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A convolutional neural network-based comparative study for pepper seed classification: Analysis of selected deep features with support vector machine

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Abstract

The seeds of high quality are very important for the cultivation of the pepper. The required cultivation practices and growing conditions may be affected by the cultivar. Also, the productivity and properties of pepper depend on the cultivar. The selection of appropriate seed cultivars may be necessary for the breeding programs. The cultivar differentiation of pepper seeds may be tested by the human eye. However, small sizes and visual similarities make it difficult to distinguish between seed cultivars. Computer vision and artificial intelligence can provide high cultivar discrimination accuracy and the procedures are objective and fast. This study aimed to classify pepper seeds belonging to different cultivars with convolutional neural network (CNN) models. The seeds were obtained from green, orange, red, and yellow pepper cultivars. A flatbed scanner was used to acquire the pepper seed images. After the image acquisition, the procedure applied was preprocessing of the images, data augmentation using different techniques and then deep learning-based classification. Two approaches have been proposed for classification. In the first approach, CNN models (ResNet18 and ResNet50) were trained for pepper seeds. In the second approach, different from the first, the features of pretrained CNN models were fused, and feature selection was applied to the fused features. Classification using all features and selected features was performed with the support vector machine (SVM) with different kernel functions (Linear, Quadratic, Cubic, Gaussian). The accuracies in the first approximation were 98.05% and 97.07% for ResNet50 and ResNet18, respectively. In the second approach, CNN-SVM-Cubic achieved up to 99.02% accuracy with the selected features.

Practical applications

In precision agriculture, it is very important that the seeds be of the same type for the purification and standardization of the crop culture. Performing this classification manually with human assistance will result in subjective, slow, and low standard outcomes. To overcome such problems, classification supported by artificial intelligence and machine vision systems emerges as an important tool. In this study, a highly successful classification system is presented according to the visual characteristics of pepper seeds. The proposed models can be preferred in practice for identifying pepper seeds and detecting falsification or ensuring their reliability. It will prevent mixing of different pepper seeds with different attributes for processing.

1 | INTRODUCTION

The pepper (*Capsicum annum* L.) belongs to the Solanaceae family (Nogueira, Silva, Mógor, Grzybowski, & Panobianco, 2017). The *Capsicum* is native to Central and South America (Rani, Jindal, Vikal, & Meena, 2021). The domesticated species of *Capsicum* can be characterized by genetic diversity involving a wide range of colors and forms of fruits. The peppers belonging to the species *Capsicum annum*, which can be cultivated almost worldwide, have a very high morphometric diversity (Saleh, Kasili, Mamati, Araia, & Nyende, 2016). The pepper fruit may have different colors, such as, red, orange, yellow, green, purple, black, or brown (Olaes, Arboleda, Dioses, & Dellosa, 2020). The pericarp flesh with a crisp texture is edible (O'Donoghue et al., 2020). Bell pepper may be eaten in raw or processed forms as frozen peppers, pickled peppers, paprika (dehydrated products) (Castro et al., 2008). The bell pepper contains dietary fibers, minerals, vitamins including vitamin C (Frans, Aerts, Ceusters, Luca, & Ceusters, 2021).

The fruit may be cultivated in open fields, as well as in a protected environment that may ensure higher productivity and quality of fruit. The pepper is cultivated using seeds or seedlings from seeds. Therefore, the cultivation of peppers may be performed for the production of seeds. The ripening stage of fruit may result in the quality of the seeds (Nogueira et al., 2017). The breeding programs for ensuring for farmers the seeds of cultivars with high quality and productivity may be necessary (Saleh et al., 2016). The pepper seed quality depends on the size, texture, and color (Tu, Li, Yang, Wang, & Sun, 2018). The seed quality directly affects the yield. Plant breeding using seeds of high quality may ensure the identification of a better crop cultivar and is economically beneficial (Medeiros et al., 2020). The poor seed quality may be caused by, for example, wrong agronomic practices. The genotype may influence the properties of the seeds and then the quality of fruit. The cultivar may affect, for example, the seed germination, 1,000 seed weight, seed number, and weight per fruit (Mends-Cole, Banful, & Tandoh, 2019). Therefore, the selection of appropriate cultivar of seeds is important. Some seeds may be suited for selected cultivation practices and the required growing conditions may be related to the cultivar. The selection of cultivars for cultivation can be based on the catalog description of seeds provided by the seed company (Boyhan, McGregor, O'Connell, Biang, & Berle, 2020).

1.1 | Computer vision and artificial intelligence trend and previous studies

In the literature, there are many studies in the field of agriculture using computer vision and artificial intelligence (Lopes, Ludwig, Barbin, Grossmann, & Barbon, 2019; Oliveira, Cerqueira, Barbon Jr, & Barbin, 2021; Pereira, Barbon Jr, Valous, & Barbin, 2018; Pourdarbani, Sabzi, Kalantari, Hernández-Hernández, & Arribas, 2020; Ropelewska & Szwejda-Grzybowska, 2021; Sabanci, Aslan, & Durdu, 2020).

The genetic diversity of cultivars of pepper germplasm may be tested using morphological parameters (Saleh et al., 2016). The seeds that differ in the terms of the internal anatomical features and chemical composition may be difficult to visual observation. Methods based on optical sensors combined with machine learning algorithms can be used for the evaluation and classification of seeds (Medeiros et al., 2020). Machine vision can be an alternative for the human eye, which may have difficulty distinguishing between pepper seeds belonging to different species (Jesusimo & Dioses, 2020). So, the discrimination of cultivars of pepper seeds may be even more difficult. Due to visual similarities and small sizes of pepper seeds, the expert eye cannot easily distinguish cultivars. Computer vision and artificial intelligence algorithms allow for the discrimination of different cultivars of pepper seeds (Kurtulmus, Alibas, & Kavdir, 2016). The color image analysis with the use of a flatbed scanner can ensure very high accuracies of cultivar discrimination of pepper using an objective and fast procedure (Ropelewska & Szwejda-Grzybowska, 2021). The application of nondestructive image analysis using a mobile phone camera or digital camera for the examination of the quality of seeds has also many advantages. It is easy and cheap. The combination of image processing with the neural network can increase the precision of the results (Pornpanomchai, Jongsriwattanaporn, Pattanakul, & Suriyun, 2020). Therefore, image analysis techniques have great potential for pepper seed research.

Recently, computer vision and artificial intelligence have been preferred in automatic seed classification studies. Li et al. (2020) acquired multispectral images for the classification of three classes of pepper seeds. It extracted features from these spectral data with the Successive Projection Algorithm (SPA) method. These features were then classified and compared by 1D-Convolutional Neural Network (CNN), K-nearest neighbors (KNN), and SVM (Support Vector Machine) methods. As a result, SVM showed superior performance with 97.7% accuracy. Raju Ahmed, Yasmin, Wakholi, Mukasa, and Cho (2020) obtained images of five-year-old pepper seeds using an X-ray Computed Tomography (CT) scanner. Korean pepper seeds with high economic value are preferred as a sample. Gray-level co-occurrence matrix (GLCM) textural features were extracted from seed images that consist of two classes, and then they were classified by Partial Least-Squares Discriminant Analysis (PLS-DA), SVM, and KNN algorithms. In that study where cross-validation was also used, PLS-DA provided the most successful classification with 88.7%. Tu et al. (2018) used 400 seeds of Cultivar 101 peppers to distinguish high-quality pepper seeds from low-quality pepper seeds and aimed to automate seed quality recognition. Single seed density, single seed weight, and physical properties of pepper seed were used as features. Physical traits were extracted by Seed Identification software. In that study where multilayer perceptron (MLP) and binary logistic regression (BLR) methods were used, the classification accuracy was around 85%. Orrillo et al. (2019) performed multivariate analysis and Near-Infrared Hyperspectral Imaging (NIR-HSI) to distinguish black pepper seeds mixed with papaya seeds. In classifications made through principal component analysis (PCA) and soft independent modeling of class analogy (SIMCA), a sensitivity of over 90% was achieved. Gagliardi and Marcos-Filho (2011) used X-ray images of pepper seed in order to investigate the seed abnormality. The authors exposed the seed to a 10 kV radiation for 260 s. The seeds were divided into four groups as an occupied area in the seed with the values of 0, <50%, 50–75%, and 100%. Seed samples from each group were submitted to germination test at 25°C for 14 days. It was reported that 50%–75% and 100% occupied seeds produced abnormal seedlings. And the relation between X-ray images and germination performance was clearly introduced. Mo et al. (2014) in their studies proposed a nondestructive pepper seed quality evaluation method. An RGB mix lighting structure was presented to create individual colored lighting (single red, single blue, or single green) and a mixture of them. It was reported that by using partial least squares-discriminant analysis model for RGB LED illumination, the accuracies were 96.7% and 99.4% for viable or non-viable seed respectively. And for red LED illumination, the accuracy was 100%.

1.2 | Purpose and contributions of this paper

The aim of this study was to classify the seeds of different pepper cultivars (four classes) using the different CNN models and SVM algorithms with different kernel functions. For this purpose, first pepper seed images were acquired, then classification was performed after preprocessing and data augmentation methods. Two different experimental studies were performed for classification. In the first, ResNet18 and ResNet50 models were trained and tested with seed images. In the second, pretrained structures of these two CNN models were used to improve existing results, and features extracted from both models were fused. More effective features were selected with the feature selection algorithm from among many features. Classification of these selected features was done by SVM, which has Linear, Quadratic, Cubic, and Gaussian kernel functions. The results were very satisfactory. The contributions of our study can be briefly summarized as follows:

- Classification of four classes of pepper seed by two popular state-of-the-art CNN models,
- Classification of features extracted from ResNet models using SVM, that is, CNN-SVM structure,
- Fusing the features of two CNN models and implementing a feature selection algorithm,
- High classification accuracy was obtained among different pepper cultivars under different ResNet-based architecture conditions.

2 | METHODOLOGY

This section presents various pepper seed classification methods. The general process of the proposed method is presented in Figure 1. First, the pepper images were photographed as a group. Each pepper seed image was then separated from the grouped image using image processing methods. The cropped pepper seed images were converted into the same 300x300 pixel size and recorded. To achieve better performance with deep CNN models, data augmentation was employed after preprocesses of the images. As a final step, two different state-of-the-art CNN models and SVM were used for classification. The details of the mentioned steps were explained below.

2.1 | Image acquisition, and preprocessing

Four pepper cultivars Souleria F1—"green," Milena F1—"orange," Sprinter F1—"red," and Devito F1—"yellow" were used in the experiments. The seeds were extracted manually from pepper fruit purchased in the local supermarket. Fifteen fruits of each cultivar were obtained. During seed extraction, ripe, undamaged, and fully colored fruits were manually handled. The pepper fruits were cut using a knife to extract the seeds. The seeds were separated from the flesh. The seeds of the individual cultivars were visually similar in size and color. For each pepper cultivar, over 135 seeds were extracted. In order to obtain images of the pepper seeds, the seeds were washed, cleaned of the fruit residue in-depth, and dried by air. By using the Epson Perfection flatbed scanner, the pepper seed images were acquired. To ease the image processes employed to separate pepper seeds, they were scanned on a black background. The seed images were scanned with the 800 dpi resolution. The TIFF format was selected during the saving process. Four cultivars of peppers seed images are presented in Figure 2.

During image acquisition, it was ensured that the seeds grouped on a black background do not come into contact with each other. The grouped raw images that were used in preprocess in the pepper seed separation had 6,592 × 3,332 pixels resolution. Raw pepper images were first converted to binary images using the Otsu method (Otsu, 1979). Then the noise in the image was removed. The boundaries of each seed in the main image were determined. The interested seed image was cropped with 300 × 300 pixels size. In order to avoid the appearance of neighbors of the seed that was going to be cropped, the background of the cropped image was removed. So, in the cropped image, only the seed of interest appeared. The seed image created as a result of image preprocessing is as in Figure 2b. The obtained seed images of green, red, yellow, and orange pepper cultivars are labeled as 1, 2, 3, and 4, respectively. Then, the data augmentation was performed, which is explained in the next section.

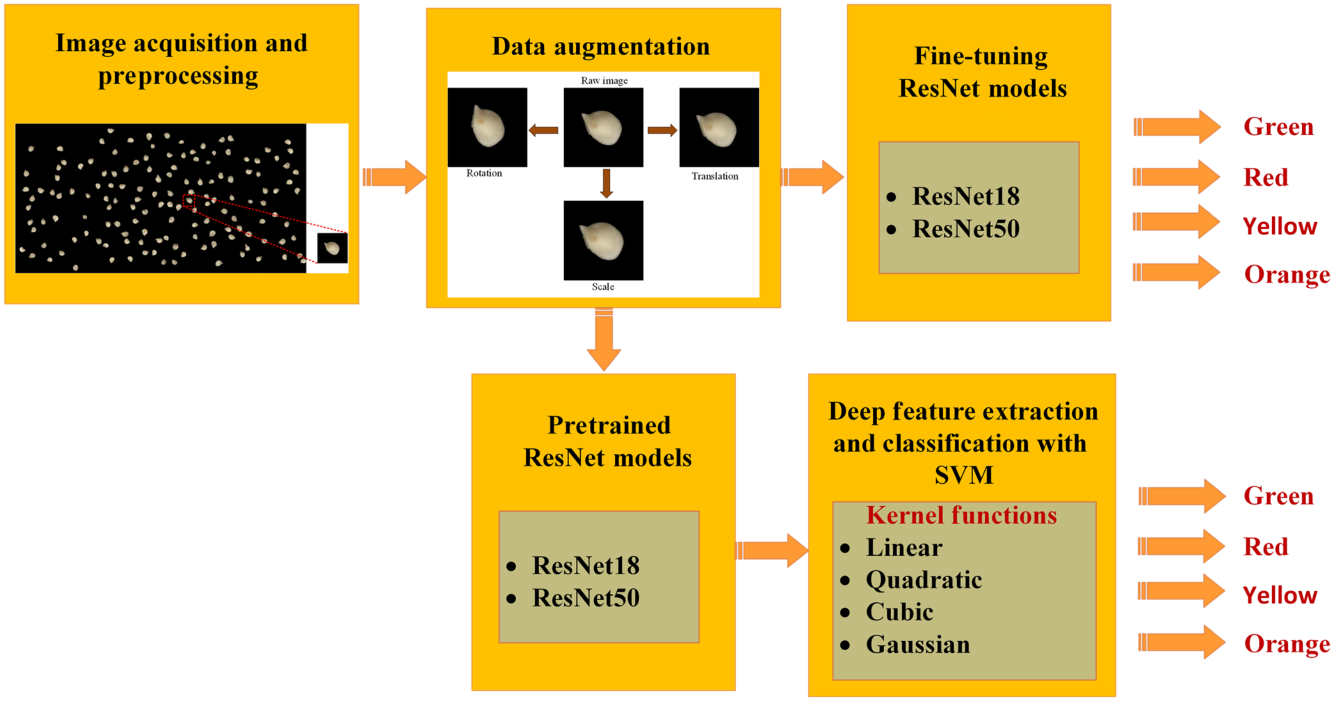

FIGURE 1 The steps of the proposed method (first, image acquisition and preprocessing were performed. Then data augmentation techniques were applied to the images. Finally, the ResNet-based feature extraction and SVM-based classification were performed)

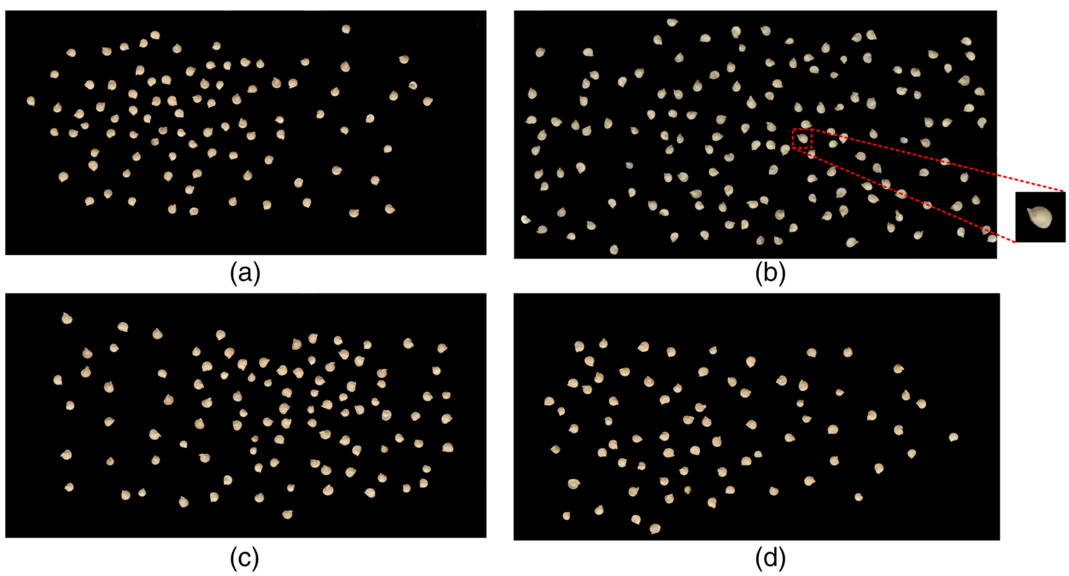

FIGURE 2 Images of four pepper cultivars' seeds: (a) Sprinter F1; (b) Souleria F1; (c) Devito F1; (d) Milena F1

2.2 | Data augmentation

It is a known fact that a rich dataset increases the success of classification in deep learning (Aslan, Unlersen, Sabanci, & Durdu, 2021). Hence, the images in the dataset can be increased artificially to obtain a rich dataset by various manipulation techniques (Mikołajczyk & Grochowski, 2018; Shorten & Khoshgoftaar, 2019). The data augmentation is whole actions conducted on raw images for increasing the number of records in the dataset. Since it is not possible to obtain a sufficient number of pepper seed images without repeating at various angles and various sizes with image acquisition, data augmentation techniques were used in this study. To increase data diversity, data augmentation methods like rotation, scaling, and translation as presented in Table 1 were used in this study. Although these techniques were conducted on each pepper seed image together, they were separately applied to demonstrate the effect on a pepper image in

TABLE 1 The data augmentation method limits (the image data were increased by choosing random values at the specified limits)

Techniques	Lower limit	Upper limit
Rotation (degree)	−30°	30°
Scale (percentage)	90%	110%
Translation (pixel)	−10 px	+10 px

Figure 3. The applied rotation angle, scaling factor, and translation pixel amount were randomly determined in certain limits presented in Table 1.

The created dataset contains 288, 156, 188, and 135 images of seeds belonging to green, red, yellow, and orange pepper cultivars, respectively. During data augmentation, the multiplier of seed image number was determined as three. Thus, 2,301 additional images were obtained by augmentation. With 767 original images, the number of images in the dataset has been achieved to 3,068 samples. The number of images before and after data augmentation methods are given in Table 2.

2.3 | Classification of the seeds of pepper via state-of-the-art ResNet models

After data augmentation was completed, both ResNet models were fed with new pepper seed images. A new CNN architecture was not designed for the training of pepper seed images in this study, existing ResNet models were preferred instead. In the experimental study, ResNet18 and ResNet50, which are frequently preferred in deep learning studies, were applied. The architecture of both models consists of different numbers and types of layers. A comparative analysis of these models is important, as these models provide different advantages to each other in terms of size, a range of parameters, and depth. Already, such CNN models are frequently preferred in deep learning-based benchmarking studies (Ardakani, Kanafi, Acharya, Khadem, & Mohammadi, 2020). The input image size for both models was 224 × 224, so each image was resized and given to models (see Figure 4). Of the 3,068 images, 80% were reserved for training and 20% for testing. Metric values and figures for training and test results are discussed in Section 3.

2.4 | Classification of pepper seeds by fusion of ResNet18 and ResNet50 deep features

In the second method, deep features were extracted from pretrained ResNet models. As in the first method, ResNet18 and ResNet50 architectures were used. The block diagram of the second method is shown in Figure 5. For both models, the input size of the images was 224 × 224 and the feature layers were fc1000. One thousand features were extracted for each pepper seed image from the feature layer of both ResNet models. These features were fused and there were 2,000 features of each pepper seed image. Of these, the 500 most effective features were selected to increase classification accuracy. Minimum redundancy maximum relevance (MRMR) algorithm was used for feature selection.

2.4.1 | MRMR feature selection algorithm

In the machine learning community, the MRMR that is mentioned between the most powerful filters, was developed by Peng, Long, and Ding (2005) (Ramírez-Gallego et al., 2017). The MRMR method is a feature selection algorithm that creates rank for features according to their correlation with class and other features. While a high correlation with class is increasing the rank of a feature, a correlation with other features makes its rank decrease. In this concept, two correlation calculation methods are needed for the determination of the correlation between one feature and the class (also called Relevance) and the correlation between features (also called Redundancy) (Radovic, Ghalwash, Filipovic, & Obradovic, 2017). The correlation between any feature and class could be calculated by using the mutual information (MI) method. Mutual information I is a measure between two random variables X and Y. This measurement quantifies the amount of information obtained about one variable through the other variable. The formulation of I is presented as follows.

$$I(X;Y) = \int_X \int_Y p(x,y) log \frac{p(x,y)}{p(x)p(y)} dxdy \tag{1}$$

In this equation, $p(x)$ and $p(y)$ are the marginal density functions and $p(x,y)$ is the joint probability density function of X and Y. If X and Y are unrelated, then the $p(x).p(y)$ is equal to $p(x,y)$. So, the logarithm of 1 is zero, and the integral of zero would be zero. In feature selection, it is needed to maximize the mutual information between the subset of selected features X and the target variable c (Hoque, Bhattacharyya, & Kalita, 2014). It is calculated by using the expression presented in Equation (2).

$$\max D(X,c); D = \frac{1}{|X|} \sum_{X_i \in X} I(X_i, c) \tag{2}$$

The correlation between features could be calculated by the formula presented in Equation (3).

$$\min R(X); R = \frac{1}{|X|} \sum_{X_i, X_j \in X} I(X_i, X_j) \tag{3}$$

So, the feature selection becomes an optimization problem that has two outputs (the correlation value between each feature and the class, and the correlation value between all features) while one of which needs to be maximized, the other one needs to be minimized (Radovic et al., 2017). Then a greedy search method was employed to select features and the objective function was tried to be maximized. The inputs of the mentioned objective function are relevance and

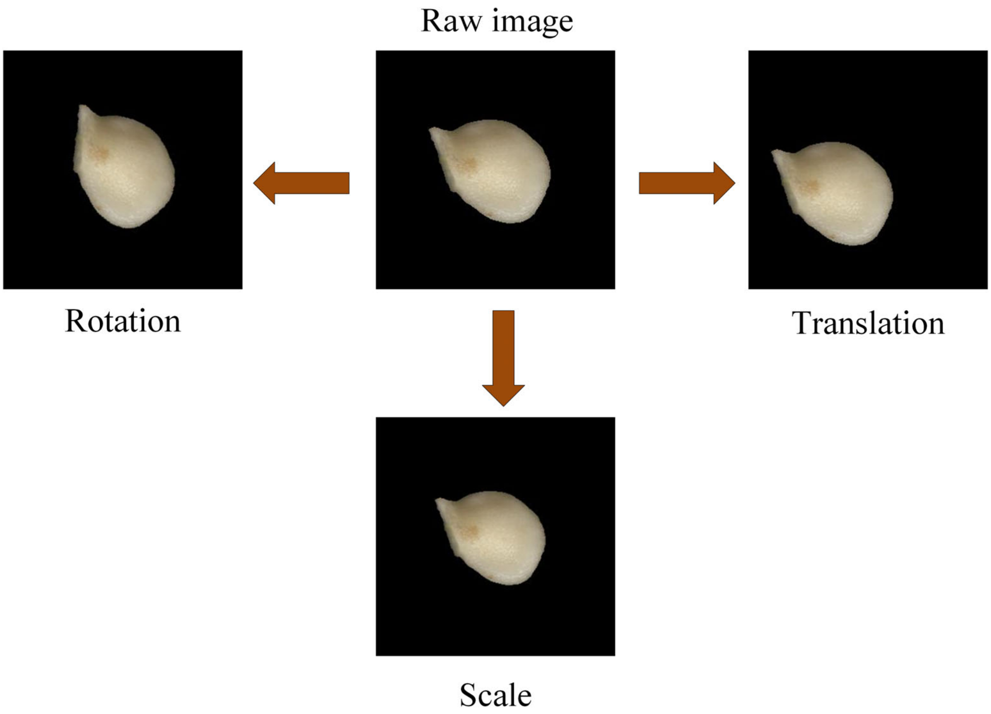

FIGURE 3 The results of data augmentation techniques on a sample pepper seed image

TABLE 2 Change in amount of data in the dataset with data augmentation process (images created as a result of data augmentation were used in training and classification processes)

Pepper seeds	Green (Souleria F1)	Red (Sprinter F1)	Yellow (Devito F1)	Orange (Milena F1)	Total
Before data augmentation	288	156	188	135	767
After data augmentation	1,152	624	752	540	3,068

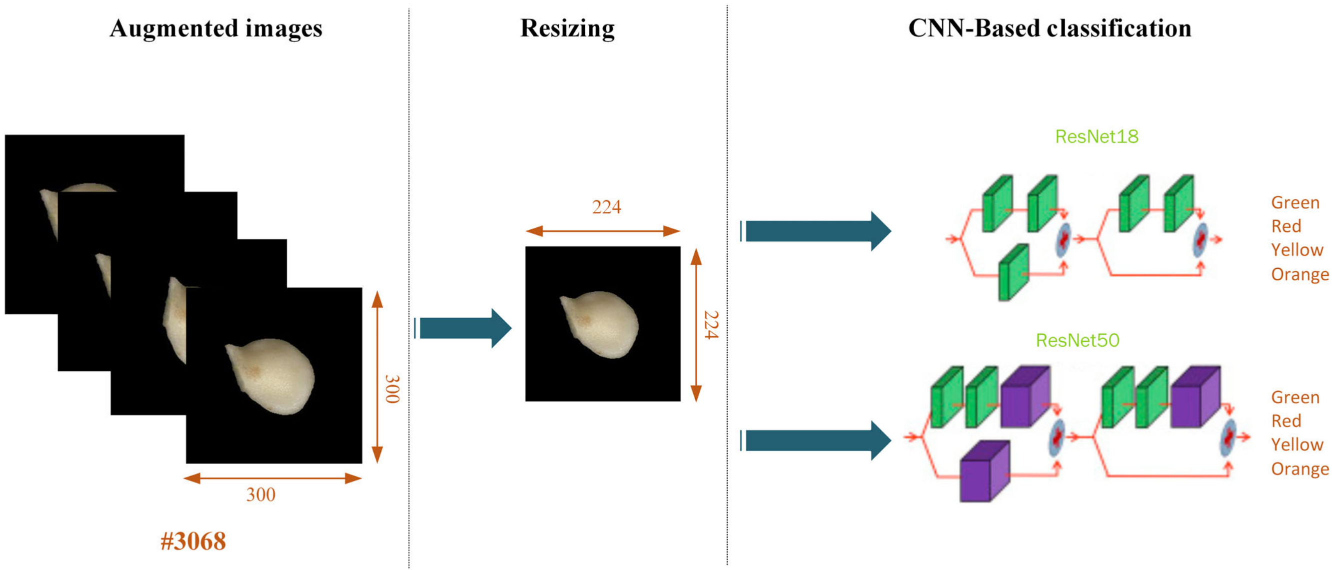

FIGURE 4 Classification of pepper seed images with ResNet18 and ResNet50 models (The cropped seed images of 300 × 300 were first resized to 224 × 224. Finally, these images were classified with ResNet models)

redundancy. The MIQ (Mutual Information Quotient criterion) and MID (Mutual Information Difference criterion) are the most commonly used types of the objective function.

In practice, the extracted features with ResNet18 and ResNet50 are combined. By collecting 1,000 features from each models output, a total of 2,000 features were created for each pepper seed image.

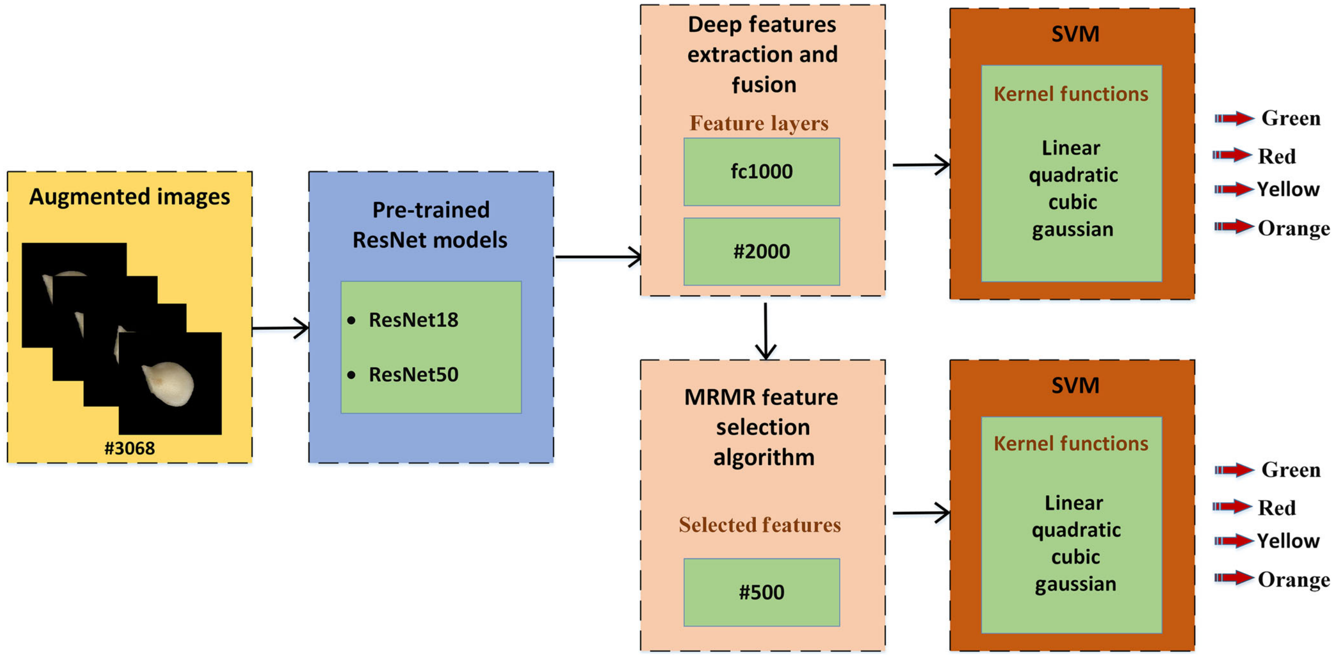

FIGURE 5 Deep features extraction, feature selection, and classification steps (First, features were extracted with pretrained ResNet models. The features from each model were combined. Finally, the most effective features were determined and classification was performed with SVM)

FIGURE 6 Confusion matrices of ResNet models

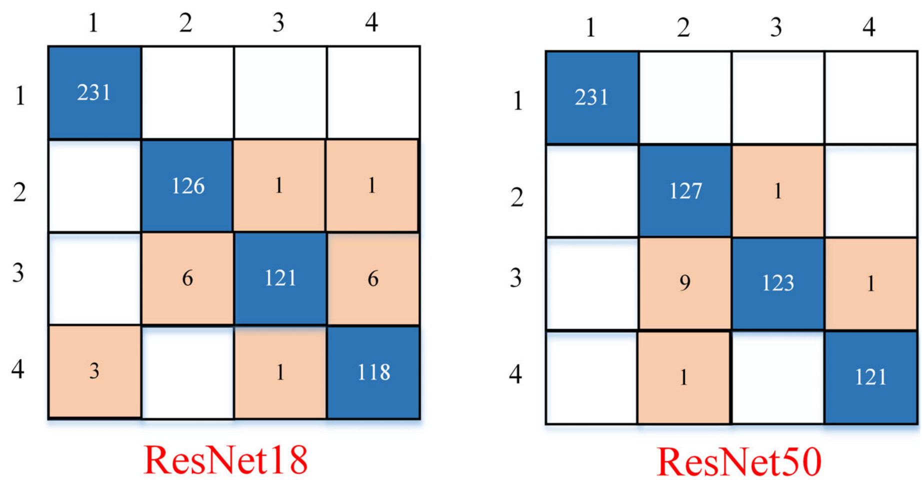

TABLE 3 Performance metrics of ResNet models

Model	Acc. (%)	Spec.	Prec.	Sens.	F1-Score	MCC	AUC
ResNet18	97.07	0.9904	0.9674	0.9653	0.9659	0.9568	0.9779
ResNet50	98.05	0.9938	0.9777	0.9772	0.9769	0.9711	0.9855

Using all these features can reduce training performance and slow down the training. To determine this, the first 2,000 featured images were classified with SVM. Then, with the MRMR algorithm, the 500 features that represent the strongest target were selected. These 500 features were then classified using SVMs containing different kernel functions.

3 | RESULTS AND DISCUSSION

This section examines the success of the state-of-the-art ResNet18 and ResNet50 models for pepper seed classification. ResNet18 and ResNet50 have a deep structure of 18 and 50 layers, respectively, and the input layer requires a 224 × 224 × 3 image. The deep learning

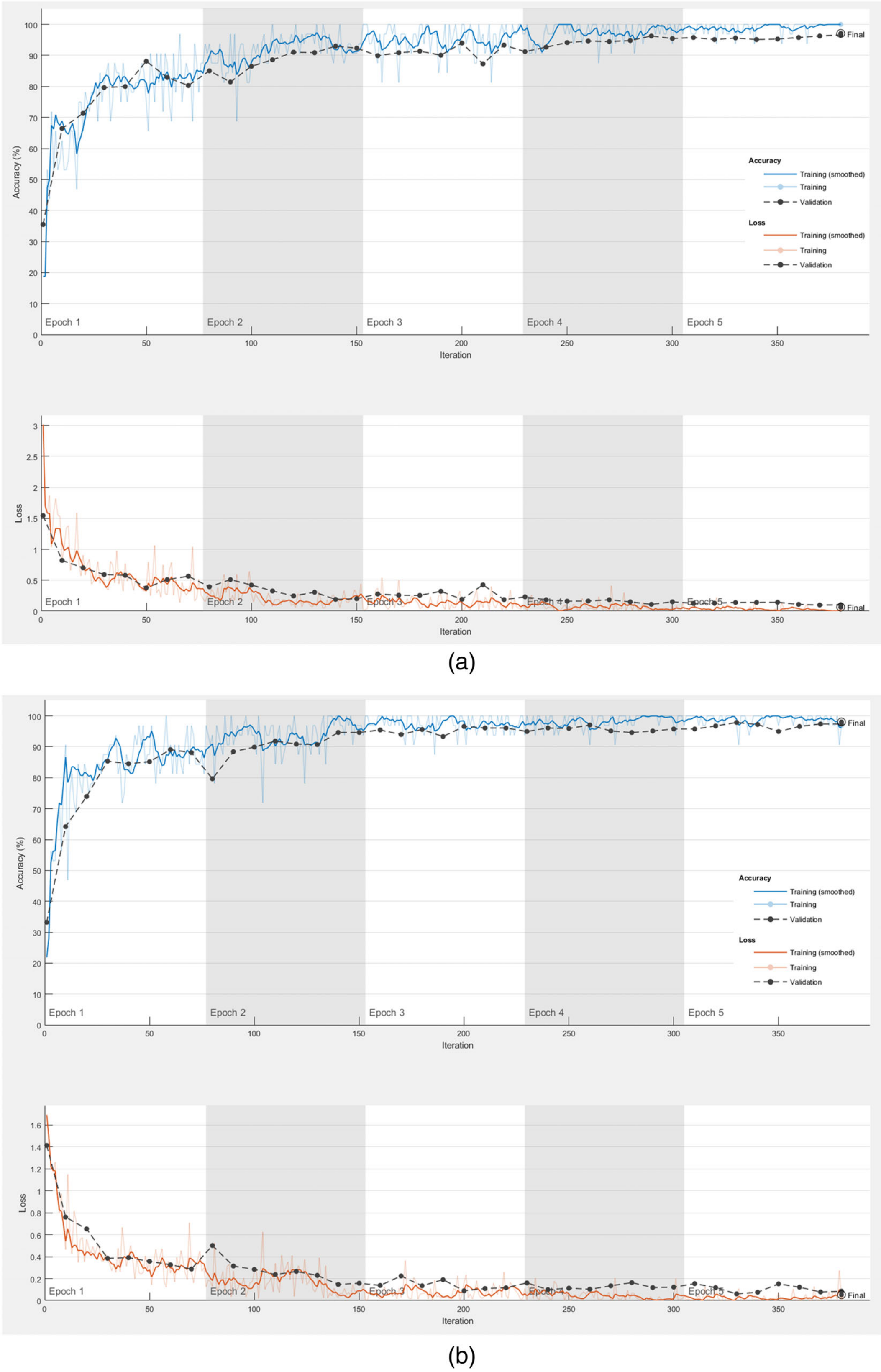

FIGURE 7 Training, validation, and loss graphics of ResNet models: (a) ResNet18; (b) ResNet50

experiments applied in this study were carried out on a laptop with Intel Core i7-7700HG CPU, NVIDIA GeForce GTX 1050 4 GB,16 GB RAM. After resizing the new images created by the data augmentation step, ResNet models were trained. Of the 3,068 images, 80% were reserved for training and 20% for testing. Parameter values used for training in ResNet models were as follows: Execution Environment:

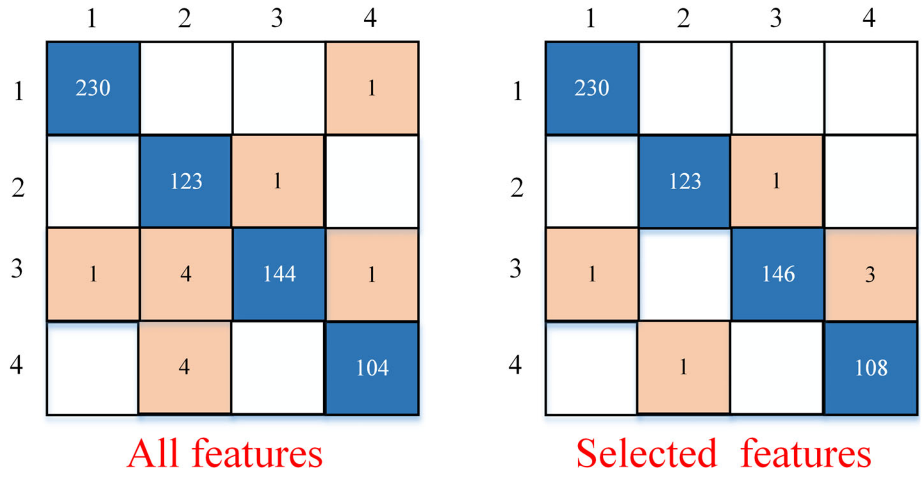

FIGURE 8 Confusion matrices for all features (2,000) and selected features (500)

TABLE 4 Performance metrics obtained as a result of SVM classification with different kernels using all features and selected features

Pretrained model	SVM kernel function	Accuracy (%)	Specificity	Precision	Sensitivity	F1-Score	MCC	AUC
All features (#2,000)	Linear	92.17	0.9742	0.9144	0.9051	0.9078	0.8839	0.9397
	Quadratic	96.74	0.9895	0.9640	0.9611	0.9614	0.9518	0.9753
	Cubic	98.04	0.9937	0.9772	0.9776	0.9772	0.9710	0.9857
	Gaussian	96.90	0.9900	0.9650	0.9640	0.9637	0.9543	0.9770
Selected features (#500)	Linear	91.84	0.9730	0.9121	0.9049	0.9078	0.8815	0.9390
	Quadratic	98.21	0.9940	0.9807	0.9815	0.9811	0.9750	0.9878
	Cubic	99.02	0.9968	0.9884	0.9890	0.9887	0.9855	0.9929
	Gaussian	97.06	0.9903	0.9675	0.9669	0.9672	0.9575	0.9786

GPU, Max Epochs: 5, Learn Rate Drop factor: 0.1, Learn Rate Drop period: 20, Initial Learn Rate: 0.001, and Mini Batch Size: 32. The optimization algorithm used for training and reducing error value was Stochastic Gradient Descent with Momentum (SGDM).

Result values were obtained after training and testing for each ResNet model. The confusion matrices obtained for ResNet18 and ResNet50 based on the classification results are shown in Figure 6. In the confusion matrix, seeds of green, red, yellow, and orange pepper cultivars are labeled 1, 2, 3, and 4, respectively. Columns show true class and rows show predicted class. Also, empty cell values in the confusion matrix are zero. In addition, specificity, precision, F1-score, MCC, sensitivity, and area under curve (AUC) performance metrics were calculated according to the confusion matrices, and the obtained values are shown in Table 3. The formula for each metric is defined between Equations (4) and (10) (Idrees, Rajarajan, Conti, Chen, & Rahulamathavan, 2017).

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} x100 \tag{4}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{5}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{6}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{7}$$

$$F1-\text{score} = \frac{2TP}{2TP+FP+FN} \tag{8}$$

$$MCC = \frac{(TP*TN)-(FN*FP)}{\sqrt{(TP+FN)*(TN+FP)*(TP+FP)*(TN+FN)}} \tag{9}$$

$$AUC = \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right) \tag{10}$$

TP, true positive; *TN*, true negative; *FP*, false positive; *FN*, false negative.

According to Table 3, the most successful results were obtained with ResNet50 with an accuracy of 98.05%. The accuracy value obtained with ResNet18 was 97.07%. Figure 7 shows the accuracy (%) and loss graph of the training and testing (verification) steps of pepper seed classification performed with ResNet models.

In the second step, instead of using the ResNet18 and ResNet50 models separately, it was aimed to combine the advantages of both algorithms. First, the features were combined directly. Then, among all these features, the most effective 500 features were selected by the MRMR algorithm. These features were then classified with SVM. In addition, the results of SVM containing different kernel functions were also obtained in the application. Performance comparison of all features and selected features is as in Figure 8 and Table 4. When the results were examined, the SVM algorithm classified pepper seeds more successfully through the cubic kernel function. In addition, a more successful classification was achieved after the feature selection process. Additionally, in the classification process with SVM-Cubic, the duration of the training time was 4.7161 s when 2,000 features were used, while this time decreased to 1.1736 s when 500 features were used. This means that the training time for SVM-Cubic is reduced by approximately 75% thanks to the feature selection algorithm.

According to Table 4, the highest accuracy in the classification using 2,000 features was obtained with SVM-Cubic with 98.04%. In the classification made with the 500 most effective features selected by the feature selection algorithm, the accuracy was found to be 99.02%. This result confirms the great effectiveness of the application of the CNN for the classification of peppers seeds. Ropelewska and Szwejda-Grzybowska (2021) classified three cultivars of pepper seeds using the textures from the images and discriminative classifiers. The accuracies were slightly lower and reached 90% in the case of models built based on textures selected from the color space Lab. Kurtulmus et al. (2016) determined the accuracy of 84.94% for the discrimination of 8 pepper seed cultivars with the use of neural networks. Our results proved higher than the exemplary literature data reported for the cultivar classification of pepper seeds. It prompts to carry out further research on pepper seed classification using the CNN models.

4 | CONCLUSIONS

In the study, the classification of pepper seeds with two popular ResNet CNN models was successfully performed. Unlike previous studies, this study enabled the more efficient use of CNN models in seed classification. For this purpose, CNN features were classified with SVM, and the most effective 500 features were determined by the MRMR feature selection algorithm. In the study, first, the ResNet18 and ResNet50 models were used directly, then the SVM and feature selection algorithm was added to show that the accuracy was increased. While SVM increased the classification success, MRMR provided more accurate results from fewer features. In addition, the results showed the success of CNN-based methods for pepper seed classification. This study guides researchers for future studies that deep learning-based CNN can be applied to determine the cultivar of pepper seed.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

AUTHOR CONTRIBUTIONS

Kadir Sabanci: Conceptualization; data curation; formal analysis; investigation; methodology; software; supervision; validation; visualization; writing – original draft; writing – review and editing. **Muhammet Fatih Aslan:** Conceptualization; data curation; formal analysis; investigation; methodology; software; validation; visualization; writing – original draft; writing – review and editing. **Ewa Ropelewska:** Conceptualization; data curation; investigation; methodology; resources; supervision; validation; writing – original draft; writing – review and editing. **Muhammed Fahri Unlersen:** Investigation; methodology; software; supervision; writing – review and editing.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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