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Classification of Some Barley Cultivars with Deep Convolutional Neural Networks

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ABSTRACT

The homogeneity of the seeds is an important factor in terms of processing, transportation, storage, and product quality of agricultural products. It is possible to classify the grain polymorphism of barley cultivars, which are economically important among cereal crops, in a short time with computer vision methods with high accuracy rate and almost zero cost. In this research, a novel image database consisting of 2800 images were created to classify 14 barley cultivars. Six different deep convolutional neural network models were designed based on a transfer learning method with pretrained DenseNet-121, DenseNet-169, DenseNet-201, InceptionResNetV2, MobileNetV2 and Xception networks. The models were trained and evaluated with test-time augmentation method, the best performance was obtained from DenseNet-169 model with average 96.07% recall, 96.29% precision, 96.07% F1-score, and 96.07% accuracy on a test set independent of the training set. The results showed that the transfer learning method performed using additional layers such as dropout and data augmentation with sufficient data samples in these images with high similarities prevented overfitting by increasing the model performance. As a result, it can be suggested that the provided web tool based on the transfer model has an encouraging performance in identifying seeds with a high number of cultivars such as barley.

Keywords: Computer vision, Automatic seed recognition, Transfer learning, Barley classification

1. Introduction

Barley is the genus *Hordeum* from the Triticeae tribe of the *Poaceae* family (El Rabey et al. 2014). There are 30 species in the genus *Hordeum*, about 3/4 of them are perennial. The cultivated barley cultivars are located under the *Hordeum vulgare* L. taxon. Although the majority of Hordeum species are diploid (2n = 14), there are also tetraploid (2n= 28) and hexaploid (2n= 42) species (Bothmer 1992). One of the first cultivated plants, barley is primarily used in animal feed and malt industry (Kün 1988).

Artificial intelligence development efforts which first started with the mathematical modelling of the human nerve cell in 1943 (McCulloch & Pitts 1943) pave the way for very successful results in many disciplines today. Convolutional Neural Network (CNN) can also be regarded as the milestone of these efforts with their successful results in recent years. Although it was developed by LeCun et al. (1998), as the first convolutional neural network as it is today, it has not been able to achieve sufficient success for many years because of hardware deficiencies due to the excessive computational load required and the lack of high-resolution digital image sources.

In recent years, developments in graphic processing unit hardware and increasing digital image sources have enabled the development of deeper network structures with high performances by developing layer types, layer numbers, and connection types in the convolutional neural networks. LeNet, the introduction of the CNN concept, has 7 layers (LeCun et al. 1998), AlexNet with parallel computing on 2 GPUs has 8 layers (Krizhevsky et al. 2012), VGG model with multi-layer structure has 19 layers (Simonyan & Zisserman 2014), GoogleNet with inception module has 22 layers (Szegedy et al. 2015), ResNet with skip connection has 50 layers (He et al. 2016), and DenseNet with connected all layers has 169 layers (Huang et al. 2017).

Studies on computer-based image recognition of cultivars of cereal plants are showed difference in parallel with the improvement in methods and hardware in this field. The cultivars belonging to 5 different wheat classes cultivated in Canada are classified in scores ranging from 15 to 96% with the help of plan-form spatial shape features and elliptic Fourier descriptors of kernel perimeters (Neuman et al. 1987). A discriminant analysis-based algorithm has been developed using colour, texture, and morphological properties to classify Canadian western summer wheat, Canadian western amber durum wheat, barley, oat, and rye seeds. In the classification according to performance ratios, success rates for 5 cultivars/species were determined as 98.9, 93.7, 96.8, 99.9, and 81.6% (Majumdar & Jayas 2000a) using 23 morphological features, 94.1, 92.3, 93.1, 95.2, and 92.5% using 18 colour features (Majumdar & Jayas 2000b), 85.2, 98.2, 100, 100, and 76.3% using 15 most prominent tissues (Majumdar & Jayas 2000c), and 99.7% mean accuracy using 20 most significant morphological, colour, and texture features, respectively (Majumdar & Jayas 2000d).

Paliwal et al. (2001) developed 9 different neural network architectures in order to classify 5 different cereal cultivars: hard red summer wheat, Canadian western amber durum wheat, barley, oats, and rye. They carried out the training and testing of the neural network with 8 different morphological features obtained from a dataset consisting of 7500 grains from 1500 grains of each cultivar. According to their test results, they were able to distinguish barley and rye by 88%, wheat and oats by 97%. Choudhary et al. (2008) classified accuracy from 89.4% to 99.3% using linear and quadratic statistical classifiers, with 135 wavelets, 93 colours, 56 textures, and 51 morphological properties of wheat, barley, oat, and rye grains with a total of 335 properties. Mebatsion et al. (2013) used the least squares method to classify grains of wheat, barley, oat, and rye varieties, and they used geometric and colour attributes obtained with elliptic Fourier identifiers. According to the results of the analysis, the researchers differentiated the grain varieties from 98.5% to 100%. Martinez et al. (2018) classified 5 different olive cultivars (Picudo, Lucio, Cortijuelo, Manzanillo de Montefrio, and Negrillo de Estepa) with an average accuracy rate of 89% using a dataset consisting of 250 images with various texture features and least squares discriminant analysis method. Demir et al. (2019) compared the longitudinal, surface and gravitational properties of 7 almond cultivars (Bertina, Ferragnes, Ferradual, Ferrostar, Glorieta, Lauranne, and Marta) with the elliptic Fourier descriptors of their shapes. They observed that the greatest difference feature is in horizontal orientation and thickness dimension in suture orientation of almond shape. Three different deep learning architectures (AlexNet, GoogleNet, and ResNet) were investigated on a dataset consisting of 4800 grains for the classification of 4 different sunflower (Reina, Sirena, Armada, and Palanci) seeds (Kurtulmuş 2021). Accordingly, the GoogleNet model gave the best result with a 95% accuracy rate. A computer image analysis technique was applied to identify the seeds (100 grains for each genotype) of three maize (*Zea mays* L.) genotypes (Beyaz & Gerdan 2021). They reported that the success of prediction accuracy was found as 99% for Random Forest and Gradient Boost Decision Tree, 97.66% for Multilayer Perceptron, 96.66% for Decision Tree, and 97.40% for Majority Voting algorithms by using the Knime Analytics Platform.

With the advances in image recognition, while the studies for image recognition of different grain types were carried out in the past, the studies for the recognition of different varieties belonging to the same grain have increased in recent years. For the classification of barley varieties, Zapotoczny et al. (2008) used linear and nonlinear discriminant analysis and principal component analysis methods with the help of 74 morphological features obtained from grains of 5 different summer barley varieties cultivated in Poland. According to the test results, the researchers obtained the least classification error rate of 5.06% using the linear discriminant analysis method. Szczypiński et al. (2015) classified the cultivars belonging to 11 different barley classes cultivated in Poland with the help of 590 shape, colour, and texture features using linear classifiers and Artificial Neural Network (ANN) with an accuracy ranging from 67% to 86%.

This study aims to develop an effective computer vision system to classify some barley cultivars using Deep Convolutional Neural Network and help reduce the errors of traditional methods by avoiding human intervention. Few studies have been conducted on the classification of barley cultivars using artificial neural networks (Szczypińskia et al. 2015; Hailu & Meshesha 2016; Dolata & Reiner 2018; Kozlowski et al. 2019; Shi et al. 2021; Singh et al. 2021). For this aim, a novel image dataset of the seeds were created in order to classify the 14 barley cultivars. The images obtained were cropped in small sizes and made suitable for neural network training, and then data augmentation methods were applied to the training datasets. Six different deep convolutional neural networks were trained and evaluated using the Fine-Tuning and test-time augmentation method. A web-based barley classification tool was developed from the most successful network.

2. Material and Methods

2.1. Obtaining images of barley cultivars

In this study, the seeds of 14 barley (*Hordeum vulgare* L.) cultivars (Akar, Başgül, Burakbey, Bülbül 89, Çetin 2000, Durusu, Efes 98, Erciyes, Özen, Tarm 92, Tosunpaşa, Yalın, Yıldız and Zeynelağa) were evaluated which were obtained from Ankara Field Crops Research Institute in 2017. The barley seeds were photographed at 24 Bit 3456 × 5184 resolution using Canon EOS 600D camera to diagnose cultivars due to differences in surface morphology. A total of 56 high-resolution images (each include ~3000 barley seeds) of 14 barley cultivars were cropped, then the cropped images that did not contain barley seeds were deleted and a dataset of 2800 images was obtained. Figure 1 shows sample images of the seeds of 14 barley cultivars that differ morphologically.

Figure 1- Morphological surface images of 14 barley cultivars

2.2. Image preprocessing and dataset preparation

Image sizes used to train the convolutional neural network are crucial for training time and system performance. For this purpose, the images, each occupying 6 ~ 7 MB in memory, were cropped into 432 × 648 small images before being given to the neural network. Finally, images were resized to 256 × 256 dimensions and given to neural network input. Figure 2 shows the preprocessing of an image in the dataset.

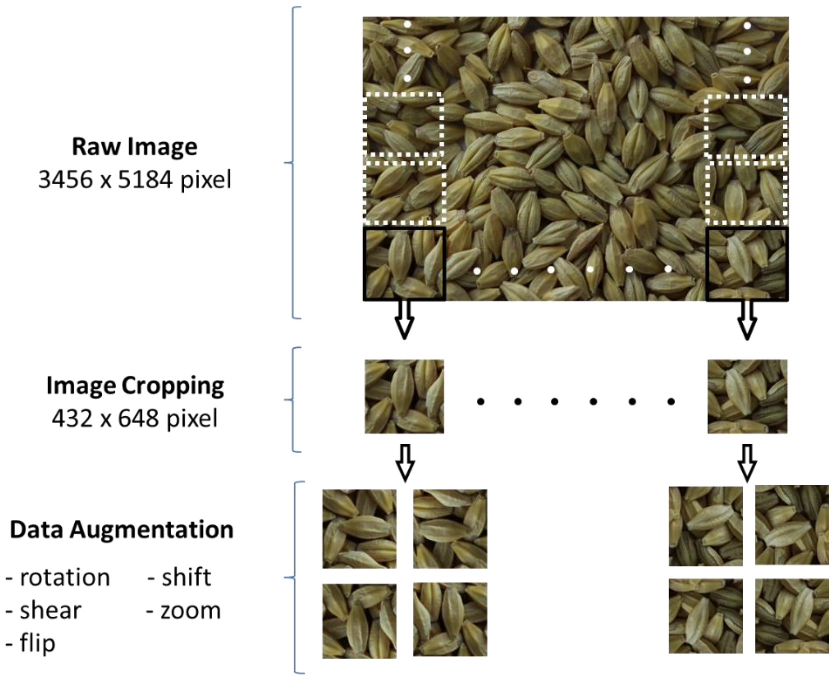

Figure 2- Preprocessing steps of raw image in a barley cultivar

All dataset was divided into 3 parts: training (60%), validation (20%), and testing (20%). Then, the images in the training dataset were subjected to 5 different data augmentation processes: rotation (90º), shear (25%), flip (horizontal, vertical), shift (width, height), and zoom (25%) (Table 1).

Table 1- Dataset for image classification of barley cultivars

	Number of images in the dataset			
Barley cultivars	***Train***	***Validation***	***Test***	***Total***
Akar	120	40	40	200
Başgül	120	40	40	200
Burakbey	120	40	40	200
Bülbül 89	120	40	40	200
Çetin 2000	120	40	40	200
Durusu	120	40	40	200
Efes 98	120	40	40	200
Erciyes	120	40	40	200
Özen	120	40	40	200
Tarm 92	120	40	40	200
Tosunpaşa	120	40	40	200
Yalın	120	40	40	200
Yıldız	120	40	40	200
Zeynelağa	120	40	40	200
Total number of augmented images	11760		**Total number of original images**	2800

2.3. Convolutional neural network architecture and transfer learning

The difference of convolutional neural networks from classical neural networks is that it determines which feature is more important and which feature is less important, with the millions of parameters it has obtained using different filters and methods. During these operations applied in layers: The initial and middle layers are revealed the edge features of the image and the shape and texture features of the image, respectively. The entire object is acquired towards in the final layers.

CNN now achieve high success in many common computer vision problems such as object detection, tracking, recognition, segmentation, classification, and so on compared to other traditional methods. In this success, the deepening of the network plays an important role by improving the layer structures and connections. In this study, six different deep neural network models consisting of DenseNet-121, DenseNet-169, DenseNet-201, InceptionResnetV2, MobileNetV2, and Xception were developed. These models have a functional network structure. In this structure, the data flow can branched and layer outputs can concatenated. Among these models, in addition to the traditional neural network connection of DenseNet networks, all layers had connections with all other layers, providing high accuracy and generalization potential for this network (Figure 3).

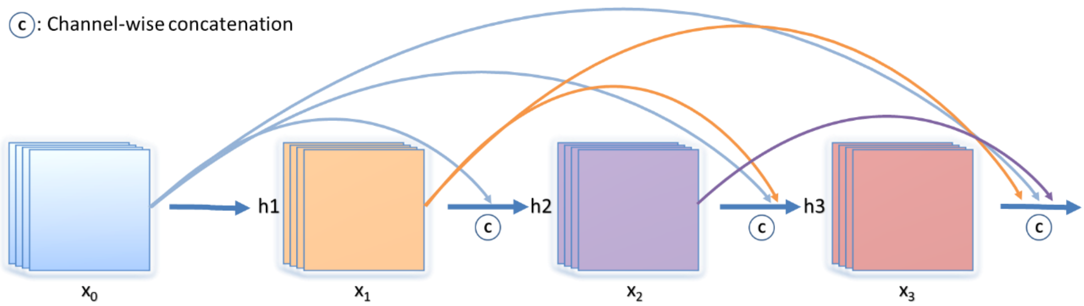

Figure 3- DenseNet neural network architecture (modified from Huang et al. 2017)

Unlike the shortcut links in the ResNet network, these links are not just $x_n = h_n(x_{n-1}) + x_{n-1}$ the sum of the values in the previous layer, but a combination of their values in all their previous layers $x_n = h_n([x_0, x_1, . . . , x_{n-1}])$. With these links, each layer uses as input feature-maps of all previous layers and sends its own feature-maps as input to all subsequent layers (Huang et al. 2017).

To create a modern deep CNN from scratch, determining many parameters such as filter dimensions, weights, layers, connections, and then training and testing the entire model requires high speed hardware and is a very time-consuming process. Instead, using a pre-trained network with thousands of categories and millions of images provides faster and more successful results. In our study, 6 different pre-trained models were used in the ImageNet dataset. Except for the top layers of Deep Convolution Neural Network (DCNN) architectures, the rest is called the 'base model'. To build our models, we replaced the original top layers with the following layers in sequence: The last layer of each base model is connected to the dropout layer with a probability of 0.5 and global average pooling layer, respectively, thus reducing the risk of overfitting. The feature map obtained from the previous layer was then fed into the first dense (fully connected) layer, which consists of 1024 neurons and has the ReLU activation function. Then it connects to the last dense prediction layer which has SoftMax activation function. The number of neurons in this layer is 14 according to the number of barley cultivars (Figure 4).

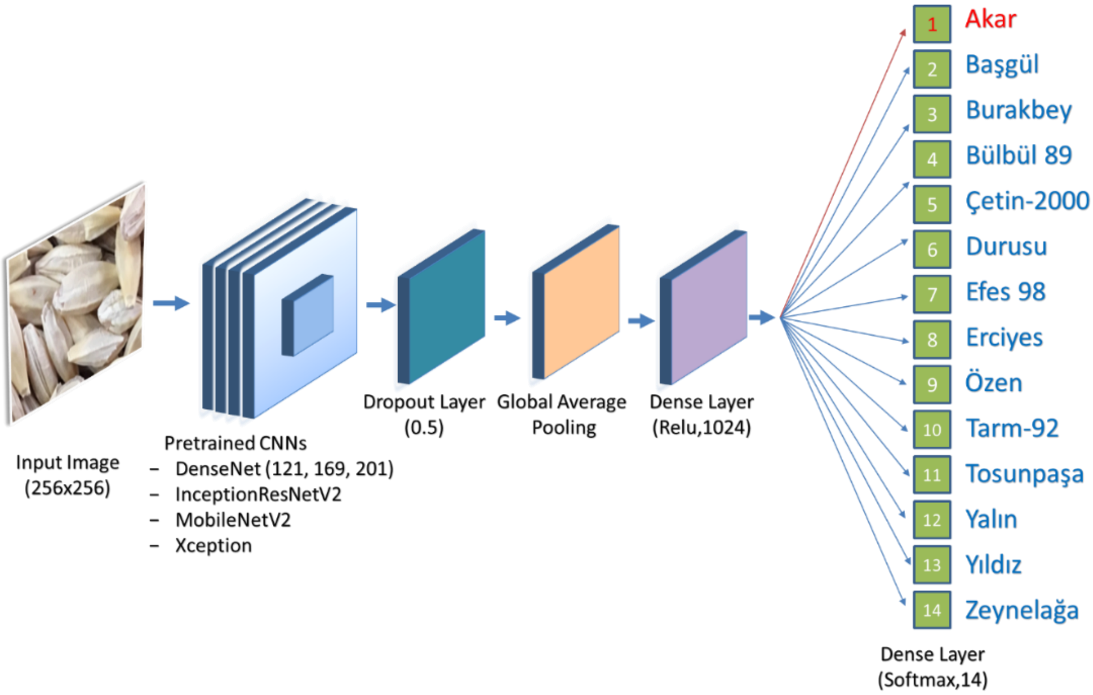

Figure 4- Identification of a barley cultivar with the transfer learning architecture of six different CNN models

A confusion matrix is used for evaluating the performances of classification model. This matrix, with as many rows and columns as the number of classes, compares the actual target values with those predicted by the model. With the help of this created matrix, the number of true positives (TP) (that is, the sum of the samples correctly predicted by the model in the calculated class), the number of true negatives (TN) (that is, the sum of the samples correctly predicted by the model in the except calculated class - the values shown in bold in the matrix), the number of false positives (FP) (that is, the sum of samples that the model predicted in this class even though it is not in the calculated class - values below and above the gray values in the matrix), and the number of false negatives (FN) (that is, in the calculated class, but the model predicted in a different class - values to the right and left of the gray values) were calculated for each class. With the help of these values, the precision (1), recall (2), F1 Score (3), and accuracy (4) rates of each barley cultivars of the CNN model were calculated (Table 4).

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{3}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

3. Results and Discussion

The code in this study was written by Python and run using the Colab environment. Tensorflow and Keras deep learning frameworks were used to define the CNN models. Six different ImageNet pre-trained CNN models such as DenseNet-121, DenseNet-169, DenseNet-201, InceptionResnetV2, MobileNetV2, and Xception have been fine-tuned. To train the models, the maximum epoch value among 30, 60 and 90 was determined as 60. Since the model could not be trained any more, the program stopped automatically and the maximum epoch value of 30 was reached. In the models, stochastic gradient descent was used as a learning algorithm and categorical cross entropy as loss function. The learning rate starts with 0.01. If the validation loss does not decrease for a total of 5 epochs the learning speed automatically reduce by 0.75. If it does not decrease for a total of 10 epochs, training is automatically stopped. In this way, the model with the lowest loss value was calculated in every 5 epochs and the weight matrix was saved without overfitting. The epochs, accuracy and loss values of the models converging to the lowest validation loss value were obtained during the training performances (Table 2).

Table 2- Training performances of the CNN in current study

Model	*Epochs to Converge*	*Training Loss*	*Training Accuracy (%)*	*Validation Loss*	*Validation Accuracy (%)*
DenseNet-121	22	0.1940	94.01	0.1972	93.96
DenseNet-169	26	0.1504	94.82	0.1902	94.29
DenseNet-201	28	0.1988	93.75	0.2352	92.71
InceptionResNetV2	21	0.2125	93.12	0.2428	91.45
MobileNetV2	30	0.2407	91.46	0.2543	91.23
Xception	18	0.2824	90.76	0.2975	90.18

According to the training performance results of the models (Table 2), it is understood that DenseNet models were obtained lower errors and higher performance results compared to other models. Among all models, the DenseNet-169 model was the best performing model with 94.29% validation accuracy. In order to determine the best epoch value, the DenseNet-169 model was trained with 3 different epoch values (30, 60, and 90) and early stopping method, and the highest accuracy rate was obtained in 60 epochs (Figure 5a). In addition, the model was trained with and without the dropout layer to observe the effectiveness of the dropout layer in the DenseNet-169 model (Figure 5b). Without the dropout layer, it was observed that the model was tendency to overfitting so that although the training loss continued to decrease after a while in the loss graph of the model, the validation loss remained constant and the gap between the training loss and the validation loss increased (Figure 5b).

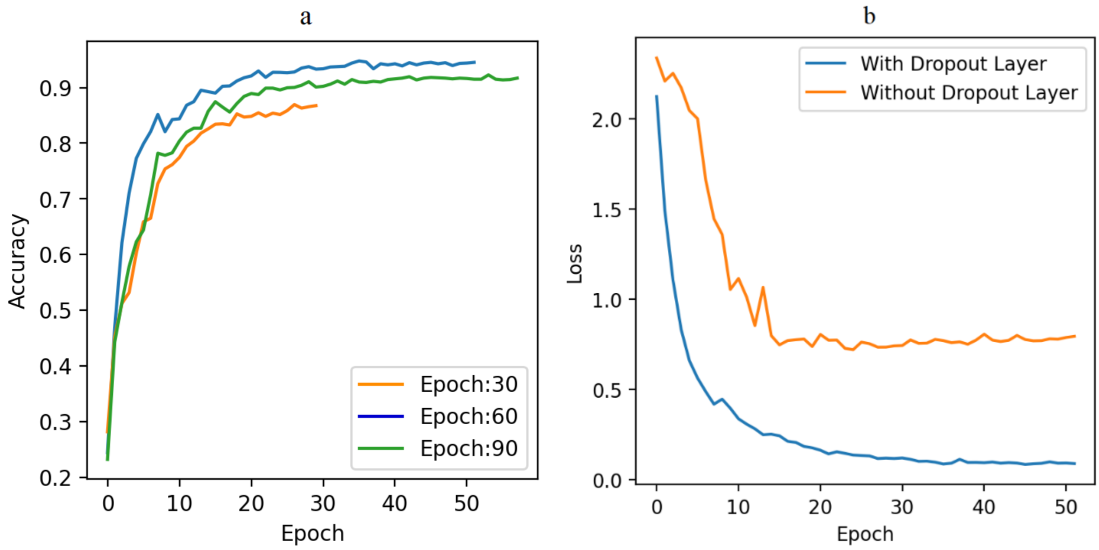

Figure 5- The graph of training accuracy with respect to different epoch values (a) and loss graph with and without the dropout layer in the DenseNet-169 model (b) using the data set of 14 barley cultivars

Recently, various methods have been developed to improve the performance of deep learning models, the test-time augmentation method is one of them (Howard 2013). During the testing of the trained model in this method, unlike the traditional network test method, in addition to a single prediction output for the original image, more predictions output is obtained as the number of augmented images. These predictions are then aggregated and the class with the highest prediction percentage becomes the classification final result (Figure 6).

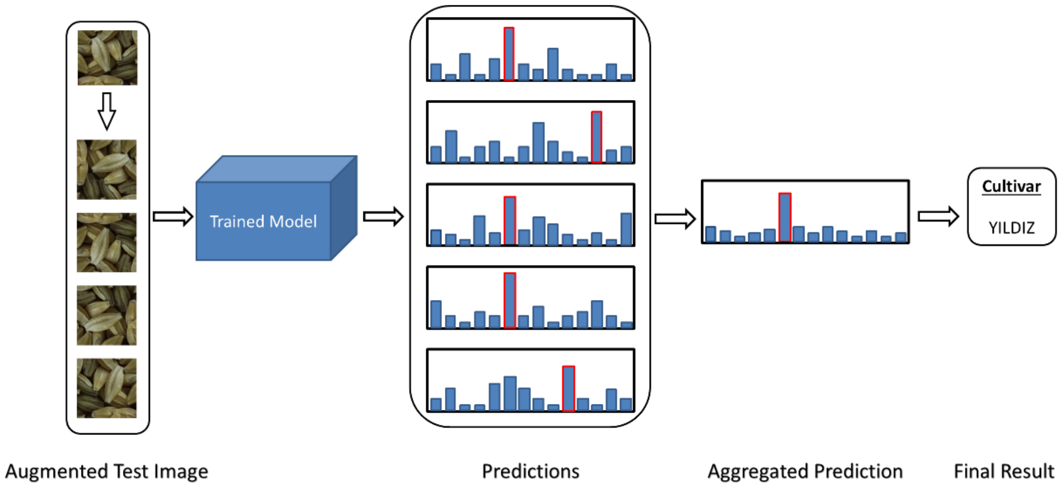

Figure 6- Flowchart designed to identify a barley cultivar at test time by image augmentation

As a result of the experiment performed with the 4 different image augmentations (rotation, vertical flip, horizontal flip, shear) used in the test-time augmentation method on the test data set, the classification accuracy increased by 1.78% and reached 96.07%. In our current study, confusion matrix was created from the classification results in order to perform detailed performance analyses of the DenseNet-169 model (Table 3).

Table 3- Confusion matrix of the tested CNN model for the classification of barley cultivars

Barley cultivars	*Akar*	*Başgül*	*Burakbey*	*Bülbül 89*	*Çetin 2000*	*Durusu*	*Efes 98*	*Erciyes*	*Özen*	*Tarm 92*	*Tosunpaşa*	*Yalın*	*Yıldız*	*Zeynelağa*
Akar	**34**	0	0	0	0	2	0	0	0	0	4	0	0	0
Başgül	0	**36**	4	0	0	0	0	0	0	0	0	0	0	0
Burakbey	0	0	**40**	0	0	0	0	0	0	0	0	0	0	0
Bülbül 89	0	0	0	**38**	0	0	2	0	0	0	0	0	0	0
Çetin 2000	0	0	0	0	**40**	0	0	0	0	0	0	0	0	0
Durusu	0	0	0	0	0	**40**	0	0	0	0	0	0	0	0
Efes 98	0	0	0	0	0	0	**40**	0	0	0	0	0	0	0
Erciyes	0	0	0	2	0	0	0	**38**	0	0	0	0	0	0
Özen	0	0	0	0	0	0	0	0	**40**	0	0	0	0	0
Tarm 92	0	0	0	0	0	0	0	0	0	**40**	0	0	0	0
Tosunpaşa	2	0	0	0	0	0	0	0	0	0	**38**	0	0	0
Yalın	0	0	0	0	0	0	0	0	0	0	0	**40**	0	0
Yıldız	0	0	0	0	0	4	0	0	0	0	0	0	**36**	0
Zeynelağa	2	0	0	0	0	0	0	0	0	0	0	0	0	**38**

When model classification performance rates (Table 4) are examined, it is seen that Akar and Tosunpaşa cultivars have the lowest F1 scores. It can be argued that this result is due to the fact that these two cultivars are very similar to each other polymorphically.

Table 4- Classification performance rates of the tested CNN model for the recognition of barley cultivars (%)

Barley Cultivars	*Precision*	*Recall*	*F1 Score*
		%	
Akar	89.47	85.00	87.18
Başgül	100.0	90.00	94.74
Burakbey	90.91	100.0	95.24
Bülbül 89	95.00	95.00	95.00
Çetin 2000	100.0	100.0	100.0
Durusu	86.96	100.0	93.02
Efes 98	95.24	100.0	97.56
Erciyes	100.0	95.00	97.44
Özen	100.0	100.0	100.0
Tarm 92	100.0	100.0	100.0
Tosunpaşa	90.48	95.00	92.68
Yalın	100.0	100.0	100.0
Yıldız	100.0	90.00	94.74
Zeynelağa	100.0	95.00	97.44
		Accuracy	**96.07**

3.1. Web-based model deployment

A web application has been developed to eliminate the different needs of the trained model, such as complex background applications, architectural connections, and communication protocols and to enable to be used the platform-independent by the end user. TensorflowJS application was used to convert the model to API format. Based on the developed web application, the classification process of the image uploaded by the user was performed without requiring any additional installation, such as any driver, library, and so on. In this context, the web-based classifier is available at https://fatih-tr.github.io/barley.

The performances of the convolutional neural networks highly depend on the characteristics of the training data. Our methods such as using images containing more seeds in a single image, data augmentation in the training data set, and adding a dropout layer to the network structure (because CNN tends to overfitting it causes generalization to decrease) provide the CNN model to perform better than similar studies. Demir et al. (2019) used some size and shape features of almond cultivars and comparison of the almond shapes with elliptic Fourier descriptors. Kurtulmuş (2021)has determined the best DCNN models to identify sunflower seeds and showed that the identification of sunflower seeds was feasible using deep learning technology. This researcher suggested that the main limitation of this work is that it requires manual adjustment of sunflower seeds before they are captured on camera. In Table 5, the results obtained in this study were compared with the studies on the classification of barley cultivars in recent years (Hailu & Meshesha 2016; Dolata & Reiner 2018; Kozlowski et al. 2019; Shi et al. 2021; Singh et al. 2021). Dolata & Reiner (2018) reported an accuracy rate of 97.24%. If they calculated according to the confusion matrix as in our study (Equation 4), the accuracy rate would have been calculated as 87.68%. According to our research with 14 barley cultivars, the fine-tuned DenseNet-169 model was performed better than other models and the state-of-the-art literature. On the other hand, Singh et al. (2021) achieved the best accuracy rate of 98.38% with CNN because of near-infrared hyperspectral imaging.

Table 5- Comparison of accuracy rates of barley cultivars classified using ANN and CNN

References	*Number of barley cultivars*	*Method*	*Accuracy (%)*
Szczypińskia et al. (2015)	11	ANN	86.90
Hailu & Meshesha (2016)	4	ANN	95.10
Dolata & Reiner (2018)	8	CNN	97.24
Kozłowski et al. (2019)	6	CNN	93.21
Shi et al. (2021)	9	CNN	95.70
Singh et al. (2021)	35	CNN	98.38
Current Study	**14**	**CNN**	**96.07**

4. Conclusions

This study consisted of literature review, obtaining of seeds, taking images, preprocessing images, defining, training, and testing of CNN models, and deploy of web-based application. At the first stage, the seeds brought together were preserved in appropriate conditions in the laboratory environment, the photos were taken, then the images were cropped to small sizes and the training images were augmented. With this image data set, six different networks were trained and evaluated. According to the test results performed, the DenseNet-169 CNN model showed the best performance by classifying 14 different barley seed cultivars with 96.07% test accuracy. At the last stage, a web-based application was developed, enabling the classification process from all web tools to be done independently from the platform.

The successful result obtained from the classifier will be the basis for the classification of other grain cultivars such as wheat, rice, and corn. In later studies, the success rate can be increased with the different deep learning models and classification techniques. The performance rate could be improved by increasing the number and quality of the images using the different types of microscopes. The classification of other cereal cultivars and the detection of foreign objects in their contents were targeted as the next studies.

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