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Classification of Distortions in Agricultural Images Using Convolutional Neural Network

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ABSTRACT

Monitoring products is important for quality and ripening control in an efficient agricultural production process. Monitoring is mostly done with captured images and videos in accordance with the developed technology. The quality of these images and videos directly affects the evaluation. If there is a distortion in image or video, first of all, this distortion must be detected and classified to eliminate. In this study, a method is presented to classify distortions in agricultural images. Eleven different distortions are synthetically added to agricultural images. A convolutional neural network (CNN) is designed to classify distorted images. The designed CNN model is tested with four different datasets obtained from various agricultural fields. Also the designed CNN model is compared with previously presented CNN architectures. The results are evaluated and it is seen that the designed CNN model successfully classifies distortions.

Keywords: Distortion classification, Agricultural image, Convolutional neural network

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Evrişimli Sinir Ağı Kullanarak Tarımsal Görüntülerdeki Bozulmaları Sınıflandırma

ÖZ

Ürünlerin izlenmesi, etkili bir tarımsal üretim sürecinde kalite ve olgunlaşma kontrolü için önemlidir. İzleme, gelişen teknolojiye uygun olarak çoğunlukla çekilen görüntü ve videolarla yapılmaktadır. Bu görüntü ve videoların kalitesi değerlendirmeyi doğrudan etkilemektedir. Görüntü veya video da bir bozulma varsa, öncelikle bu bozulmanın ortadan kaldırılması için tespit edilmesi ve sınıflandırılması gerekmektedir. Bu çalışmada, tarımsal görüntülerdeki bozulmaları sınıflandırılmak için bir yöntem sunulmaktadır. On bir farklı bozulma tarımsal görüntülere sentetik olarak eklenmiştir. Bozuk görüntüleri sınıflandırmak için bir evrişimli sinir ağı (ESA) tasarlanmıştır. Tasarlanan ESA modeli, çeşitli tarım alanlarından elde edilen dört farklı veri seti ile test edilmiştir. Ayrıca tasarlanan ESA modeli daha önce sunulan ESA mimarileri ile karşılaştırılmıştır. Sonuçlar değerlendirilmiş ve tasarlanan ESA modelinin bozulmaları başarıyla sınıflandırdığı görülmüştür.

Anahtar Kelimeler: Bozulma sınıflandırma, Tarımsal görüntü, Evrişimli sinir ağı

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1. Introduction

Image distortions may occur due to various reasons during or after acquisition. When it is necessary to analyse and use the information obtained from the image, these distortions affect the information undesirably. Distortion classification is one of the processes that supports image restoration and image quality assessment (IQA).

Many academic studies examining or using distortion classification are presented. Chetouani et al. [1] propose an image quality estimation approach. The proposed method classifies distortions by using linear discriminant analysis to decide optimal image quality measure. They obtain around 15% better results. Lee and Kim [2] present a new IQA method based on distortion classification and a new metric. The presented method achieves better results than the other 15 existing methods. Alaql et al. [3] examine different classification techniques and different features for image distortions. Multiclass classifier with logistic regression is determined as best performing. They state that the proposed model outperforms state-of-the-art classification methods. Wang et al. [4] suggest a CNN based method to recognize distortion and evaluate image quality. The proposed method is superior to several state-of-the-art methods according to the results. A new image distortion classification algorithm which uses the generalized Benford's law is proposed by Al-Bandawi and Deng [5]. Based on experimental results, the proposed algorithm outperforms existing ones. Ha et al. [6] introduce a new selective deep convolutional neural network to classify distorted images. An extra small CNN is improved to recognize distortion type and degree. Introduced network performs up to 2.18x better than the previous state-of-the-art deep convolutional neural networks. Messai et al. [7] propose an approach which recognizes the type of distortion in stereoscopic images. Support vector machine is used to identify distortion type. Proposed classifier provides good accuracy. Buczkowski and Stasiński [8] present two different CNN architectures for distortion classification. Both CNNs have better results than the method which they compared. Liang et al. [9] suggest a deep multitask CNN model to identify image distortion. They state that the algorithm performs well on several databases. An IQA strategy for laparoscopic images is proposed by Khan et al. [10]. Neural network is used for distortion classification and quality ranking. Encouraging results are obtained. The potential of deep visual representations to characterize image distortions is examined by Bianco et al. [11]. The results show that deep visual representations are useful for this process. Roccapriore et al. [12] introduce a study which identifies and corrects distortions in scanning transmission electron microscopy. Zhang et al. [13] propose a quality assessment approach that includes distortion analysis for distorted stereoscopic images. As compared with other state-of-the-art algorithms, proposed method performs better on several 3-dimension image datasets. Yan et al. [14] present a no-reference IQA study consisting of distortion identification and targeted quality evaluation. They state that the proposed method outperforms state-of-the-art no-reference IQA methods. Liang et al. [15] suggest a distortion analysis algorithm for image processing systems. Experimental results show that proposed algorithm is effective. Wang et al. [16] propose a method for image restoration. The type and level of distortion is detected then this information is used for image restoration process. A superior performance is achieved by the proposed method. Fazlali et al. [17] present a study which removes rain streaks and snow particles in images by using CNN based distortion classifier as a part of method. They get better results than existing methods. A no-reference IQA study is proposed by Xu and Jiang [18]. They use a perception-based distortion classification method in their study that provides a good performance. Li et al. [19] introduce a multi-channel attention network to classify underwater degraded images. The proposed network achieves 98.737% classification accuracy.

In agricultural fields, the use of technological tools becomes increasingly important. Especially, images acquired from fixed cameras or cameras placed on moving vehicles such as drone and robot are used to solve many problems. Silva et al. [20,21] present studies that classify and recognize distortions in agricultural images acquired by unmanned aerial vehicle. CNN is used in both studies. In [20], synthetically generated linear distortions are classified among themselves according to the parameters from which they are created. In [21], non-linear distortion is recognized.

In this study, a method is presented to classify distortions in agricultural images. Firstly, eleven different distortions are applied to images from four datasets. Then, a designed CNN model classifies distorted images. Obtained results are evaluated and designed CNN model is compared with previously presented CNN architectures.

The contributions of the proposed work can be listed as:

- It is a comprehensive study on the classification of distortions in agricultural images.
- Four different datasets obtained from various agricultural fields are used. Also, these datasets were created by using various acquisition tools. In this context, it is a highly valid study.
- It evaluates not only the distortions frequently used in the literature, but also the distortions that can be caused by mobile vehicles such as unmanned aerial vehicles.

The rest of the paper is organized as follows: Section 2 presents materials and method. Section 3 introduces experimental results and evaluations. Conclusion is addressed in Section 4.

2. Materials and Method

Used datasets, applied distortions and convolutional neural network model are explained in detail under different headings in this section.

2.1. Agricultural image datasets

Four different datasets with various contents are used in this study. Information about the existence of the first three datasets was obtained from [22].

The first one is Plant Seedlings dataset [23] created with the help of a stable ground platform. This dataset contains total 5544 images with 12 different plant classes which are maize, common wheat, sugar beet, scentless mayweed, common chickweed, shepherd's purse, cleavers, charlock, fat hen, cranesbill, black-grass and loose silky-bent. Also, resolutions of images range from 49x49 to 3991x3457 pixels. Samples from the dataset are shown in Fig. 1.

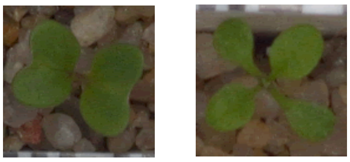


Figure 1. Samples from Plant Seedlings dataset [23]

The second is MinneApple dataset [24]. This dataset consists of apple tree images taken with a mobile phone camera. 1000 image pieces with 200x200 pixels resolution were cropped from dataset images. These images focused on apples on trees are used in the study. Cropped samples from the dataset are shown in Fig. 2.

Figure 2. Cropped samples from MinneApple dataset [24]

The third is DeepFruits dataset [25] which has total 584 images of 7 different kinds of fruit. These kinds are apple, avocado, capsicum, mango, orange, rock melon and strawberry. Resolutions of images range from 128x96 to 4000x3000 pixels. Also, this dataset was created by using a ground based platform. Samples from the dataset are shown in Fig. 3.

Figure 3. Samples from DeepFruits dataset [25]

The fourth is CoFly-WeedDB dataset [26]. This dataset consists of images obtained from the flight of an unmanned aerial vehicle over a cotton field which has weeds. 1830 image pieces with 200x200 pixels resolution were cropped from dataset images to use. Cropped samples from the dataset are shown in Fig. 4.

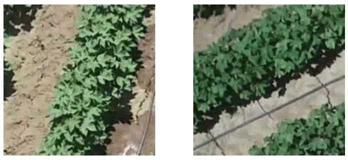


Figure 4. Cropped samples from CoFly-WeedDB dataset [26]

In this study, second and third datasets are used combining. Eleven different distortions are applied separately to each image in the datasets. Total number of images in the datasets, including new created ones, is given in Table 1.

Table 1. Total number of images in the datasets

Dataset	**Number of images in each class**	**Total number of images**
Plant Seedlings	5544	66528
MinneApple&DeepFruits	1584	19008
CoFly-WeedDB	1830	21960

2.2. Distortions

Eleven types of distortion are exanimated. These are Gaussian noise, white&black noise, Gaussian blur, low brightness, high brightness, rotation right, rotation left, translation right&down, translation left&up, distorted perspective 1 and distorted perspective 2. Rotation, translation and perspective distortions are selected inspired by [20]. Each of these distortions was synthetically added to the images in datasets by a developed software. Thus, eleven different distorted images were generated from each original image.

2.2.1. Gaussian noise

Gaussian noise is applied to images by using Gaussian probability distribution [27] defined in Eq. (1). Mean (μ) and standard deviation (σ) values are chosen as 0 and 0.5 respectively.

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{1}$$

2.2.2. White&black noise

Pixels selected randomly at the rate of 5% from the images are transformed into white colour or black colour to create noises. The ratio of white pixels and black pixels is set to the equal in this process. This type of noise is named as white&black noise in this study.

2.2.3. Gaussian blur

13x13 kernel calculated by using Eq. (2) [28] is used for Gaussian blur. Standard deviation (σ) is determined as 1.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

2.2.4. Low brightness and high brightness

Brightness of images is changed by increasing or decreasing colour values of pixels. In this study, colour values of pixels are decreased or increased by 40 units to achieve low brightness or high brightness.

2.2.5. Rotation right and rotation left

Rotated images are obtained by rotating original images to the right or left. The angle of rotation is set 15° for this process.

2.2.6. Translation right&down and translation left&up

First type of translated image is created by translating original images right and down. Second type is created by translating original images left and up. In these processes, translated amount is 30 pixels for both directions.

2.2.7. Distorted perspective 1 and distorted perspective 2

These types of distortions are generated by distorting the perspective of original images in two different ways.

After rotation, translation and distorting perspective processes, pixel colour losses occur in the images. These losses are recovered by using average colour values of other pixels. Sample of original image from CoFly-WeedDB dataset [26] and distorted images generated from it are shown in Fig. 5.

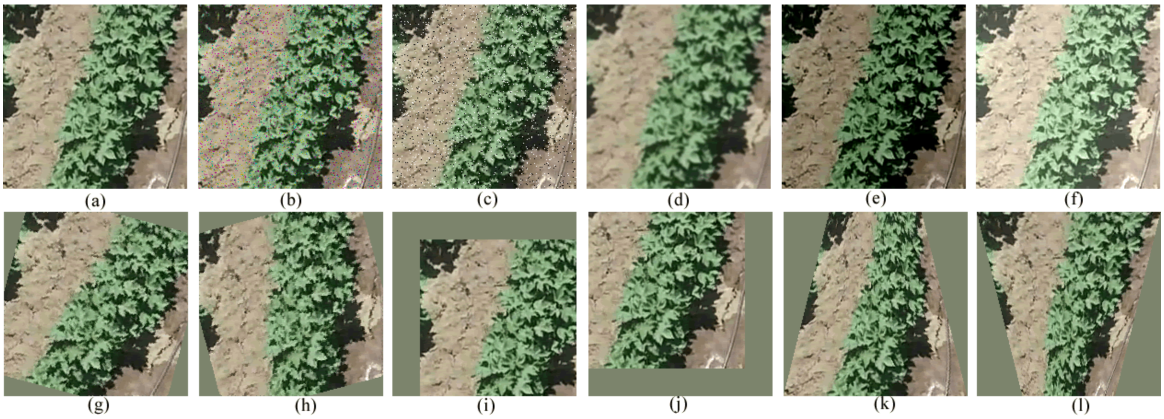


Figure 5. Sample of original image from CoFly-WeedDB dataset [26] and distorted images generated from it (a) original (b) Gaussian noise (c) white&black noise (d) Gaussian blur (e) low brightness (f) high brightness (g) rotation right (h) rotation left (i) translation right&down (j) translation left&up (k) distorted perspective 1 (l) distorted perspective 2

2.3. Convolutional neural network model

Convolutional neural networks are developed in accordance with the use of grid structured inputs such as two dimensional images [29]. In this study, a CNN model is designed to classify distorted agricultural images. The designed CNN model has 4 convolutional layers and 2 max pooling layers in the part of feature extraction. 3x3 kernel and ReLU activation function are used in all convolution layers but each convolution layer contains different number of filters. First two convolution layers which include 24 and 32 filters respectively are added back to back. A max pooling layer implemented using 2x2 kernel follows them. Third convolution layer has 64 filters and second max pooling layer follows it. Finally, fourth convolution layer has 72 filters. In the classifier part, there are 3 dense layers. First two dense layers have 96 neurons and ReLU activation function. Third dense layer is output layer. It has 12 neurons because there are a total of 12 classes representing 1 clean and 11 distorted images. Also, softmax is determined as activation function. Architecture of the designed CNN model is shown in Fig. 6.

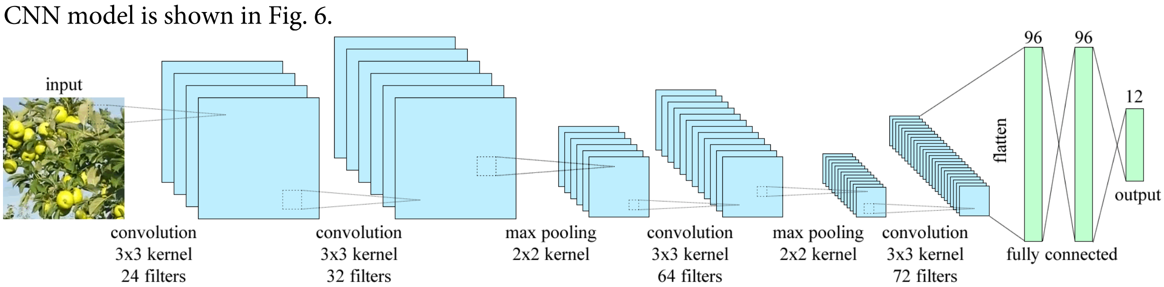


Figure 6. Architecture of the designed CNN model

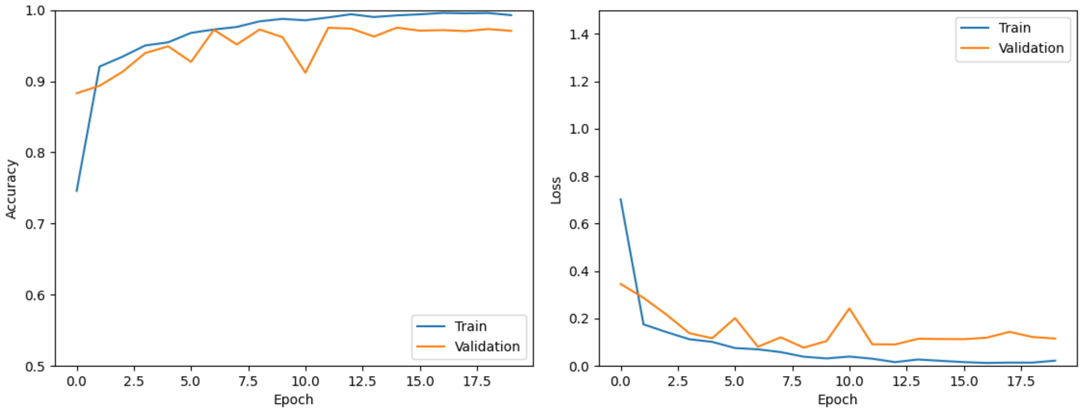
3. Experimental Results

Two different experiments were carried out and the results were evaluated. In the first one, the proposed CNN model was tested with agricultural image datasets. Input image dimensions, number of outputs, number of epochs and number of steps per epoch were determined as 150x150 pixels, 12, 20 and 400 respectively. The datasets were divided into 3 parts: 70% train, 10% validation and 20% test. Accuracy values were calculated separately. The obtained accuracy values are given in Table 2. When accuracy values in Table 2 are examined, it is seen that train accuracy values are close together. For each dataset, train accuracy value is higher than validation and test accuracy values. The dataset created by combining MinneApple dataset [24] and DeepFruits dataset [25] has slightly lower validation and test accuracy values than others.

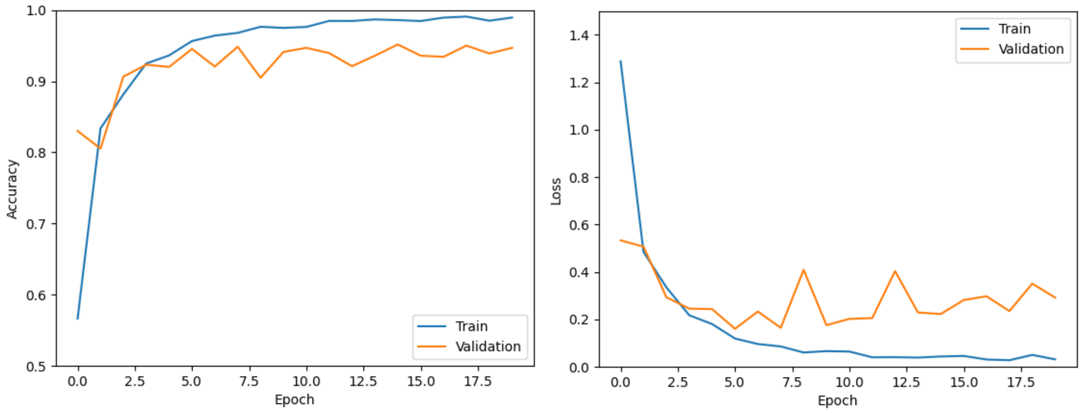
Table 2. Accuracy values of the proposed CNN model

Dataset	**Train accuracy**	**Validation accuracy**	**Test accuracy**
Plant Seedlings	0.9984	0.9706	0.9731
MinneApple&DeepFruits	0.9975	0.9468	0.9331
CoFly-WeedDB	0.9979	0.9913	0.9877

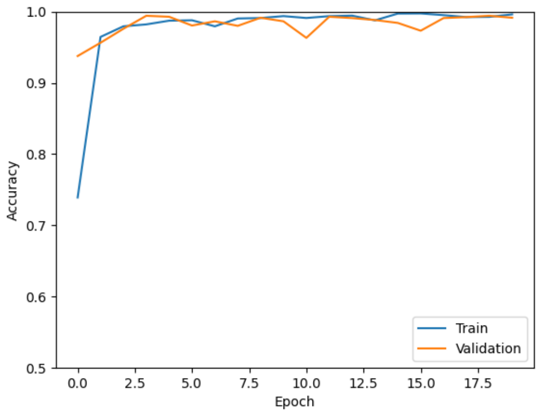
Accuracy vs. epoch graphs and loss vs. epoch graphs formed during training for each dataset are shown in Fig. 7, Fig. 8 and Fig. 9.



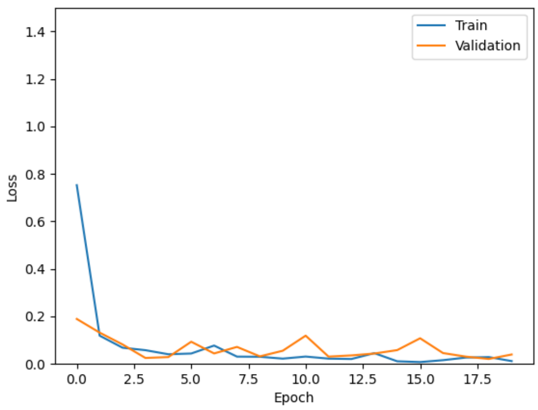
(a) (b)
Figure 7. (a) Accuracy vs. epoch graph (b) loss vs. epoch graph of Plant Seedlings dataset [23]



(a) (b)
Figure 8. (a) Accuracy vs. epoch graph (b) loss vs. epoch graph of MinneApple[24]&DeepFruits [25] dataset



(a)



(b)

Figure 9. (a) Accuracy vs. epoch graph (b) loss vs. epoch graph of CoFly-WeedDB [26] dataset.

In the second experiment, the proposed CNN model was compared with LeNet-5 [30], AlexNet [31] and VGG-11 [32]. Simple and less layered architectures such as the proposed CNN model were preferred for comparison. The dataset created by combining MinneApple dataset [24] and DeepFruits dataset [25] was used in the experiment. Unlike the first experiment, number of steps per epoch was determined as 50. Other experiment settings were not changed. The accuracy values and total number of parameters are given in Table 3. The results illustrate that LeNet-5 [30] has the lowest accuracy values. Proposed CNN model has higher accuracy values than LeNet-5 [30] and AlexNet [31]. In addition to the network architecture, variables such as kernel size and activation function affect the success of the network. This situation is effective in obtaining these results. Also, the proposed CNN model has the highest train accuracy value but VGG-11 [32] has the highest validation and test accuracy values. Proposed CNN model and VGG-11 [32] have close accuracy values but their total number of parameters which affects processing time is very different. VGG-11 [32] has more parameters and processing time.

Table 3. Accuracy values and total number of parameters of CNN models.

CNN model	**Train accuracy**	**Validation accuracy**	**Test accuracy**	**Total number of parameters**
LeNet-5	0.1294	0.1273	0.1217	9,124,096
AlexNet	0.6501	0.6470	0.6336	30,024,460
VGG-11	0.9688	0.9510	0.9510	59,609,484
Proposed	0.9922	0.9189	0.9176	7,605,396

4. Conclusion

In this study, a CNN-based classification method for distortions in agriculture images is presented. In order to make this work comprehensive, four different datasets obtained from various agricultural fields and eleven different distortion types were used. Also, the CNN model was designed to be simple in order to save process time. Two different experiments were set to test the designed CNN model. In the first one, the designed CNN model classified distortions in each dataset. In the second one, the designed CNN model was compared with LeNet-5 [30], AlexNet [31] and VGG-11 [32]. According to the results obtained from both experiments, the designed CNN model has high accuracy values.

This study will support future studies on distortion classification, convolution neural networks and agricultural images.

Conflict of Interest Statement

The authors declare that there is no conflict of interest.

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