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Research paper

Waste management using an automatic sorting system for carrot fruit based on image processing technique and improved deep neural networks

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ABSTRACT

In this study, we address the problem of classification of carrot fruit in order to manage and control their waste using improved deep neural networks. In this work, we perform a deep study of the problem of carrot classification and show that convolutional neural networks are a straightforward approach to solve the problem. Additionally, we improve the convolutional neural network (CNN) based on learning a pooling function by combining average pooling and max pooling. We experimentally show that the merging operation used increases the accuracy of the carrot classification compared to other merging methods. For this purpose, images of 878 carrot samples in various shapes (regular and irregular) were taken and after the preprocessing operation, they were classified by the improved deep CNN. To compare this method with the other methods, image features were extracted using Histograms of Oriented Gradients (HOG) and Local Binary Pattern (LBP) methods and they were classified by Multi-Layer Perceptron (MLP), Gradient Boosting Tree (GBT), and K-Nearest Neighbors (KNN) algorithms. Finally, the method proposed based on the improved CNN algorithm, was compared with other classification algorithms. The results showed 99.43% of accuracy for grading carrot through the CNN by configuring the proposed Batch Normalization (BN)-CNN method based on mixed pooling. Therefore, CNN can be effective in increasing marketability, controlling waste and improving traditional methods used for grading carrot fruit.

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1. Introduction

Maintaining safety of agricultural products in the post-harvest stage becomes highly important when trying to have sustainable agriculture. Reducing waste is directly related to the safety of food and agricultural products. So, it is currently considered as a topic worthy of immediate attention by macro-level policy-makers in different countries. Of the 67 million tons of the agricultural products produced in Iran every year, 20 million tons turn into agricultural waste in the post-harvest stage; a figure that makes up more than 30% of the total annual production. That value is equivalent to the food of 20 million people in a year. In fact, not only are 30% of agricultural products destroyed, but 30% of water consumed in agriculture is also wasted. Thus, this much waste in agricultural products and in water can be largely controlled, and the products and water can be saved through proper harvesting, transportation, warehousing and processing methods. Reducing agricultural waste can help increase Gross Domestic Product (GDP) and the added value of the agricultural products (Shahgholi et al., 2020; Jahanbakhshi et al., 2019; Ahangarnezhad et al., 2019; Jahanbakhshi and Salehi, 2019).

Carrots are one of the most widely consumed agricultural products in the world. They are a good source of vitamins and minerals that are good for the body and the human health. Carrots are a good source of carotenoids (vitamin A precursors) that are helpful in improving vision (Jahanbakhshi and Kheiralipour, 2020).

Carrots are used mostly as a raw edible product. One of the carrot image analysis problems is its shape non-homogeneity. Despite the fact that carrots with undesirable shapes do not have any problems with respect to their nutritional properties, customers do not commonly reach out for them in the market. As a result, carrots remain in the market for a long time and this leads to material loss increase. So, in order to increase its marketability and reduce its wastage, appropriate methods must be adopted for sorting and packaging the carrot products.

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Qualitative evaluation of agricultural products in the past was traditionally done by experts and through the eyes and hands of human inspectors. Evidently, in that method the performance is slow and the traditional methods proved to be expensive and inefficient in responding to the increase in consumers' demands since there appeared the need to higher quality products and faster sorting procedures. One of the most basic and important operations after harvest is the sorting of agricultural products based on their quality and shape. Sorting operations assist customers in recognizing products quality more easily and leads to a more organized distribution and supply of agricultural products (Momeny et al., 2020; Azarmdel et al., 2020).

Machine learning and computer vision have made huge progress in addressing real image analysis problems during the recent decades. Visual machine systems can be used to control the quality of food products by ensuring the accuracy and uniformity of the control process. Also, the use of computer vision systems for objective and non-destructive evaluation of food products has been proved to be successful in different scenarios (Singh et al., 2020; Fashi et al., 2019; Beyaz et al., 2019; Azarmdel et al., 2019).

In a study, Jahanbakhshi et al. (2020) classified sour lemons based on apparent defects using deep convolutional neural networks. They reported that the classification accuracy for the CNN was 100%. Biswas et al. (2020) proposed a robust multi-label fruit classifier based on deep CNNs. They reported a classification accuracy of 98% for four classes of 1200 fruit images. Steinbrener et al. (2019) classified hyperspectral fruit and vegetables using CNN. The results of their research showed that hyperspectral image data increased the average classification accuracy from 88.15% to 92.23%. Kheiralipour and Pormah (2017) classified cucumber fruits based on their appearance shape using image processing techniques and artificial neural networks (ANN). They reported that ANN classification accuracy was 97.1%. Przybyło and Jabłoński (2019) used deep convolutional neural networks to diagnose oak acorn viability. They reported accuracy of 85% for the deep neural network.

Much research has been done on the classification of agricultural products such as apple (Wu et al., 2020; Bargoti and Underwood, 2017), tomatoes (Foysal et al., 2020), orange (Ganesh et al., 2019), potato (Marino et al., 2019), peaches (Sun et al., 2019), pineapple (Nawawi et al., 2018), barley (Kozłowski et al., 2019) and date (Nasiri et al., 2019) using image processing techniques and convolutional neural networks.

Researchers have reported that improper shapes of agricultural products are one of the most important factors in increasing agricultural waste due to the fact that unfavorable shapes of the products reduce their marketability (Momeny et al., 2020; Kheiralipour and Pormah, 2017; Fu et al., 2016).

Therefore, a market standard for agricultural products is the shape and the appearance of them. Irregular shapes of the carrot fruits are caused by the genetic disorders in their development. These irregular shapes result in poor marketability and cause the product to remain unsold in the market for a long time and decay. However, adopting suitable methods of quality grading and, proper packaging of this product can prevent its wastage and increase its marketability. This study aims at proposing a practical method based on improved deep CNN to accurately classify carrot fruit and apply it in an automatic industrial computer vision system. Two important criteria for the assessment of such a method are its accuracy and practicality in grading the product.

2. Materials and methods

2.1. Fruit preparation and imaging

In this study, fresh carrot fruits were purchased from a farmer in Kermanshah-Iran. In total, 878 carrot samples with different shapes (450 carrot samples with regular shape and 428 carrot samples with irregular shape) were selected (Fig. 1). Then, using the imaging system, the image of the samples was acquired (Fig. 2). The imaging system had a lighting box including two LED lamps as well as a camera (Canon, Japan).

2.2. Preprocessing images

In this study, pre-processing and classification are done by removing the background image. Also, carrot images have a large size (4128 × 3096 pixels), which reduces the speed of image analysis and processing. Thus, in order to compare and achieve the highest classification accuracy, the image size was reduced to three sizes (16 × 16), (24 × 24) and (48 × 48) pixels.

2.3. Data augmentation

It is well-known fact that Convolutional Neural Networks are greedy techniques, in order to learn to classify objects they need large amount of annotated data. Data augmentation is a fundamental technique for achieving large amount of training data and thus for improving the generalization of deep learning models. Recently, Fast AutoAugment has been proposed as an algorithm for automatically searching augmentation methods (Shorten and Khoshgoftaar, 2019). This method minimizes the computational complexity of the Deep learning methods and achieves significant speed and considerable performance in improving the image classification results (Lim et al., 2019). Controller, Augmenter, and Child model are components of Deep Augment. The controller is a search algorithm that samples a data augmentation policy from the search space. The images of the dataset are transformed by the augmenter with the new policy. The augmented images created with the new policy are inputs of a child model. According to Fig. 3, to augment the data in the proposed Fast AutoAugment-based approach, the data is first divided into five equal folds. Then data augmentation politics is applied to each of the folds without repetition. In the next step, each fold is processed by the Child Model. The output of each CNN is controlled by a Bayesian optimizer. The controller discards weak politics and maintains strong politics. It also introduces new politics. This cycle continues until the appropriate politics for data augmentation is found.

2.4. Model implementation based on improved CNN

A convolutional neural network is made up of a series of convolutional layers, pooling layers, and fully connected layers. In the following, we will describe each of the layers:

2.4.1. Convolutional layer

The core of the CNNd is the convolution layer. The function of these layers is to identify and extract nonlinear features of objects in the images. The CNN output can be thought of as a three-dimensional set of neurons. Filters with learning capacity form the convolution layer parameters. In each convolutional layer, the features map is extracted from the image by these filters and a two-dimensional activation map is created. In the early layers of the convolution, low-level features such as corners, lines, and edges are revealed, and in deeper layers, features with higher levels, such as parts of or even objects in the images, are identified. Fig. 4 shows the function of the convolution layer.

Fig. 1. Carrot fruit with different shapes being (a) irregular and (b) regular appearance (Jahanbakhshi and Kheiralipour, 2020).

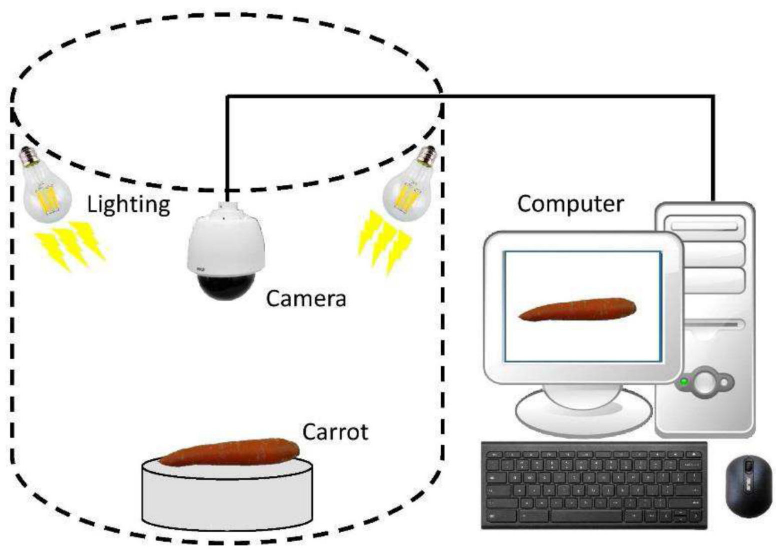

Fig. 2. Imaging system to acquire carrot images.

2.4.2. "Mixed" max-average pooling

In CNN-based image classification systems, pooling operations play an important role in reducing network parameters. Average pooling and max pooling have been widely used in many CNN-like architectures. The combination of these two methods is called "mixed pooling" (Lee et al., 2017). In this study, the mixed pooling method is used in the pooling layer as follows:

$$f_{mix}(X) = a_l \cdot f_{max}(X) + (1 - a_l) \cdot f_{avg}(X) \quad (1)$$

where $a_l \in [0,1]$ is the value that determines the combination of max pooling and average pooling. How mixed pooling works is illustrated in Fig. 5.

2.4.3. The proposed CNN architecture

The proposed CNN configuration for carrot fruit classification is shown in Fig. 6. According to Fig. 6, Configuration 1 in the proposed model consists of two convolution layers, two batch normalization layers, a pooling layer and a fully connected layer. Configuration 2 in the proposed model, consists of six convolutional layers, three layers of batch normalization, two pooling layers and a fully connected layer. Configuration 3 of the model consists of eight convolutional layers, four batch normalization layers, three pooling layers and a fully connected layer. In the proposed architecture, ReLU was used as activation function (Krizhevsky et al., 2012; Hahnloser et al., 2000).

One technique that can be used for improving the speed, performance, and stability of artificial neural networks is the Batch normalization. This technique normalizes the input layer through adjusting and scaling activations. At the beginning, it was proposed to solve internal covariate shift. The distribution of inputs in the current layer changes in accordance with change in the parameters of the preceding layers during the training stage of networks. Thus, the current layer must readjust to new distributions on a constant basis. The problem gets even more serious when it comes to deep networks, since the propagation of the small changes in shallower hidden layers of the network amplifies them; hence causing considerable change in deeper hidden layers. So, batch normalization method is applied to decrease the undesirable changes, to speed up the training and produce a model that is more reliable for carrot classification.

Batch normalization has several other advantages in addition to reducing internal covariate shift. This additional layer enables the network to have a higher learning rate without vanishing or exploding gradients. Batch normalization also regularizes the network in such a way that the generalization becomes easier, which in turn removes the necessity of using dropout to mitigate overfitting. Yet another benefit is that the network becomes more robust and applicable with different initialization schemes and learning rates.

Each input channel is normalized across a mini-batch by a batch normalization layer. Batch normalization is used between convolutional layers and the nonlinear layers, such as the ReLU layers in order to accelerate the convolutional neural networks training and decrease network initialization sensitivity.

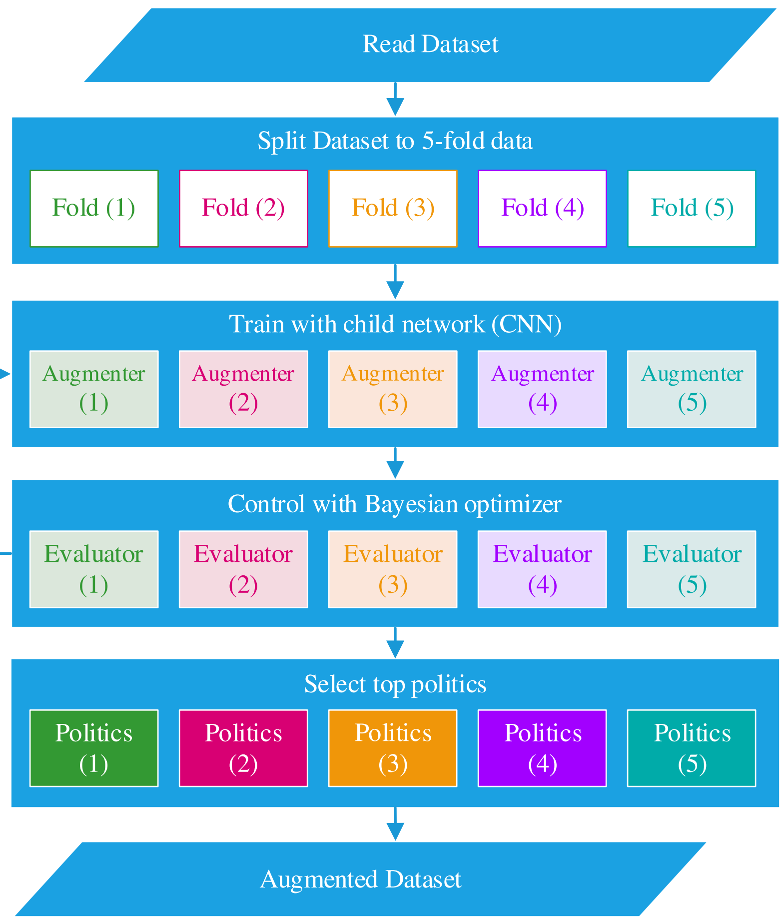

Fig. 3. Fast AutoAugment-based data augmentation architecture.

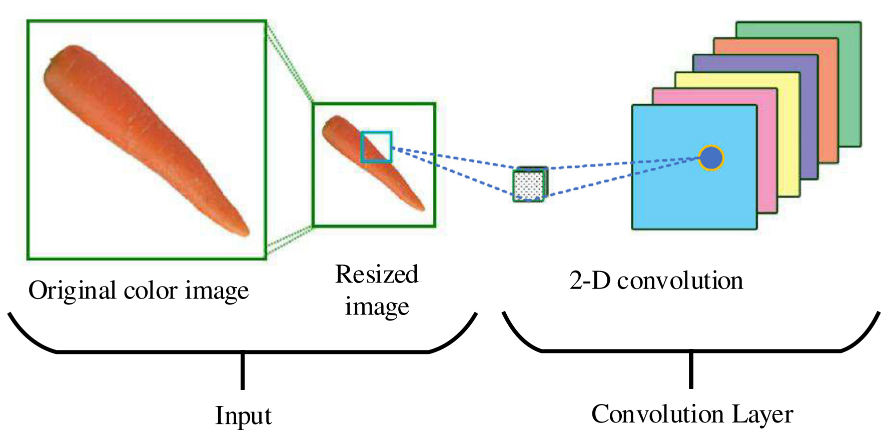

Fig. 4. Input image and the convolutional layer in the proposed CNN.

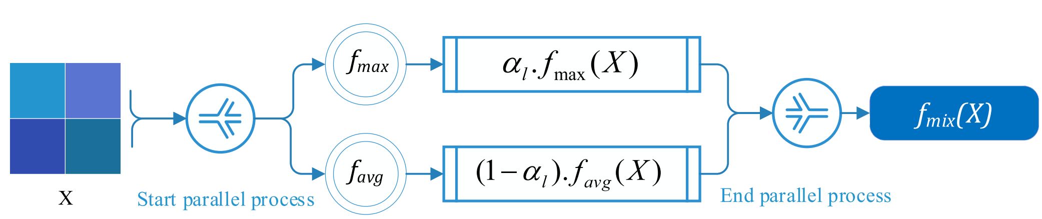

Fig. 5. Combined pooling layer of our CNN based on mixed pooling.

First, activations of each channel are normalized by the layer, i.e. the mean of the mini-batch is subtracted and divided by its standard deviation. After that, the layer shifts the input by a learnable offset, β and scales it by a learnable scale factor, γ.

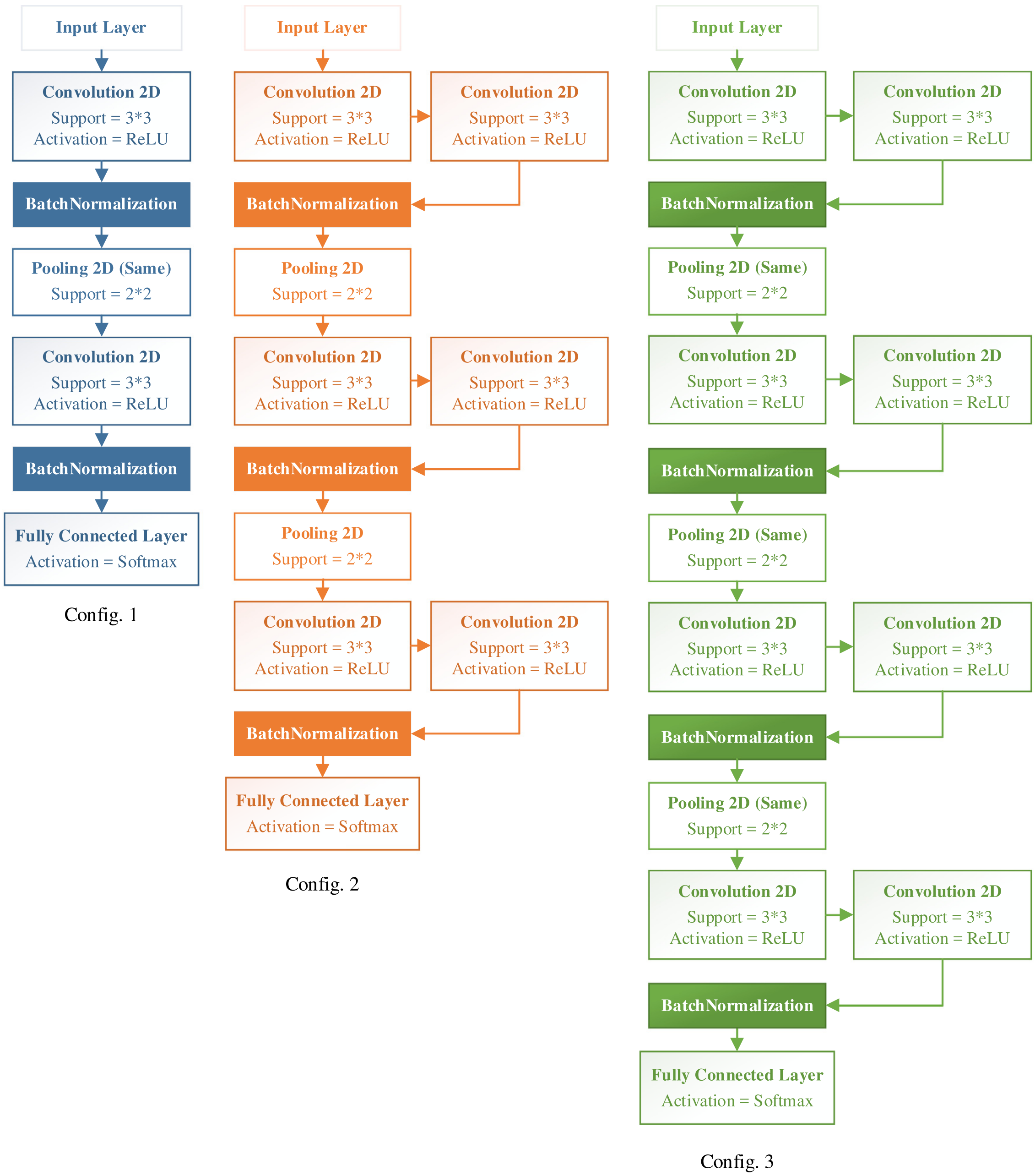

Fig. 6. Our proposed CNN architecture for carrot fruit classification.

By calculating the mean μ_B first, the batch normalization normalizes its inputs x_i and variance σ_B^2 on each input channel over a mini-batch. Inputs can be calculated through the following formula:

$$x_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}} \tag{2}$$

When the mini-batch variance is very small, the parameter ϵ improves the numerical stability. Inputs with zero mean and unit variance might not be optimal for the layer following the batch normalization layer. To allow for this possibility, the batch normalization layer shifts more and scales the activations as follows:

$$y_i = \gamma x_i + \beta \tag{3}$$

where the offset β and the scale factor γ (offset and scale properties) are learnable parameters updated during the network training.

Using Batch Normalization leads to better results including faster network training, higher learning rate, easier weight initialization, more viable activation functions, simplification of creating deeper networks, and regularization of the classification model.

2.5. Validation

In this study, the performance of the proposed CNN model was compared with the performance of other classification methods for carrot images. For comparison, the desired features were first extracted from the carrot color images by Local Binary Pattern (LBP) and Histograms of Oriented Gradients (HOG) methods. Features extracted from the images were then categorized with

Table 1
Parameters used for the algorithms.

Algorithms	First parameter		Second parameter		Third parameter	
	Parameter name	Value	Parameter name	Value	Parameter name	Value
KNN	k	3	–	–	–	–
MLP	Number of hidden layers	2	Number of neurons per hidden layer	25	–	–
GBT	Limited number of levels (tree depth)	4	Number of models in the boosting	100	Learning rate	0.1
CNN	Batch size	25	Learning rate	0.001	Maximum no. epochs	250

MLP, GBT, and KNN algorithms. Finally, the results of applying different algorithms for classification were compared in terms of the accuracy of the algorithms. The parameters used for the different algorithms are reported in Table 1. In this research, pre-processing and classification operations of carrot images were carried out in MATLAB R2020b software. The convolutional neural Networks were built with the Deep Network Designer toolbox of Matlab software. Other classifiers were simulated with Classification Learner App of Matlab software.

2.6. Statistical analysis

Accuracy, Loss and MAE were criteria taken into account for the validation and comparison between the proposed CNN and other classification models in accordance to the following relations (Jahanbakhshi et al., 2020; Zheng et al., 2017; Arqub, 2019; Arqub and Rashaideh, 2018):

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

where,
TP: True positive
TN: True negative
FP: False positive
FN: False negative

$$Loss = -\left(X \mathrm{Log}\left(p\right) + \left(1 - X\right) \mathrm{Log}\left(1 - p\right)\right) \tag{5}$$

where Log is the natural log; X is a binary indicator (0 or 1) if class label c is the correct classification for observation o and p is the predicted probability observation that o is of class c.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \hat{y}_i\right| \tag{6}$$

where:
y_i: ith real instance
$\hat{y}_i$: ith predicted instance

The most common criteria for evaluating classifiers are Recall, Precision, Sensitivity, Specificity, F-measure and accuracy which were used to compare the performance of the classifiers. Sensitivity is the fraction of correctly classified positive samples (i.e. samples corresponding to the class in question), specificity is the fraction of correctly classified negative samples (i.e. samples not corresponding to the given class), F-measure is obtained through a precision–recall comparison, and the accuracy is the classifier's total classification rate. These criteria are computed using Eqs. (7)–(11):

$$\text{Recall} = \frac{TP}{TP + FN} \tag{7}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{8}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{9}$$

$$\text{Specificity} = \frac{TN}{FP + TN} \tag{10}$$

$$\text{F-Measure} = \frac{2 \times \text{ Precision } \times \text{ Recall}}{\text{Precision } + \text{ Recall}} \tag{11}$$

Table 2
Selecting the positive and negative classes of carrot images in order to evaluate the recall, precision, sensitivity, specificity and F-measure.

Steps and classes	Irregular shapes	Regular shapes
Step 1: Irregular shapes	Positive	Negative
Step 2: Regular shapes	Negative	Positive

3. Results and discussions

In this study, data augmentation was used in the CNN training process. Also, 70% of the data was used for training, 10% for validating and 20% of the data were randomly chosen and fixed to test the proposed CNN model. Classification performance was evaluated by once considering the carrots with irregular shapes as positive class (In this step, regular images of carrots are selected as negative class) and once taking the carrots with regular shapes as the positive class (In this step, irregular images of carrots are selected as negative class) (Table 2). Then, the classification accuracy of the different methods was evaluated through the Accuracy, Loss and MAE criteria, and the results were reported in Tables 3–5.

The overall accuracy results show that the proposed BN-CNN model based on mixed pooling with the proposed configuration (Config. 3 in Fig. 6), in the image size of 24 $\times$ 24 pixels in the training, validation and testing phases, was the optimal one. It has a values equal to 1.00, 1.00 and 0.99, respectively. Also, the proposed configuration (Config. 3 in Fig. 6) with image size of 24 $\times$ 24 pixels in the test phase has the lowest Loss and MAE values of 0.01 and 0.01, respectively (Table 5). Because to improve the pooling process, the mixed pooling method has been used, which has the advantages of max pooling and average pooling.

Classification performance criteria including recall, precision, sensitivity, specificity and F-measure for different classifiers are given in Table 6. Comparison of the results from Table 6 shows that the HOG image feature extraction method has a better performance than LBP in the MLP, GBT and KNN classifiers. The proposed model (CNN) based on mixed pooling with an image size of 24 $\times$ 24 pixels and in all performance criteria (recall, precision, sensitivity, specificity and F-measure) has values equal to one (100%). Therefore, through these criteria, the excellent performance of the classification system can be appreciated. In order to optimize the pooling process, mixed pooling was used to benefit from the max pooling and average pooling advantages. Also, applying CNN optimization using mixed pooling has shown to achieve better results than the baseline pooling. To summarize, 100% sensitivity value in a given class indicates that all its samples have been classified correctly. A specificity value of 100% in a class means that no samples from other classes have been misclassified in that class.

The results of the classification accuracy for the different classifiers are given in Fig. 7 according to the image size for grading carrot images. The results show that the proposed BN-CNN model based on mixed pooling with the proposed configuration (Config. 3 in Fig. 6) based on total accuracy has been able to classify carrot images in all sizes (16×16, 24×24, and 48×48 pixels) with 96.02%, 99.43% and 97.16%, respectively. The results suggest that

Table 3
Comparison of the proposed model (CNN) with other models for carrot fruit grading (according to Config. 1 in Fig. 6).

Metrics	Image size	Non BN-CNN						BN-CNN					
		Baseline pooling			Mixed pooling			Baseline pooling			Mixed pooling		
		Train	Validation	Test	Train	Validation	Test	Train	Validation	Test	Train	Validation	Test
Accuracy	16 × 16	0.73	0.73	0.70	0.78	0.78	0.76	1.00	1.00	0.93	1.00	1.00	0.93
	24 × 24	0.76	0.76	0.73	0.80	0.82	0.79	1.00	1.00	0.93	1.00	1.00	0.94
	48 × 48	0.80	0.79	0.72	0.77	0.76	0.76	1.00	1.00	0.86	1.00	1.00	0.87
Loss	16 × 16	0.53	0.54	0.54	0.46	0.48	0.46	0.01	0.01	0.23	0.02	0.02	0.20
	24 × 24	0.50	0.50	0.55	0.42	0.44	0.49	0.00	0.00	0.22	0.00	0.00	0.20
	48 × 48	0.30	0.45	0.55	0.46	0.47	0.47	0.00	0.00	0.54	0.00	0.00	0.55
MAE	16 × 16	0.37	0.37	0.37	0.32	0.32	0.32	0.01	0.01	0.08	0.01	0.01	0.08
	24 × 24	0.34	0.34	0.36	0.29	0.30	0.31	0.00	0.00	0.08	0.00	0.00	0.08
	48 × 48	0.44	0.31	0.34	0.32	0.33	0.32	0.00	0.00	0.13	0.00	0.00	0.13

Table 4
Comparison of the proposed model (CNN) with other models for carrot fruit grading (according to Config. 2 in Fig. 6).

Metrics	Image size	Non BN-CNN						BN-CNN					
		Baseline pooling			Mixed pooling			Baseline pooling			Mixed pooling		
		Train	Validation	Test	Train	Validation	Test	Train	Validation	Test	Train	Validation	Test
Accuracy	16 × 16	0.83	0.83	0.83	0.63	0.62	0.62	1.00	1.00	0.94	1.00	1.00	0.95
	24 × 24	0.89	0.89	0.89	0.82	0.82	0.82	1.00	1.00	0.95	1.00	1.00	0.96
	48 × 48	0.92	0.89	0.86	0.94	0.94	0.91	1.00	1.00	0.93	1.00	1.00	0.91
Loss	16 × 16	0.40	0.40	0.40	0.61	0.61	0.62	0.00	0.00	0.17	0.00	0.00	0.14
	24 × 24	0.27	0.28	0.28	0.39	0.38	0.38	0.00	0.00	0.14	0.00	0.00	0.14
	48 × 48	0.20	0.25	0.37	0.15	0.15	0.27	0.00	0.00	0.36	0.00	0.00	0.35
MAE	16 × 16	0.27	0.28	0.28	0.44	0.44	0.45	0.00	0.00	0.06	0.00	0.00	0.04
	24 × 24	0.18	0.18	0.18	0.26	0.26	0.26	0.00	0.00	0.05	0.00	0.00	0.04
	48 × 48	0.13	0.14	0.17	0.10	0.10	0.14	0.00	0.00	0.09	0.00	0.00	0.08

Table 5
Comparison of the proposed model (CNN) with other models for carrot fruit grading (according to Config. 3 in Fig. 6).

Metrics	Image size	Non BN-CNN						BN-CNN					
		Baseline pooling			Mixed pooling			Baseline pooling			Mixed pooling		
		Train	Validation	Test	Train	Validation	Test	Train	Validation	Test	Train	Validation	Test
Accuracy	16 × 16	0.51	0.51	0.50	0.52	0.51	0.49	1.00	1.00	0.95	1.00	1.00	0.96
	24 × 24	0.52	0.51	0.50	0.53	0.54	0.54	1.00	1.00	0.95	**1.00**	**1.00**	**0.99**
	48 × 48	0.51	0.51	0.51	0.87	0.85	0.81	1.00	1.00	0.96	1.00	1.00	0.97
Loss	16 × 16	0.68	0.68	0.69	0.69	0.69	0.69	0.00	0.00	0.23	0.00	0.00	0.10
	24 × 24	0.67	0.68	0.69	0.69	0.68	0.69	0.00	0.00	0.21	**0.00**	**0.00**	**0.01**
	48 × 48	0.68	0.68	0.69	0.29	0.32	0.40	0.00	0.00	0.10	0.00	0.00	0.08
MAE	16 × 16	0.49	0.49	0.50	0.49	0.49	0.50	0.00	0.00	0.05	0.00	0.00	0.04
	24 × 24	0.48	0.49	0.50	0.50	0.50	0.50	0.00	0.00	0.05	**0.00**	**0.00**	**0.01**
	48 × 48	0.50	0.49	0.50	0.19	0.21	0.23	0.00	0.00	0.04	0.00	0.00	0.03

the CNN, as a simple, fast, and non-destructive method, can be useful in managing and controlling carrot fruit waste in the post-harvest stage, which is the main goal of this study. These results are similar to the results reported by Jahanbakhshi et al. (2020) and Momeny et al. (2020) about the classification method used to control sour lemon and cherry fruit waste. Fig. 7 also shows that the HOG method of extracting features in MLP, GBT, and KNN classification techniques yields better results than the LBP. The advantage of the HOG method over the LBP is a result consistent with the findings of Jahanbakhshi et al. (2020) and Momeny et al. (2020).

Due to the great importance and high consumption rate of carrot, achieving an appropriate and non-destructive method for controlling their quality and grading them is particularly significant. The extent of each kind of defects in carrots can be considered as a factor in grading this product. Due to the unique characteristics of carrots and many operations such as harvesting, transportation, warehousing, etc. carried out to deliver the product to the market to be consumed by the users, providing a totally healthy and perfect product with uniform shapes would be a difficult task. Based on different defects in their physical shape, such as fracture, abnormal size, malformation as well as surface damage caused by diseases and pests, carrots can be placed in different levels (e.g. grade 1, grade 2, etc.) for different purposes. These purposes can be as varied as home use (fresh or cooked consumption), use in product processing industries (making jams and pickles), or even use as a food supplement for livestock. The results of this study showed that our CNN model was very effective and useful for the purposes of this type of research. In addition, this study concluded that increase in marketability and waste control for carrots can be performed through the above-mentioned techniques and methods.

4. Conclusions

The marketability of agricultural products in the consumer market plays an important role in reducing agricultural waste. In this study, in order to increase marketability and control waste, carrots were graded based on their appearance shape. Using the Fast AutoAugment algorithm, dataset samples were augmented and images were categorized using the CNN proposed methods. The mixed pooling was used to improve its generalization in the CNN model. The results showed that the proposed CNN using mixed pooling was able to classify carrot images in size of 24

Table 6
Evaluation of carrot images classification in testing phase by the proposed models (CNN) compared to other classifiers.

Performance criteria	Image size	Classes	Classification algorithms											
			MLP		GBT		KNN		BN-CNN: Baseline pooling			BN-CNN: Mixed pooling		
			LBP	HOG	LBP	HOG	LBP	HOG	Config. 1	Config. 2	Config. 3	Config. 1	Config. 2	Config. 3
Recall	16 × 16	Regular	0.48	0.83	0.62	0.86	0.65	0.81	0.93	0.95	0.97	0.92	0.97	0.98
		Irregular	0.46	0.83	0.60	0.85	0.63	0.79	0.93	0.93	0.93	0.94	0.93	0.94
	24 × 24	Regular	0.52	0.89	0.59	0.88	0.63	0.83	0.94	0.96	0.97	0.93	0.97	**1.00**
		Irregular	0.50	0.87	0.56	0.85	0.60	0.82	0.92	0.94	0.94	0.94	0.95	**0.99**
	48 × 48	Regular	0.53	0.72	0.52	0.82	0.59	0.74	0.86	0.95	0.97	0.88	0.92	0.98
		Irregular	0.51	0.69	0.50	0.80	0.58	0.71	0.87	0.91	0.95	0.86	0.90	0.97
Precision	16 × 16	Regular	0.48	0.83	0.62	0.86	0.64	0.80	0.93	0.93	0.93	0.94	0.93	0.94
		Irregular	0.47	0.83	0.59	0.85	0.64	0.80	0.93	0.95	0.97	0.92	0.97	0.98
	24 × 24	Regular	0.53	0.88	0.57	0.86	0.61	0.82	0.92	0.94	0.94	0.94	0.96	**0.99**
		Irregular	0.49	0.88	0.58	0.87	0.62	0.83	0.94	0.95	0.97	0.93	0.97	**1.00**
	48 × 48	Regular	0.52	0.70	0.50	0.81	0.60	0.71	0.88	0.91	0.96	0.87	0.90	0.97
		Irregular	0.51	0.71	0.52	0.81	0.57	0.73	0.85	0.95	0.97	0.87	0.92	0.98
Sensitivity	16 × 16	Regular	0.48	0.83	0.62	0.86	0.65	0.81	0.93	0.95	0.97	0.92	0.97	0.98
		Irregular	0.46	0.83	0.60	0.85	0.63	0.79	0.93	0.93	0.93	0.94	0.93	0.94
	24 × 24	Regular	0.52	0.89	0.59	0.88	0.63	0.83	0.94	0.96	0.97	0.93	0.97	**1.00**
		Irregular	0.50	0.87	0.56	0.85	0.60	0.82	0.92	0.94	0.94	0.94	0.95	**0.99**
	48 × 48	Regular	0.53	0.72	0.52	0.82	0.59	0.74	0.86	0.95	0.97	0.88	0.92	0.98
		Irregular	0.51	0.69	0.50	0.80	0.58	0.71	0.87	0.91	0.95	0.86	0.90	0.97
Specificity	16 × 16	Regular	0.46	0.83	0.60	0.85	0.63	0.79	0.93	0.93	0.93	0.94	0.93	0.94
		Irregular	0.48	0.83	0.62	0.86	0.65	0.81	0.93	0.95	0.97	0.92	0.97	0.98
	24 × 24	Regular	0.50	0.87	0.56	0.85	0.60	0.82	0.92	0.94	0.94	0.94	0.95	**0.99**
		Irregular	0.52	0.89	0.59	0.88	0.63	0.83	0.94	0.96	0.97	0.93	0.97	**1.00**
	48 × 48	Regular	0.51	0.69	0.50	0.80	0.58	0.71	0.87	0.91	0.95	0.86	0.90	0.97
		Irregular	0.53	0.72	0.52	0.82	0.59	0.74	0.86	0.95	0.97	0.88	0.92	0.98
F-measure	16 × 16	Regular	0.48	0.83	0.62	0.86	0.65	0.80	0.93	0.94	0.95	0.93	0.95	0.96
		Irregular	0.46	0.83	0.60	0.85	0.64	0.80	0.93	0.94	0.95	0.93	0.95	0.96
	24 × 24	Regular	0.53	0.88	0.58	0.87	0.62	0.83	0.93	0.95	0.96	0.94	0.96	**0.99**
		Irregular	0.49	0.88	0.57	0.86	0.61	0.82	0.93	0.95	0.95	0.94	0.96	**0.99**
	48 × 48	Regular	0.53	0.71	0.51	0.82	0.60	0.72	0.87	0.93	0.96	0.87	0.91	0.97
		Irregular	0.51	0.70	0.51	0.81	0.57	0.72	0.86	0.93	0.96	0.87	0.91	0.97

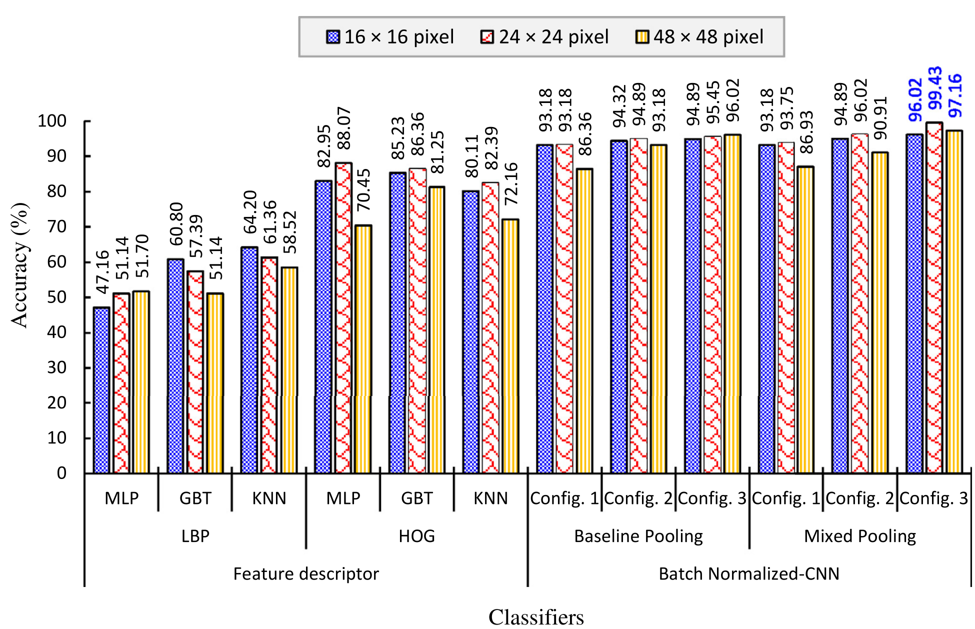

Fig. 7. Comparing the accuracy of different classification methods for grading carrot fruit.

× 24 pixels with 99.43% of accuracy. To compare the proposed method with other methods, image features were extracted with the proposed HOG and LBP methods and classified by MLP, KNN and GBT machine learning algorithms. A comparison of the performance of different classifications showed that our CNN model was able to perform better than the other machine learning algorithms. So, traditional methods for grading carrots fruit can be upgraded through improved and customized CNNs. Doing so would increase product marketability in addition to controlling natural products waste.

CRediT authorship contribution statement

Ahmad Jahanbakhshi: Conceptualization, Methodology, Investigation, Data curation, Software, Formal analysis, Validation, Writing - original draft, Writing - review & editing. **Mohammad Momeny:** Conceptualization, Methodology, Investigation, Software, Formal analysis, Validation, Writing - original draft, Writing - review & editing. **Majid Mahmoudi:** Conceptualization, Methodology, Writing - review & editing. **Petia Radeva:** Supervision, Validation, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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