as RGB, x-ray, multi- or hyper-spectral and NIR imaging, can be used.

(5) Develop quality control protocols for data representation or completion. Standardised data collection protocols should be the most effective measure to guarantee quality data among contributors.

6) Develop peer-reviewed performance evaluation methods and procedures, such as validation or verification on a specific test.

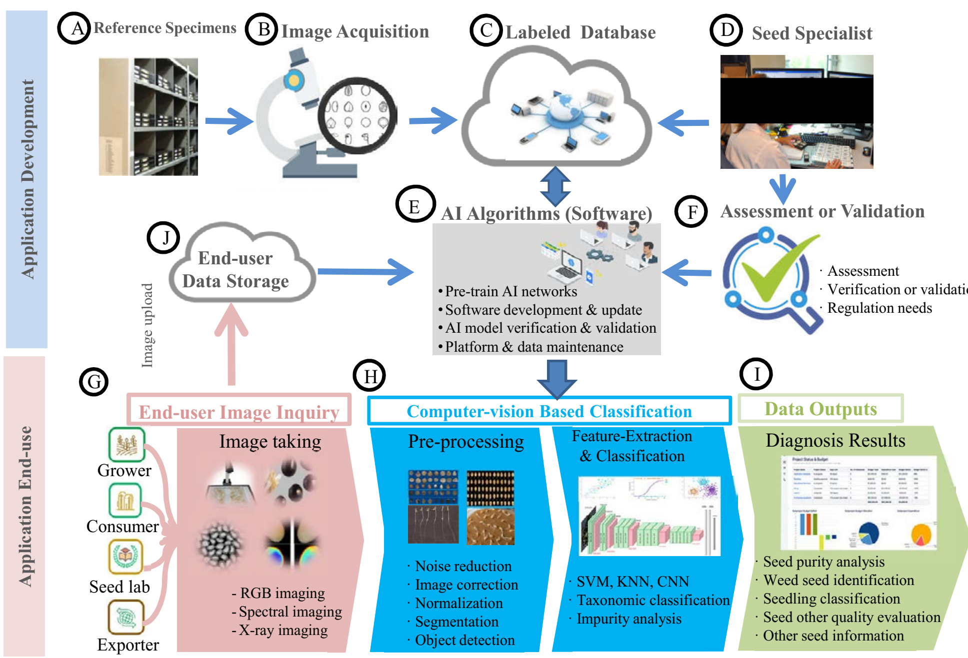

Figure 5. A proposed workflow for seed quality assessment with AI techniques in referencing to other agricultural applications (Mochida *et al.*, 2019). The control points for quality and validity of the workflow were labeled. In dataset construction, reference specimens (**A**) will go through image acquisition stage (**B**) and the images will be verified and correctly labelled by seed specialists (**D**), ensuring the quality of image annotation and seed or seedling specimen selection. The collected images will be stored in image databases (**C**), which are used to develop and train AI algorithms (**E**). The image data can also be collected through end users (**J**). The performances of the developed AI algorithms in accuracy or consistency can be evaluated by standard organizations when necessary (**F**). An analysis or diagnostic testing starts from taking images for seed samples with instruments (**G**), followed by image processing and classification by the integrated AI algorithms (**H**) for the intended output data (**I**).

When end-users use a well-developed computer vision system, they could also contribute data to the established system by real sample image-taking, especially when a reduced level of accuracy is detected in specific samples. When a computer-vision system has been pre-trained and high-performance AI models are developed, the designed outcome (i.e., AI seed identification) will be achieved without the requirement of regular proficiency demonstration from time to time, and from laboratory to laboratory.

Because the data infrastructure and dataset building require significant investment in cost and time which limits progress, computer vision application can be in stages. The initial stage could design with limited scope or function, for example, to have a limited number of targeted species, to combine human and AI, or to assist testing components, instead of full automation. The species targeted could consider the challenging species that are not readily identified by analysts, particularly for entry-level analysts, or low accuracy rate species. The initial stage should also analyse and prioritise the most feasible test that AI has significant advantages over manual analysis. For example, application in Other Seed Determination (OSD) under the ISTA rules (ISTA, 2022) has a significant advantage over the percentage test and inert separation in purity analysis without changing rules or methods. The OSD application can be further used in other seeds or contaminated seeds classification in purity analysis. The second stage could be to target full automation without too much demand on human intervention, or to have expanded scope which is comparable or superior to current situations in real testing. If a computer vision system could identify 300-500 species with over 90% accuracy, it would be comparable to the current requirement of an accredited or registered seed analysts (CFIA, 2015; ISTA, 2022; AOSA, 2021). To achieve full automation using computer vision in seed testing, additional hardware for seed sample presentation is required. Having a system that is capable of delivering the minimum sample amount of 2,500 (purity analysis) or 25,000 (Other Seeds Determination) automatically and speedily for image acquisition is a big challenge, especially since a sample could potentially contain variation in seed size, e.g., large seeded crops contaminated with small weed seeds. Sample pre-screening or pre-separation to separate the sample into similar sized portions may be required in those situations. Other constraints also exist in real world operation, such as maintenance of this system to keep up with the changes of accuracy requirement and regulatory or quality control policies.

Funding

This research was supported by ISTA Special Project (ISTA 19-1) and CFIA project (SAS-P-1706) to Dr. R. Wang.

Conflict of Interest

The authors declare that the review was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Acknowledgements

We thank colleagues and reviewers for their constructive suggestions for the paper.

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