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Achieving high buckwheat sorting accuracy in a deep learning based model by applying fine scaling method

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ABSTRACT

Automated seed sorting is widely used in the agricultural industry. Deep learning is a new field of study in agricultural seed sorting applications. In this study, a classification of buckwheat seeds and foreign materials, such as sticks, chaff, stones was performed using deep learning. The main purpose of the study was to show the effect of scaling the images on the classification results, while creating a dataset. An industrial experimental setup was used to generate the datasets of buckwheat seeds and foreign materials to be sorted by deep learning. The images in the created dataset were rescaled with two different techniques, precision scaling and direct scaling, which were labelled as Type1 dataset and Type2 dataset, respectively. To classify buckwheat seeds and foreign materials, AlexNet architecture was used. The classification accuracy was calculated as 98.57% for Type1 Dataset and 97.34% for Type2 Dataset. As a result, it was concluded that the Type1 dataset had a higher accuracy and the use of precision scaling can be used to improve the classification results in industrial applications.

1. Introduction

Deep learning architectures are widely used in many applications such as object classification (Sharma et al. 2018), sorting food and beverage (Nasiri et al. 2020), face detection (Sun et al. 2018), speech recognition (Zoughi et al. 2020), plate recognition (Omar et al. 2020) etc. Object classification is one of the main applications, which is used in many industries as well as in food and agriculture (Unal 2020). In 2012 and with the achievement of AlexNet (Krizhevsky et al. 2012) in ImageNet Large Scale Visual Recognition Challenge, convolutional neural network (CNN) architectures became much more popular in classification applications. Following AlexNet, many other CNN structures were proposed in literature such as VGGNet (Simonyan and Zisserman 2015), GoogleNet (Szegedy et al. 2015), ResNet (He et al. 2016), MobileNet (Howard et al. 2017).

Classification algorithms are also widely used in agriculture. The use of deep learning for classification problems in agriculture makes these problems more applicable and achieves a high accuracy of results. One of the problems, which is widely covered in the literature, is the problem of seed classification. Kurtulmus et al. 2016 proposed a neural network to classify eight different varieties of pepper seeds. The proposed network had three layers, including an input layer, a hidden layer with 30 neurons and an output layer. Although the proposed network was not a deep convolutional neural network, it had a classification accuracy of 84.94%. In a similar study, to classify Chinese cabbage seeds, the features were extracted from seeds' images and for the classification of features back-propagation neural network was proposed (Huang and Cheng 2017). According to this study, classification accuracy was calculated as 91.53% and 88.95% for good and bad seeds respectively. In another study, a custom CNN architecture was proposed to classify diploid and haploid maize seeds (Veeramani et al. 2018). The proposed custom CNN architecture classification accuracy was calculated as 96.70% and SVM accuracy was calculated as 87.60%. To compare machine learning algorithms and deep learning algorithms, another study was done by Huang et al. 2019. In this study, they classified defect and good maize seeds with deep learning (GoogleNet) and machine learning techniques, such as speeded up robust features, (SURF) and support vector machines (SVM). Experimental results showed that GoogleNet had an accuracy of 95% and SURF+SVM had an accuracy of 79.2%. In a recent study, to identify sunflower seeds, three deep learning architectures (AlexNet, GoogleNet and Resnet) were investigated. The highest classification accuracy (95%) was calculated from GoogleNet algorithm (Kurtulmus 2021).

Sorting the seeds from all kinds of foreign materials such as sticks, chaff, stones etc. before the packaging stage, and even classifying them according to their size, color and shape, provides a higher quality product for the market. The process of classifying seeds with a deep learning algorithm consists of three main sub-processes such as image acquisition, image pre-processing and image classification (Khirade and Patil 2015). Although feature extraction is not required in deep learning algorithms, acquisition of images that reflects important information clearly is very important (Devaraj et al. 2019). In industrial applications, it is not possible to take such images of seeds as they move on the conveyor belt or fall from the reservoir. For this reason, seeds must be extracted from current frames, which is called blob analysis (Yusuf et al. 2018). The other important case is that the images need to be resized to adapt to the requirements of the Deep Learning model (Kamilaris and Prenafeta-Boldú 2018). It was found in the literature review, that there are many studies on seed classification with CNN architectures. However, there are a lack of studies in the literature that explain in detail how to create a seed dataset for a CNN architecture, how to scale the seed data precisely to required size, and which emphasizes how these processes will affect the classification.

In this study, buckwheat seeds were sorted from foreign materials, such as sticks, chaff and stones with deep learning. the generation of datasets were performed by using an industrial experimental setup which is described in the materials and methods section. In order to show the scaling effect to the classification results, the images in the initial dataset were processed to form two datasets which were labeled as Type1 and Type2 (Aktaş 2020). Type1 Dataset was obtained using precision scaling by locating the blob in the middle of NxN Template Image. Type2 Dataset was obtained using direct scaling by generating NxN data from raw blob. To classify buckwheat seeds and foreign materials, AlexNet architecture was used. The classification accuracy was calculated as 98.57% for Type1 Dataset and 97.34% for Type2 Dataset.

2. Materials and Methods

2.1. Experimental setup and image collection

The experimental setup shown in Figure 1a consists of four mechanical parts including hopper, groove, vibration motor and a mechanical body. Inside the body there is a Basler 107649 acA1440-73gc 1440 x 1080, 73 fps, color 1/3" CMOS camera, MBJ imaging DTL-ic-1010 Diffuse Flat Dome Light and other automation cards. The parts and components of the system are shown in Figure 1b. To collect the buckwheat and foreign materials images the experimental setup works as follows: First of all the hopper is filled with buckwheat seeds. The vibration motor is run by 220v AC. A potentiometer is used to adjust the speed of the vibration motor. The vibration motor starts to work by adjusting the potentiometer. In this way, the seeds in the hopper start to move on the groove. The seeds that reach the end of the groove start to fall down. As the seeds fall down, clear images of the seeds are obtained by an industrial camera and lighting system. The industrial camera and lighting system work synchronously with each other; when the camera is ready to take an image, the lighting system is activated by the camera through I/O connection. In this way, the images are taken by the camera and saved to the computer using the pylon viewer interface program. In the next stage, all of these operations were performed for foreign objects. This experimental setup was used to collect images of buckwheat seeds and foreign materials. The classification algorithm was tested on Intel i7, 3.6 GHz, 32 GB DDR3 1600 MHz RAM, Nvidia RTX 2080 GPU, Windows 10 Pro Desktop computer. All of the image processing and deep learning applications were performed with Python version 3.8, OpenCV 4.5 and Keras Library version 2.5.

2.2. Dataset generation

Dataset generation is one of the most important steps before applying deep learning architectures. The blob detection algorithm is used widely during dataset generation to detect and extract the objects, (Dewi et al. 2021). The aim of blob detection is to find regions in an image that differ from the surroundings. Using properties such as intensity and shape, the contours of the objects are defined (Ter Haak 2018). After applying the blob detection algorithm the images need to be resized to adapt to the requirements of the Deep Learning model (for example 227x227 or 224x224) (Kour and Arora 2019). In other words, the size of the extracted blob from current frame must fit to the model input image size. Basically, this can be done by overlapping the center of the blobs with the center of the desired sized frame, and the resulting segment can be subtracted from the entire image, thus producing an image of the desired dimensions. This technique has some disadvantages such as other objects which appear on the edge of the extracted image. Another problem of this technique arises when the natural shape and size of the objects to be classified are quite different from the model input dimensions.

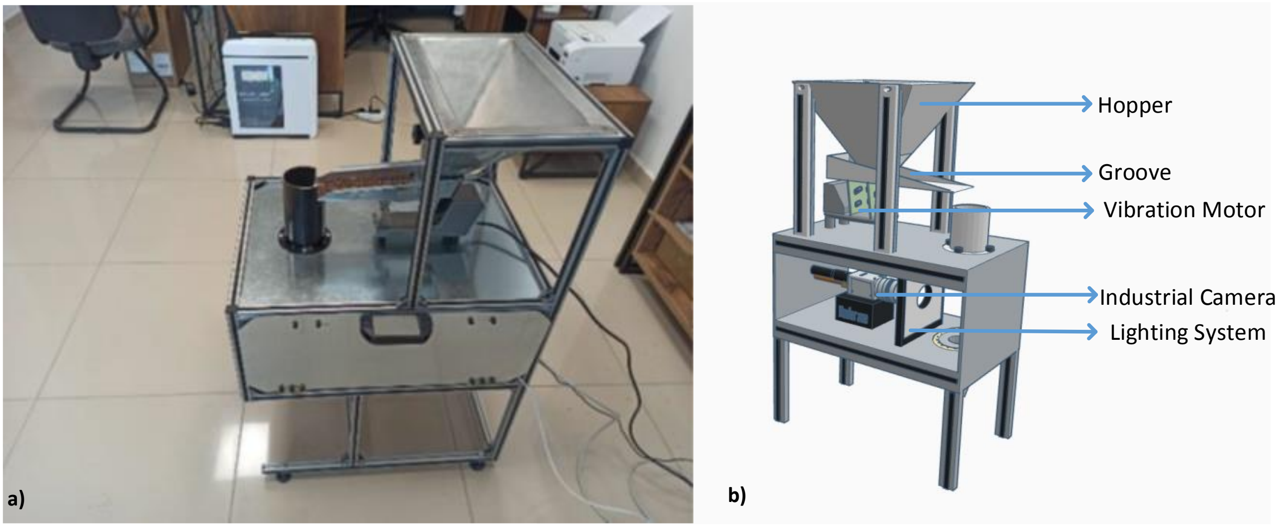

Figure 1. (a) Experimental setup (b) Working principle of experimental setup.

Then the object needs to be stretched or shrunk to fit in the desired frame. To demonstrate the effect of these problems on the classification results, Type2 Dataset was generated using the technique explained above. As a solution to the aforementioned problems it is better to extract the blob from it's borders (x_min,x_max,y_min,y_max) and then locate the blob in the middle of NxN Template Black Image. To demonstrate the effect of this solution, Type1 Dataset was generated using NxN Template Black Image. The proposed method (Aktaş 2020) using the blob detection algorithm is given in Figure 2, where it is clearly seen that in Type2 Dataset the natural shape of the classified object is distorted.

The scaling processes are explained in depth in Figure 3, in order to better understand how all of these image resize operations are done for Type1 datasets . Because the images were grabbed while the objects (buckwheat seeds and garbage objects) were in free fall, the size of buckwheat and foreign materials change too much. The maximum size of the x or y coordinate of one buckwheat seed can be 150 pixels and the minimum size can be 70 pixels. So, in order to locate buckwheat seeds in the middle of these templates, no image resize operation is needed. Because of the nature of free fall, seeds turn and move on x and/or z coordinates. This turn and move effect can be seen a lot more in foreign materials. The size of foreign materials can change over a wide range, which can be seen in Figure 4.

2.3. AlexNet architecture

Alexnet became popular with its success in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition and revolutionized the use of CNN structures in classification problems (Khan et al. 2020). AlexNet Architecture consists of 5 convolution layers, 3 max pooling layers, 2 normalization layers, 2 fully connected layers and 1 softmax layer. A total of 1376 filters, 96, 256, 384, 384 and 256, were used in 5 convolution layers, respectively (Krizhevsky et al. 2012). In this study, the AlexNet structure was produced using Keras library with Python programming language in accordance with the literature. Since there are two classes in the application, the fully connected layers wereupdated as 256, 128, and the last layer, the softmax layer, as 2, in order to classify the two classes. AlexNet architecture with modified output layers is given in Figure 5. The AlexNet architecture can be used as a pre-trained version for the classification problems. Seed classification is an industrial application, in this study instead of using a pre-trained AlexNet structure the network structure created with the keras library was trained from scratch with the created dataset.

After generating 227x227 input images as AlexNet requires for each class, each dataset must be split into training, validation and test datasets to evaluate the performance of the network. In the literature different ratios are used while creating training, validation and test datasets, and the most popular rates such as 70%, 15% and 15% were used in this study (Islam and Raj 2017, Aktaş 2022). After applying these ratios the training, validation and test dataset of each class obtained were 1141, 245 and 245, respectively. The AlexNet architecture, which was modified as in Figure 5, was used for training and testing processes. Accuracy is expected to be high when the network is trained in high epochs. However, after a while the learning process slows down and as the training process continues the network does not learn any more or starts to memorize the dataset, which causes over fitting (Li et al. 2019). One of the solutions to avoid over fitting is to use the early stopping parameter in the keras library, which is used to limit the training of the network to a certain epoch. If val_loss is low 20 times in a row, an automatic training stop has been set as the stopping criterion. The parameters used in the training are as follows: optimizer= SGD, learning rate= 1e-04, batch size= 64, loss_function= categorical_crossentropy.

3. Results and Discussion

In this study, two types of dataset were used for training and tested with the AlexNet structure. Firstly, the AlexNet structure was trained with Type1 dataset. In order to evaluate the success of this trained network, it was tested with 245 images in the test dataset and the test accuracy was calculated as 98.57%. The training of the network ended in the 43rd epoch. Then the AlexNet structure was trained with Type2 dataset from scratch. The training of the network ended at the 46th epoch. Test accuracy was calculated as 97.34% when 245 test images from Type2 dataset were applied. Considering the classification results, the network structure trained with the Type1 dataset produced a higher accuracy.

In the next step, the number of train, validate and test data was halved in order to understand the effect of the number of images in the dataset to its accuracy. Using this new number of datasets and also using the same training options, the training and test process wasrepeated. Using halved Type1 dataset (570 train, 122 validation and 122 test data for each class) the training stopped at 60th epochs by using the early stop class and the test accuracy was calculated as 95.49%. In the next step using halved Type2 dataset (570 train, 122 validation and 122 test data for each class) the training stopped at 56th epochs by using the early stop class and the test accuracy was calculated as 94.67%. The results of using the full number of datasets and half the number of datasets and the comparison of the results are shown in Table 1.

For better representation of the effect of different scaling techniques on the accuracy, the confusion matrices from which the test results were calculated are given in Figure 6a and 6b. The confusion matrix obtained from the network structure trained with Type1 dataset is given in Figure 6a and classification accuracy calculated from that matrix was calculated as 98.57%. It was easier for the network to detect buckwheat seeds because the shapes and sizes of the buckwheat seeds were similar to each other and the foreign materials had various shapes and colors. As seen in Figure 6a, only one out of 245 buckwheat seed images were misclassified, and the number of misclassified images was 6 out of the same amount of foreign matter images.

The confusion matrix obtained from the network structure trained with Type2 dataset is given in Figure 6b and classification accuracy calculated from that matrix was calculated as 97.34%. As seen in Figure 6a, 6 out of 245 buckwheat seed images were misclassified, and the number of misclassified images was 8 out of the same amount of foreign matter images. It can be clearly seen that the number of misclassified classes in the Type2 Dataset is higher than in the Type1 Dataset, which underlines the importance of precision scaling during image processing.

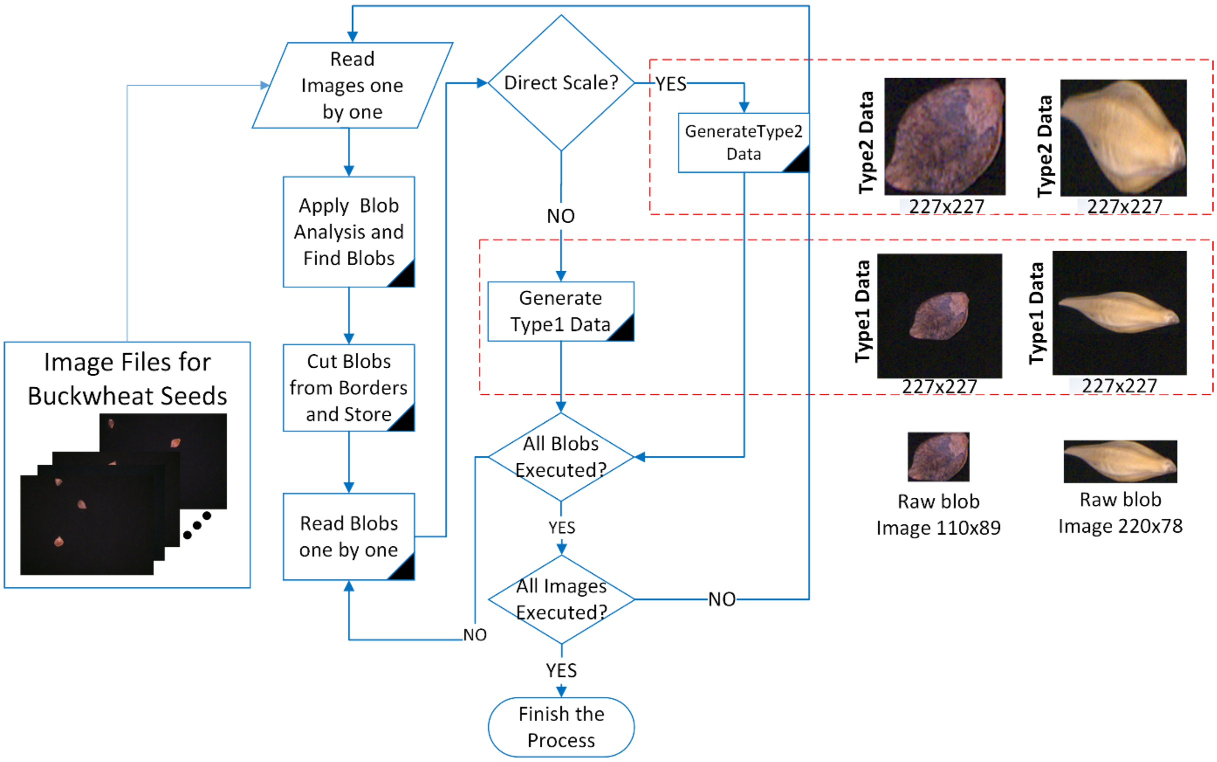

Figure 2. Flowchart for two different dataset type generation. Type1 dataset (locate the blob in the middle of NxN template) and Type2 dataset (NxN data generated from raw blob).

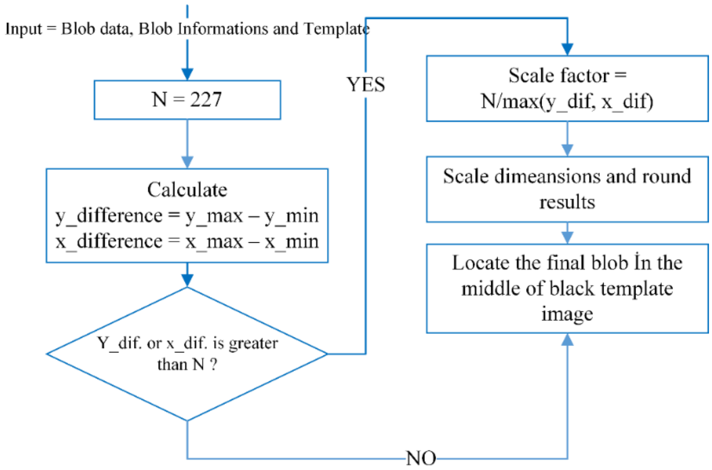

Figure 3. Image resize operations for Type1 dataset (locate the blob in the middle of NxN template black image).

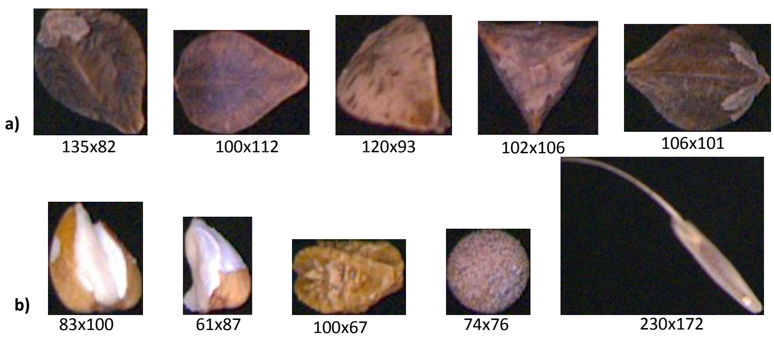

Figure 4. (a) Example of raw buckwheat seed images generated from buckwheat seed image files (b) Example of raw foreign materials images generated from foreign materials image files.

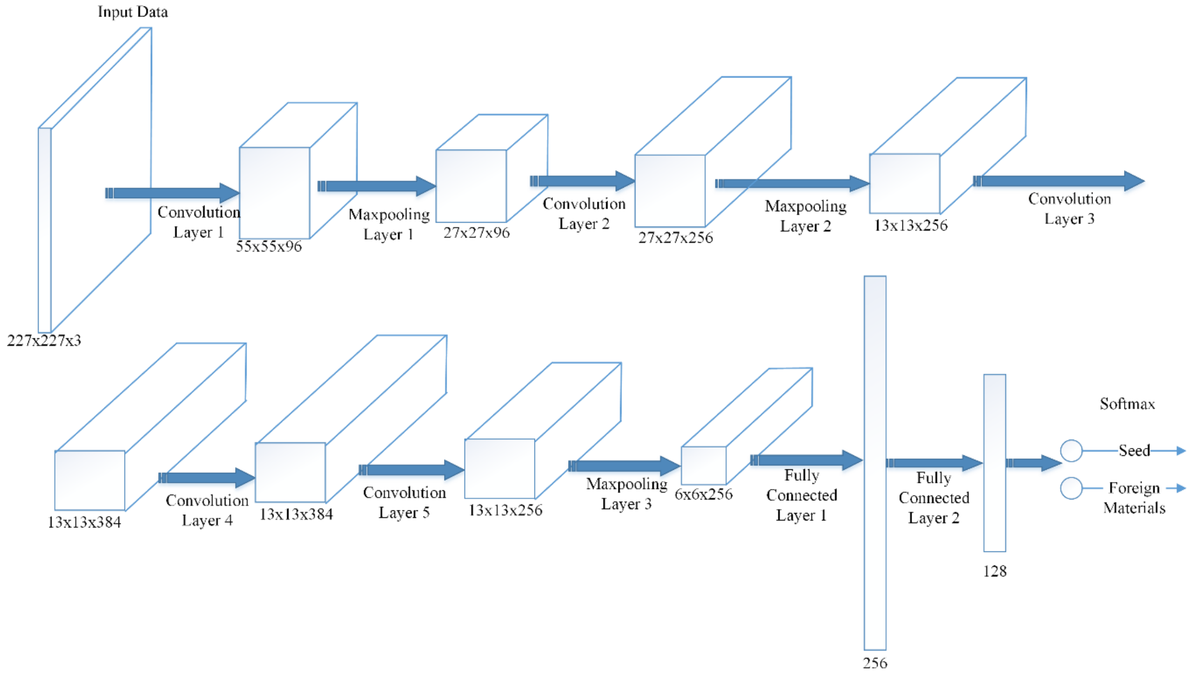

Figure 5. AlexNet architecture.

Table 1. Comparison of AlexNet accuracy results for different types and amount of datasets

Type1_Dataset				Type2_Dataset			
Train= 1141x2, Validation= 245x2, Test= 245x2		Train= 570x2, Validation= 122x2, Test= 122x2		Train= 1141x2, Validation= 245x2, Test= 245x2		Train= 570x2, Validation= 122x2, Test= 122x2	
Epochs	Test Accuracy	Epochs	Test Accuracy	Epochs	Test Accuracy	Epochs	Test Accuracy
43	98.57%	60	95.49%	46	97.34%	56	94.67%

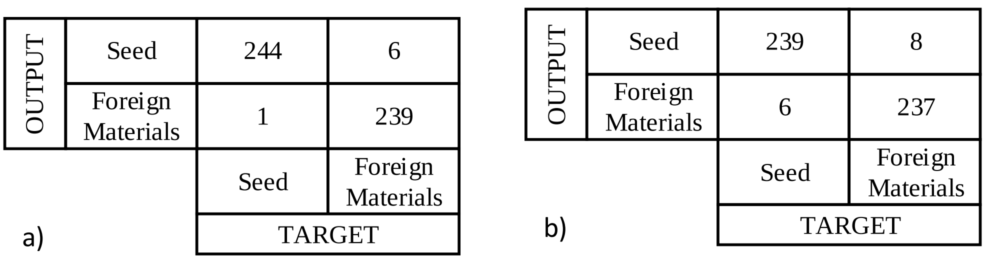

Figure 6. (a) Confusion matrix for Type1 dataset (b) Confusion matrix for Type2 dataset.

Although the numerical difference between these two datasets is not very high, it may mean a lot for farmers and commercial enterprises. The crops collected after harvest must be packaged in order to be offered for sale. Making this packaging process as error-free as possible is appreciated by the buyer, which naturally reflects on the prices. For this reason, it is very important to carefully sort the product before packaging.

The comparison of the classification made with the Type1 and Type2 datasets and the obtained confusion matrix results from Figure 6a and 6b in terms of economic value for farmers and commercial enterprises can be seen in Table 2. There is not a specific ratio in seed sorting, but it is expected that the percentage of foreign materials should be less than that of seeds. For example, as a result of sorting a 100 kg product, the amount of foreign materials removed can reach up to 1 kg. If in sorting application Type1 dataset is being used to train and test (in real time), according to the Figure 6a the false seed percentage is calculated as: 1 / 245 * 100= 0.40. That means 0.40% of the 99 kg sorted seeds were misclassified. That means 0.39 kg seeds misclassified as foreign materials. Again using Type1 dataset, from Figure 6a the false foreign materials percentage calculated as: 6 / 245 * 100= 2.44. That means 2.44% of the 1 kg sorted foreign materials were misclassified. That means 0.02 kg foreign materials misclassified as seeds. In this way, for Type1 dataset sorting 100 kg products the total misclassification is calculated as: 0.39 kg + 0.02 kg= 0.41 kg. Using the same calculations for Type2 dataset the misclassification is calculated as 2.44 kg. Although the effect of Type1 and Type2 datasets on classification is 98.57% - 97.34%= 1.23%, it can be said that the effect in practice is 5.9 times (2.44 / 0.41= 5.9) according to Table 2. Considering this information, the wrong classification of buckwheat products as foreign materials constitutes a serious loss for farmers and commercial enterprises.

Table 2. Economic effect of wrong classification in practice

Dataset Type	Seed in kg	Foreign Materials in kg	False Seed Rate	False Foreign Materials Rate	Wrong Classification of Seeds in kg	Wrong Classification of Foreign Materials in kg	Total Wrong Classification in kg
Type 1	99	1	0.40%	2.44%	0.39	0.02	0.41
Type 2	99	1	2.44%	3.26%	2.41	0.03	2.44

4. Discussion

In this study, the effect of the datasets generation methods used in the sorting processes on the test accuracy was investigated and datasets with different scaling methods have been proposed to develop high-accuracy datasets. The classification of buckwheat seeds and foreign materials using deep learning techniques was chosen as the sorting problem. AlexNet architecture was used for the classification process. Two different data types, Type1 and Type2, which were generated with different scaling methods, were used to train the AlexNet architecture. As a result of training the AlexNet structure with these datasets, the test accuracies for Type1 and Type2 datasets were calculated as 98.57% and 97.34%, respectively. It is concluded that Type1 dataset has a better test accuracy than Type2 dataset. More importantly, when Type1 dataset is used, the network structure classifies buckwheat seeds data with a higher accuracy. The effect of scaling techniques were also investigated for the economic effects of industrial sorting applications. If these scaling methods are used in industrial applications, Type1 dataset will make it possible to carry out more efficient sorting processes.

Seed sorting is an application that requires high speed and accuracy. With the use of deep learning in many classification problems, it is expected that deep learning-based sorting machines will be used more widely in the future. Since the results obtained in this study will be applicable in industrial sorting machines in the future, the aim is to realize higher efficiency sorting processes. In future studies, the aim is to develop sorting systems that can operate in real time at high speeds and accuracy by using these datasets. In order to make the system applicable in real-time, the aim is to develop optimized network structures with low processing load and high accuracy. In future studies, the aim is also to use these scaling techniques for different datasets and compare the classification results.

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