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A machine vision-intelligent modelling based technique for in-line bell pepper sorting

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ABSTRACT

The uniformity of appearance attributes of bell peppers is significant for consumers and food industries. To automate the sorting process of bell peppers and improve the packaging quality of this crop by detecting and separating the not likable low-color bell peppers, developing an appropriate sorting system would be of high importance and influence. According to standards and export needs, the bell pepper should be graded based on maturity levels and size to five classes. This research has been aimed to develop a machine vision-based system equipped with an intelligent modelling approach for in-line sorting bell peppers into desirable and undesirable samples, with the ability to predict the maturity level and the size of the desirable bell peppers. Multilayer perceptron (MLP) artificial neural networks (ANNs) as the nonlinear models were designed for that purpose. The MLP models were trained and evaluated through five-fold cross-validation method. The optimum MLP classifier was compared with a linear discriminant analysis (LDA) model. The results showed that the MLP outperforms the LDA model. The processing time to classify each captured image was estimated as 0.2 s/sample, which is fast enough for in-line application. Accordingly, the optimum MLP model was integrated with a machine vision-based sorting machine, and the developed system was evaluated in the in-line phase. The performance parameters, including accuracy, precision, sensitivity, and specificity, were 93.2%, 86.4%, 84%, and 95.7%, respectively. The total sorting rate of the bell pepper was also measured as approximately 3 000 samples/h.

1. Introduction

Bell pepper is the third most substantial crop of the *Solanaceae* family [1]. This plant contains essential nutrients such as antioxidants, lycopene, ascorbic acid, and carotenoids. Bell peppers are commonly marketed in four colors, including green, red, orange, and yellow. In General, all mature bell peppers have an initial green rind, turning red or other colors when fully ripened [2]. Uniform size and color are among the most important export standards of bell peppers [15]. At most, bell pepper is sorted manually to meet the mentioned export criteria. Also, it is worth mentioning that the fully ripen pale bell peppers (with a color ratio less than 70%) is not welcomed by consumers [32]. So, discrimination of the bell peppers based on color would be crucial to preparing high-quality products in packaging the export purposes.

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Today, various industrial processes in several fields have utilized new techniques such as machine vision (MV) technology to meet these requirements. MV has been vastly adopted in many areas, such as control systems in different medical approaches, defense, precision agriculture, and food systems. Applications of this technology in the food industry are food analysis, qualification and quantification purposes, detection, packaging, etc. [3–5]. To achieve that, image processing and image analysis steps are applied to the acquired images. The most common methods used for image analysis and recognition of crops are machine learning (ML) techniques [6]. Grading using ML is based on data mining knowledge and computational intelligence techniques. Universally, there are two grading approaches: classification and clustering. Classification is a supervised learning method, while clustering is an unsupervised one. In the classification approach, the models learn from a sizeable pre-categorized data set (so-called training set). Then, the developed models are applied to classify new items (new data). Common classification techniques include Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Tree (DT), Bayesian network, K-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), and Fuzzy Logic (FL). Also, new technique called deep learning (DL), which is a branch of the ANN method, has been recently suggested in classification problems [29,30]. Among the mentioned classification techniques, ANNs are one of the most research fields in the contemporary era that have been used in many sectors of engineering research and the food industry [4,7–10]. Determining the ripening status of fresh agricultural products raises concerns for producers, exporters, and companies. Generally, the degree of maturation and ripening is determined by appearance, color, and size. In previous studies, bell pepper [11], chili pepper [12], banana [13], and mango [14] were discriminated into different classes based on ripening status by using MV and intelligent modeling techniques. An MV system was developed to work on a mobile device to detect four levels of ripeness in chili pepper [12]. The images of chili pepper were captured from one month before harvesting until the harvesting period, and the acquired dataset was used to train and validate the system. The K-Means clustering and fuzzy logic methods were employed for image segmentation and maturity level detection, respectively. The results showed that the accuracy of detecting chili pepper ripeness was 90% [12]. Recently, Harel et al. [31] developed an image acquisition-based system coupled with two different algorithms (logistic regression and random forest algorithm) to classify bell peppers based on maturity. They concluded that the collected datasets had different characteristics, and more powerful classification models should be developed to overcome the main problem.

To automate the sorting process of bell peppers according to export needs and improve the packaging quality of this crop (by detecting and separating the not likable low-color bell peppers), developing an MV system based on computational intelligence methods would be highly recommended. To the best of our knowledge, there is no research to classify bell peppers into desirable and undesirable samples according to export criteria. This study aims to develop an in-line MV system for sorting bell peppers based on standards, with the ability to predict the maturity level and the size of the desirable bell peppers. To this end, an MV system for grading this crop to five classes along with its appropriate image processing algorithms was developed and implemented. Various intelligent classifiers, including multilayer perceptron (MLP) artificial neural networks (ANNs) and LDA models were developed, and the accuracies of the classifiers were compared.

2. Material and methods

In this study, an MV system was developed for sorting bell peppers into five classes based on some appearance features according to export preferences. An overview of the main steps of the experimental procedure is presented in Fig. 1.

2.1. Sample preparation

A total of 640 fresh bell pepper (Westland 8 108 cultivar) in three maturity levels, including full green, full red, and immature stage (red color, the ratio of 50–70%) with different sizes, were harvested in September 2019 at daybreak time from a greenhouse. The weight range of samples was 100 to 230 g. The harvested samples were packaged into 10 kg boxes according to local standards and transferred immediately to the laboratory via a refrigerated truck. All samples were processed on the same harvesting day. The samples were randomly placed on a clean table. Then, the rind of each

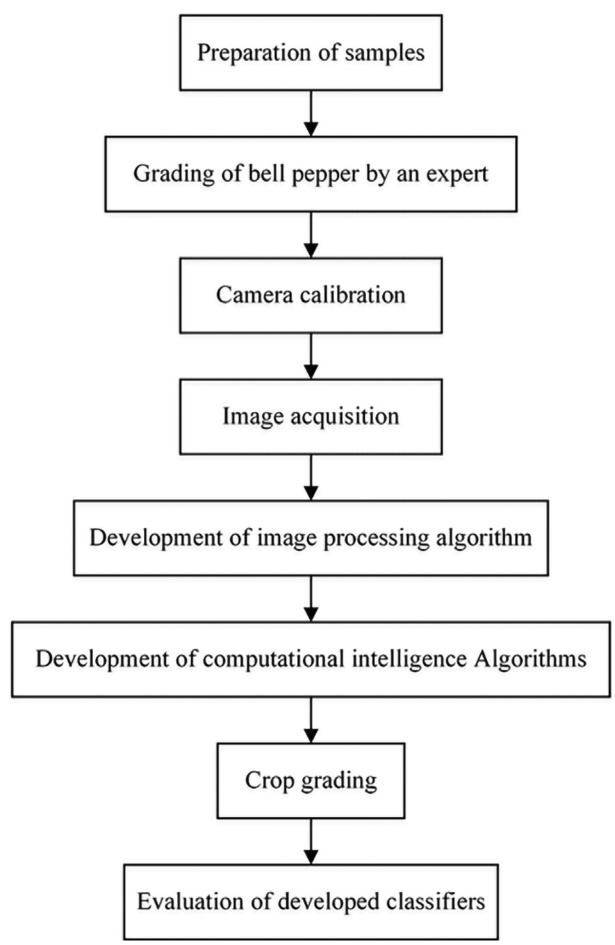


Fig. 1 – Diagram of the experimental methodology.

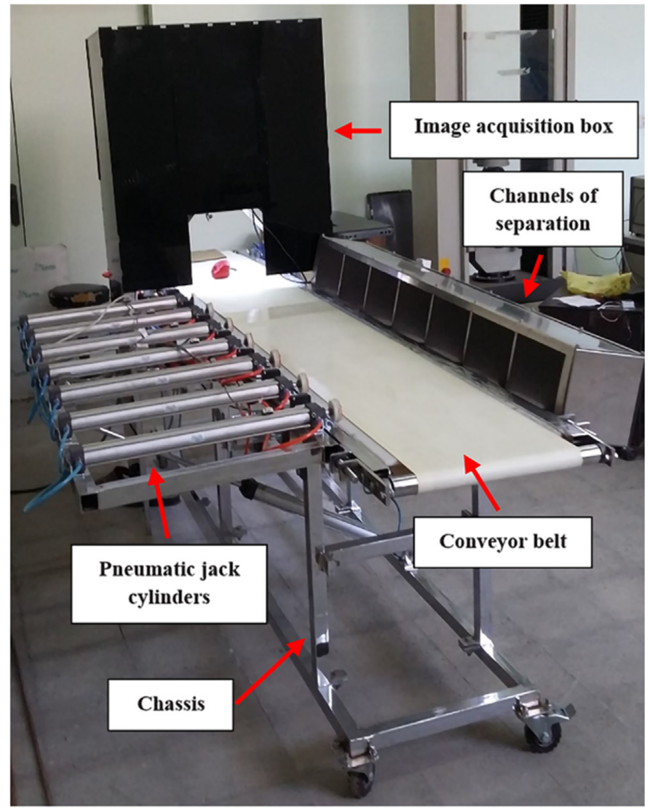
specimen was manually cleaned from dust using a soft and humid cloth. Then, samples were placed at laboratory temperature for 30 min to dry. In the next step, the bell peppers were manually graded based on the maturity level and size by an expert in horticultural science and an expert in the food industry [15]. The samples were graded into five classes according to export descriptor [15]. The selected classes included full green crop (G) with first-grade size (S1) named class 1 or GS1; full green crop with second-grade size (S2) named class 2 or GS2 class; full red crop (R) with first-grade size (class 3 or RS1 class); full red crop with second-grade size (class 4 or RS2 class); and immature bell pepper crop that contains 50–70% red color ratio (UR) with good size (class 5 or UR class).

2.2. Sorting system and image acquisition unit

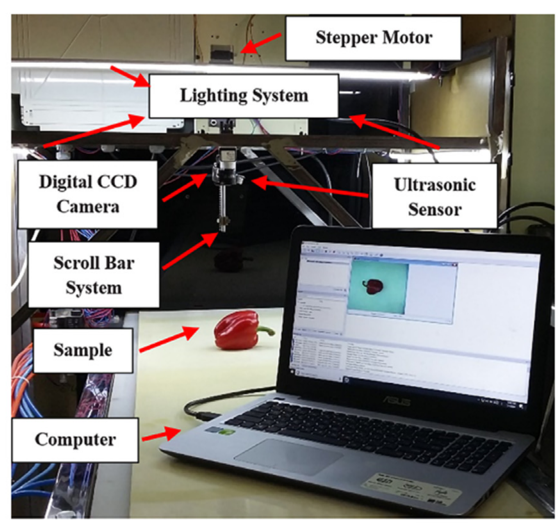
Fig. 2 shows the developed sorting system equipped with a MV unit. For in-line sorting purposes, the sorting machine was supplied with a PVC white conveyor belt with 50 cm wide, 300 cm long and a thickness of 2 mm. The conveyor belt was driven by a 180 W three-phase electric motor with a 1:15 gear reducer. Also, the sorting machine has been equipped with a proximity sensor for measuring the motor's speed and photoelectric sensors to detect moving objects on the conveyor belt. Magnetic sensors were mounted on the jack cylinder to detect the position of the pneumatic actuators. The basic parts of the sorter are shown in Fig. 2(a).

The bell pepper images were acquired by a MV box mounted on the top of the conveyor belt and fabricated in cubic shape from an acrylic sheet with dimensions of 800 × 500 × 1 000 mm and 6 mm thickness. The black acrylic sheet was selected to reduce the effects of ambient noise and light reflection. The images were acquired by an industrial digital CCD camera (ace1300-200uc, Basler Co., Germany). To set the distance between the camera and the bottom base (the conveyor belt), an ultrasonic distance sensor (HC-SR04, China) was used. Also, a stepper motor with a scroll bar system was utilized to vertically move and regulate the distance of the camera from the base. A PLC-controlled unit (FBs-32MAR2-AC, Fatek company, Taiwan of China) was utilized for controlling and regulating all parts and steps. The basic components of the designed imagine system (Fig. 2(b)) were all installed on an iron chassis constructed from a profile with a cross-section size of 20 × 20 mm^2. The camera was installed 30 cm above the conveyor belt. To achieve the uniformity of lighting inside the MV system, an artificial lighting system consisting of three LED lamps (4014-144 LED white, 50 cm, 12 V DC, China) was installed. To adjust the appropriate illumination intensity, an intensity adjuster was utilized. The selected lighting intensity and the camera settings were fixed during the entire imaging time.

The bell peppers were placed horizontally on the bottom base under the camera for imaging. Then, images of bell peppers in all different classes (Fig. 3) were acquired in off-line mode and immediately transferred and saved on a laptop using a USB 3.0 camera's port for further analysis. The images were saved in high resolution with Red-Green-Blue (RGB) color space, 1 280 × 1 024 pixels size, and 24-bit depth.



(a)



(b)

Fig. 2 – The developed bell pepper sorting system: (a) basic parts of bell pepper grading machine and (b) basic components of designed imagine system.

2.3. Image processing

An algorithm based on image processing knowledge was developed to extract some bell pepper appearance features

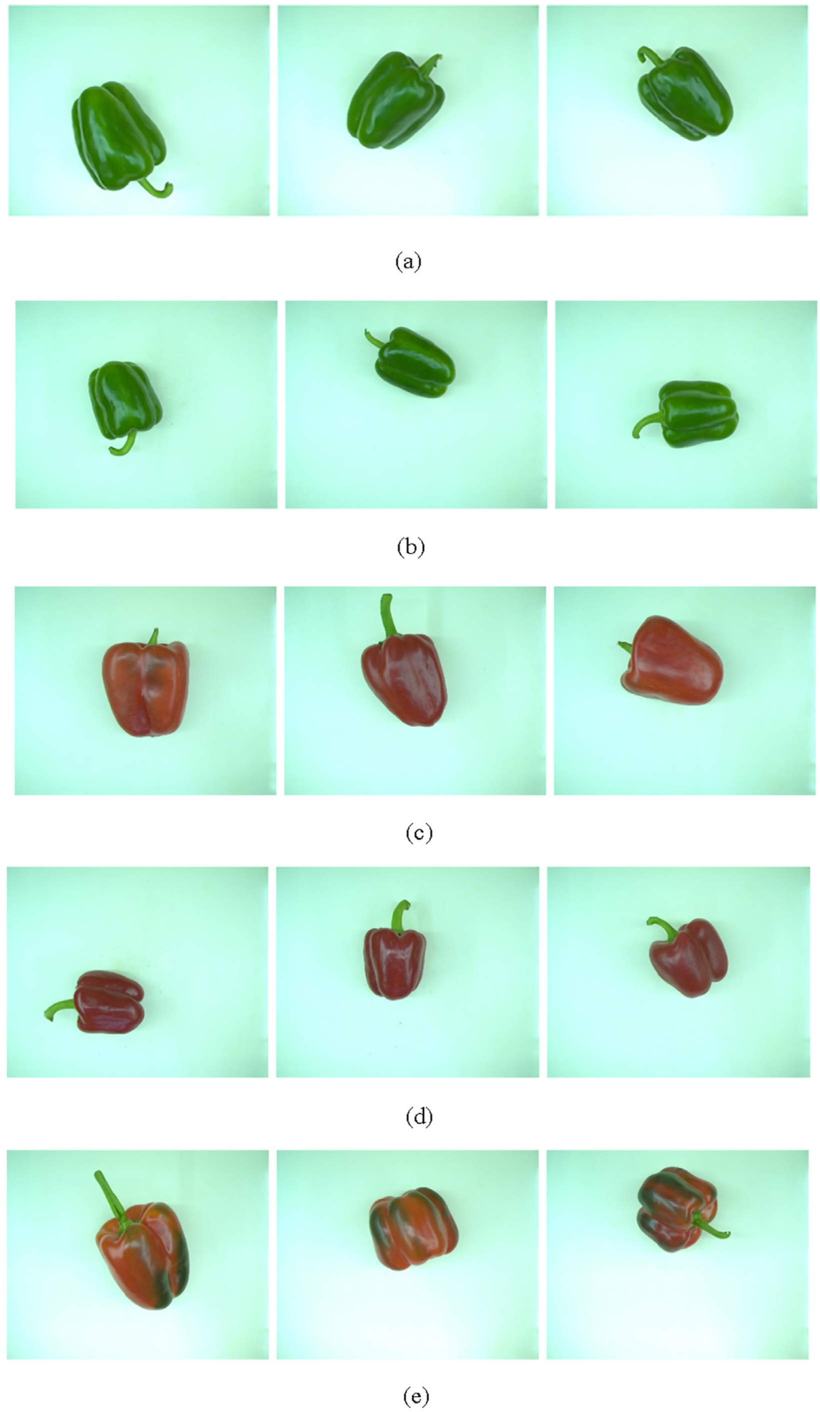


Fig. 3 – Different bell pepper classes: (a) GS1 class, (b) GS2 class, (c) RS1 class, (d) RS2 class and (e) UR class.

from the captured images. The basic steps of the image-processing algorithm are as follows:

1) The stored images of bell pepper were called.
2) The images were corrected using the distortion coefficient obtained from camera calibration.
3) The images were segmented, and the bell pepper was separated from the background.
4) All intended features were obtained just from the bell pepper's pixels.

2.3.1. Image segmentation

Image segmentation is one of the most challenging tasks in image processing techniques. This step is critical in the image-processing algorithm because the extracting accuracy of the desired features is highly related to the success of the segmentation step. In the present study, the purpose of segmentation was to isolate the bell pepper sample from the background. Generally, there are several methods for image segmentation, including edge-based methods, region-based methods, and lighting-based segmentation methods.

Thresholding is one of the simplest and most widely used segmentation methods based on lighting. In the literature, Otsu's thresholding method had been acceptable for the segmentation of agricultural and food products [4,16]. This technique is used to perform automatic image thresholding. In the segmented image, the pixels with values less than intensity threshold are transformed to 0 (black), while other pixels are transformed to 1 (white) [17]. In this research, Otsu's thresholding method was employed to separate the bell pepper in the original image (Fig. 4(a)) from background. Based on the pre-experiments on various bell pepper samples with different colors and by examining different channels of several color spaces, including RGB color space, Hue-Saturation-Value (HSV) color space, and CIELAB color space, it was found that the blue color channel (B) of the RGB color space has a high contrast between a bell pepper and background (Fig. 4 (c)). Accordingly, the B component in the RGB color space was selected to transform the RGB image of the bell peppers into the primary binary image type (Fig. 4(d)).

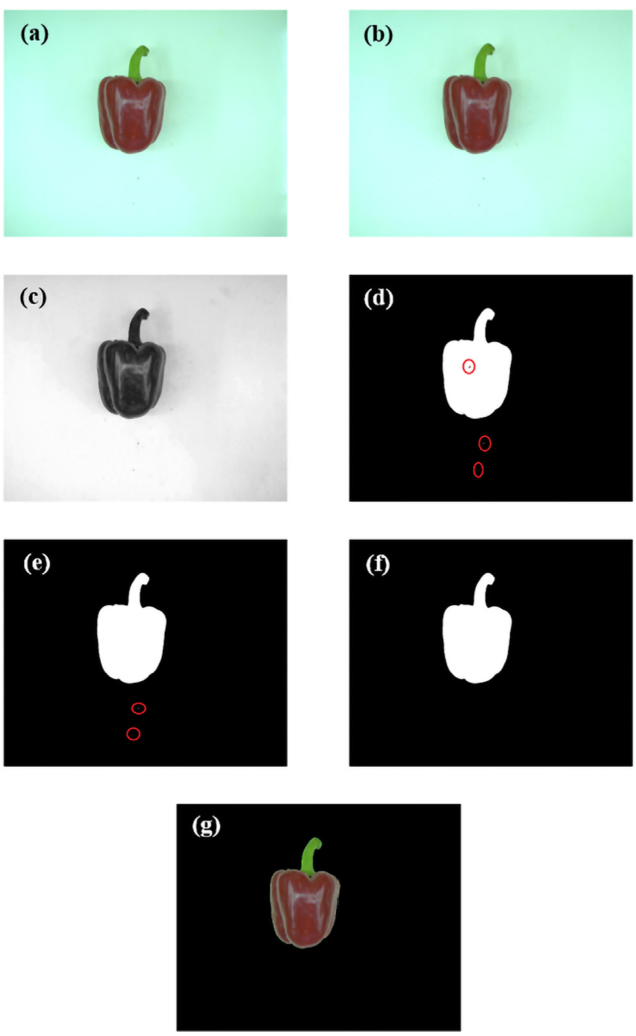


Fig. 4 – Segmentation steps of the captured bell pepper using Otsu's thresholding method in the blue channel of RGB color space: (a) Original image, (b) Calibrated image, (c) B-component of bell pepper image, (d) Primary binary image obtained from Otsu method, (e) Secondary binary image after filling the white holes, (f) Final binary image after applying the morphological operator and (g) Segmented image obtained by multiplying the final binary image in the calibrated RGB image.

The obtained binary image contained noisy areas or holes (small black points) on the white object area due to light reflection. Also, some white points can be found on the black background as a result of foreing debris on the background of the imaging system. Therefore, it is necessary to delete these noises prior to subsequent analyses. The black holes were converted to white color by applying *OpenCV's floodFill* operator (Fig. 4(e)). Next, morphological operations were employed to remove the second noise. An appropriate function was applied to remove all jointed components (objects) with pixels count less than a certain limit in the binary image. As a result, the pixels count of the objects in the resulting image will be more than 150 pixels. In the output binary image, just one object (bell pepper sample) was remained (Fig. 4(f)). The white points (equal to one value) in the output binary image refer to the bell pepper sample. In the next step, the segmented image was obtained by multiplying the final binary image (Fig. 4(f)) in the calibrated RGB image (Fig. 4(b)). The segmented image is shown in Fig. 4(g).

2.3.2. *Features extraction*

Feature extraction is the next important step in developing the classifier models. The bell pepper crops have various sizes, colors, and textures. Therefore, different features were extracted from the acquired images of the bell peppers. In the following, the extracted features are explained in detail.

Color and texture feature: The external color of the bell pepper is closely related to its maturity stage. Therefore, applying the color and texture features of the crop in the developed classifier would be very important. Color is one of the most essential features for image-based classification applications and image retrieval [11]. Color is one of the widely used features in agricultural and food quality assessment [10,18]. Using color features allows separating unripe crops from ripe or damaged products from healthy ones. In the present study, the RGB, CIELAB, and HSV color spaces were selected to extract the bell peppers color features. Four color features, including mean, variance, standard deviation, and skewness, were extracted for each color component (R, G, B, L*, a*, b*, H, S, and V). These parameters are statistical measurements that describe the color distribution in the image. Mean (Also known as arithmetic mean or average) describes the central tendency of the histogram of the image. While variance describes how far values lie from the mean. Standard deviation represents the squared root of the variance. It measures the variability or dispersion of a distribution. On the other hand, skewness measures the degree of asymmetry exhibited by the data. For a color image with size $M \times N$ pixels, the extracted color features are given by Eqs. (1) to (4). A total of 36 color features were computed [19].

$$\mu = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} x_{i,j} \tag{1}$$

$$Var = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}(x_{i,j} - \mu)^2 \tag{2}$$

$$\sigma = \sqrt{\frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}(x_{i,j} - \mu)^2} \tag{3}$$

$$S_k = \frac{\frac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}(x_{i,j} - \mu)^3}{(\sqrt{Var})^3} \tag{4}$$

where $M \times N$ is the size of the captured image; $x_{i,j}$ is the pixel value of the grey image; μ is the mean; *Var* is the variance; σ is the standard deviation; and S_k is the skewness, respectively.

The texture is a surface feature that includes the spatial distribution of gray levels in a neighborhood. Texture analysis may be valuable when color differences are minimal [20]. Green, red, and semi-ripe bell peppers have different appearances and colors. However, GS1 and GS2 classes had the same color in the captured images. It is worth noting that the color of the RS1 and RS2 classes was similar, whereas the color of semi-ripe bell peppers may be similar to the color of red bell pepper. Nevertheless, the distribution of the grey levels is different in the images related to these two ripeness stages. So, the texture features were extracted and employed accordingly. Statistical properties are widely used to describe the texture of different agricultural and food products [21,22]. Gray-level co-occurrence matrix (GLCM) is a statistical method for analyzing the texture content of a group of pixels (representing the bell pepper sample in this study) in a gray image. In this approach, the number of occurrences in a pair of pixels with particular intensity values and with defined spatial patterns (e.g., vertical neighborhood and diametrical neighborhood) in the image is checked. The spatial pattern is determined by setting the distance (d) and the angle (θ) between the pairs of pixels that are in the neighborhood. To determine the texture properties, various statistical parameters are usually calculated from GLCM.

In this research, the GLCM method was utilized to describe the texture of the bell peppers. Entropy, energy, contrast, and correlation features were obtained from GLCM for each sample. Four angles (i.e., 0°, 45°, 90°, and 135°) with a distance equal to one (d = 1) were selected and all statistical parameters were calculated from each component in RGB, CIELAB, and HSV color spaces. Overall, 144 features (4 statistical parameters × 4 angle values × one distance value × 9 color components) from GLCM were extracted. The GLCM matrix for an image (I) with the size of $M \times N$ was computed according to Eq. (5) as follows [19].

$$GL_{\Delta x \Delta y}(i,j) = \sum_{P=1}^{M}\sum_{q=1}^{N}\left\{\begin{matrix} 1,\ \text{if}\ I(p,q)\ ==i,\ \text{and}\ I(p+\Delta x, q+\Delta y)\ == j \\ 0,\ \text{otherwise}\end{matrix}\right\} \tag{5}$$

where GL is the GLCM; i, and j are the gray intensity values of the pixels; p and q represent the image coordinates; and (Δx, Δy) are the offset parameters, respectively.

Each element of the co-occurrence matrix indicates the number of occurrences of a pair of pixels with special gray levels. The formulas of statistical parameters calculated from GLCM are given in Eqs. (6) to (9) as follows [19].

$$Entropy = -\sum_{i,j} p(i,j) \times \log(p(i,j)) \tag{6}$$

$$Energy = \sum_{i=1}^{K}\sum_{j=1}^{K}(p(i,j))^2 \tag{7}$$

$$Contrast = \sum_{i=1}^{K}\sum_{j=1}^{K}(i-j)^2\ p_{ij} \tag{8}$$

$$Correlation = \sum_{i=1}^{K}\sum_{j=1}^{K}\frac{(i-m_r)(j-m_c)p_{ij}}{\sigma_r\sigma_c} \tag{9}$$

where K is the row or the column dimension of GLCM; i and j are the GLCM coordinates; $p_{i,j}$ represents the value of the element of GLCM; m_r is the mean value of GLCM calculated along the rows; and m_c is the mean value of GLCM calculated along with the columns. Also, σ_r and σ_c represent the standard deviations along the rows and the columns, respectively.

Size features: Consumers prioritize buying agricultural products with equal weight or uniform size. Since the bell pepper samples in this study had different sizes (see Fig. 3), extracting the size features can help develop the classifier. Altogether, five geometrical features related to the size of bell pepper were extracted from the binary images: area, aspect ratio, major axis, minor axis, and equivalent diameter [19].

2.4. *Feature selection*

RGB, CIELAB, and HSV color spaces were selected to extract the color features of the bell peppers. Four color features, including mean, variance, standard deviation, and skewness, were extracted for each color component (R, G, B, L*, a*, b*, H, S, and V). A total of 36 color features were computed. Furthermore, the gray-level co-occurrence matrix (GLCM) method was utilized to describe the texture of the bell peppers. Entropy, energy, contrast, and correlation features were obtained from GLCM for each sample. Four angles (i.e. 0°, 45°, 90°, and 135°) with a distance equal to one (d = 1) were selected, and all statistical parameters were calculated from each component in RGB, CIELAB, and HSV color spaces. A total of 144 features (4 statistical parameters × 4 angle values × one distance value × 9 color components) from GLCM were extracted. Also, five geometrical features related to the size of the bell peppers (i.e., area, aspect ratio, major axis, minor axis, and equivalent diameter) were extracted from the binary images. Based on that, 185 features were obtained based on the maturity status and size to classify the crop. The presence of many features creates problems such as complexity of calculations, curse of dimensionality, difficulty in knowledge extraction, and over-fitting [23]. Numerous algorithms and techniques have been proposed to select the appropriate features. Correlation-based feature selection (CFS) is the most widespread feature subset selector used in ML that works in combination with a search method such as Best First (BF), Greedy Search, or Exhaustive Search [24,25]. The CFS algorithm evaluates subsets of features regarding that proper feature subsets are highly correlated with the class while having low inter-correlation. The following equation (Eq.(10)) is used to evaluate the merit of a candidate feature subset S consisting of k features [26].

$$Merit(S_k) = \frac{k\bar{r}_{FL}}{\sqrt{k + k(k-1)\bar{r}_{FF}}} \tag{10}$$

where $\bar{r}_{FL}$ is the average value of all feature-classification correlations; and $\bar{r}_{FF}$ is the average value of all feature-feature correlations.

In the present study, the CFS algorithm with the BF search method was utilized to reduce the dimensions of the extracted features and to select the more useful attributes. For this purpose, the *WEKA 3.9* software (University of Waikato, New Zealand) was utilized. The CFS algorithm arranged the extracted features from bell pepper images according to their impact on the classification process. The CFS method was utilized because it allows choosing only a certain number of the best features to be used by the proposed classifier, which positively affects the speed of the algorithm developed. While most other feature selection methods merge all the features together (i.e. PCA). The original aim of this research was to develop a MV-based technique for in-line separating bell peppers to be used in industrial applications. Therefore, the classification speed of the proposed classifier is essential. The number of features used by the selected classifier to predict the true classes plays a significant role in the time required for data processing. Accordingly, only six features resulting from applying the CFS algorithm were used to classify the crop.

2.5. LDA classifier

The LDA method was chosen as a linear model to classify the bell peppers in this study. The LDA technique is used to find linear combinations of properties that distinguish two or more classes of objects. The main advantage of this method is its simplicity and ease of computation, which causes the speed of the final developed algorithm to be significantly improved.

2.6. MLP classifier

As a nonlinear model, the ANN method was developed to classify the bell peppers. The main components of ANNs are neurons that also called processing elements. An ANN is composed of input, hidden, and output layers. This network has the power of learning, generalization, and decision-making, like the human brain. The learning stage of ANN is carried out by adjusting its parameters (weights and bias between neurons) to meet the desired expectation such that the difference between the actual and the estimated values becomes acceptable. To develop ANNs, it is necessary to determine the number of layers, number of neurons per each layer, connection type of layers with each other, and the training method. Today, a multilayer perceptron (MLP) structure is the most frequently used type of ANNs in engineering applications. Based on the purpose of the MLP network (classification, function approximation, etc.), the transfer function types are selected as linear or nonlinear. Generally, all transfer functions in the hidden and output layer(s) are selected as the nonlinear type in classification problems (i.e. logarithm of sigmoid function, Gaussian function, and hyperbolic tangent function). Different types of MLPs were designed to classify the bell peppers in this study. The developed ANNs contained different neurons in the input layer, which are the selected features obtained from applying the CSF algorithm. Also, the output layer included five neurons, indicating different classes of the bell peppers; i.e., green with grade 1 size class, green with grade 2 size class, red with grade 1 size class, red with grade 2 size class, and immature class. Considering that the number of hidden layers would have a high effect on the operation speed of the developed algorithm in in-line sorting, therefore just one hidden layer for all designed MLP structures was selected. To select the best MLP model, several numbers of neurons in the hidden layer (2 to 20 neurons) were implemented, and the overall accuracy (OA) index related to each model for the testing dataset was compared. The network that presented the highest OA values was chosen as the optimum model. The transfer functions for all neurons in the hidden and output layers were selected as a hyperbolic tangent, which showed good performance in previous works [4,27]. To solve nonlinear classification problems, Levenberg-Marquardt algorithm (LMA) is usually used as a standard algorithm for training the ANNs [16]. A combination of gradient descent and Gauss-Newton methods appears in this algorithm [28]. Accordingly, the LMA was utilized for training and validation the developed networks. In all the developed models (LDA and MLP models), 80% and 20% of the dataset were selected as training and testing data, respectively. The C++ program using *OpenCV-3.1 library* with *Microsoft Visual Studio 2015* software was utilized to implement all image-processing steps. Also, the *MATLAB 2018b* software was applied to develop the LDA and MLP models.

2.7. K-fold cross-validation and performance evaluation of the developed models

The developed MLP models were trained and evaluated through the 5-fold cross-validation method. For this purpose, the dataset was divided randomly into 5 subsets. A single subset was used for validation (testing), while the other four subsets were used for training the models. This cross-validation procedure was reiterated 5 times. In each training time, the validation set was shifted from one fold to another. In classification problems, the confusion matrix is often used to evaluate the classifier performance. Also, different performance parameters are calculated based on this matrix. The confusion matrices associated with the testing dataset were obtained and the performances of developed classifiers were evaluated using four statistical parameters (i.e., accuracy, precision, sensitivity, and specificity), which are usually utilized in the literature [29]. The final performance of the developed models was evaluated based on the average values of the calculated performance parameters from each class. The description of each performance indicator and its formula are listed in Table 1. In the next step, for in-line sorting of the bell peppers, the accuracy results of the developed classifiers in off-line phase were evaluated and compared. After that, the parameters and the weights related to the better model were integrated with a MV-based bell pepper sorting machine. Then, the developed sorting system was evaluated in the in-line phase.

Table 1 – The performance indicators used in the evaluation of the classifiers with their description and formulas.

Performance indicator name	Description	Formula
Accuracy	Overall performance of the classifier on each class.	$ACC = \frac{TN + TP}{TN + FP + TP + FN}$
Precision	Affectivity of the classifier in recognize the positive labels.	$PR = \frac{TP}{TP + FP}$
Sensitivity	Proportion of actual positives in a certain class which are correctly identified by the classifier.	$SE = \frac{TP}{TP + FN}$
Specificity	Affectivity of the classifier in recognize the negative labels.	$SP = \frac{TN}{TN + FP}$
Overall accuracy	Overall performance of the classifier on all testing dataset.	$OAC = \frac{\sum_{i=1}^{5} TP(i)}{N}$

TP is the samples of a determined class graded correctly by the developed classification model; **FN** is the samples of a determined class graded incorrectly by the developed classification; **TN** is the samples of other classes graded correctly by the developed classification model; **FP** is the samples of other classes graded incorrectly by the developed classification model; and **N** is the total number of the testing dataset.

3. Results and discussion

3.1. *Selected features*

The CFS algorithm arranged the extracted features from the bell pepper images according to their impact on the classification process. The number of attributes used by the classifier for predicting the true classes plays a significant role in the time required for data processing. The selection of superior features has a significant impact on the accuracy and the performance of the developed classifier. By applying this step, the dimensions of features are reduced, and the model's accuracy is increased. Accordingly, only six features resulting from applying the CSF algorithm were used to classify the bell pepper crop. The selected features listed in Table 2 were used as inputs for the designed MLP networks.

3.2. *Optimum MLP model*

The performance of the developed MLP networks using different numbers of neurons in the hidden layer is shown in Fig. 5. Based on the analysis and the comparison of the overall accuracy related to training and testing dataset for various MLP structures, the best model had 8 neurons in the hidden layer. According to this diagram, we can evaluate and compare the accuracy of this model with others. Accordingly, the optimum structure of the MLP ANN is obtained as 6–8-5, having 6 input factors, 8 neurons in the hidden layer and five classes in the output layer (Fig. 6). The bell peppers are classified into five classes using this structure, including GS1, GS2, RS1, RS2, and UR.

3.3. *ROC curves and quantitative classification by optimum MLP classifier and LDA model in the off-line phase*

The performance of the two developed classifiers on the test dataset was evaluated using the receiver operating characteristic (ROC) curves. The ROC curves associated with the overall predicting of five bell pepper classes using the optimum MLP classifier and developed LDA model are shown in Fig. 7. According to the distance between the ROC curve of each class and the baseline related to each model, it can be noted that the optimum MLP classifier outperforms the LDA model. ROC curves shown in Fig. 7(a) confirm the capability of the optimum MLP classifier in classifying bell peppers.

The confusion matrix contains the information about actual and predicted classifications accomplished by the classifier. The normalized confusion matrices were calculated to assess the classification performance of the optimum MLP classifier and LDA model on the test data in the off-line phase. Fig. 8 illustrates results as a percentage.

As shown in Fig. 8, the performance of the LDA model for the immature class was as low as 72.72% of immature samples were placed into RS1 and RS2 categories wrongly. Also, the grading of GS1 class was not good. The highest performance level of the LDA method was obtained in GS2 class. On the other hand, it can be seen that the optimum MLP model correctly discriminated the GS1 and RS1 classes. Although the optimum MLP model also showed low performance for the immature class, the optimum MLP classifier was better than the LDA model in discrimination of this class. However, the performance (i.e. ACC, PR, SE, and SP) obtained from the confusion matrix related to the LDA classifier in off-

Table 2 – The selected features obtained from the CSF technique.

Feature name	Description
Area	Area of the projected surface from the sample.
Equivalent diameter	Minimum diameter of the projected area of bell pepper.
$Meancolor_R$	Average value of R component in RGB color space.
$Stdcolor_B$	Standard deviation of B component in RGB color space.
$Stdcolor_{a^*}$	Standard deviation of a star component in CIE Lab color space.
$Contrast_R^{\theta=0,\ d=1}$	Contrast amount of R component in RGB color space with $\theta = 0^{\circ}$ and distance (d) equal to 1.

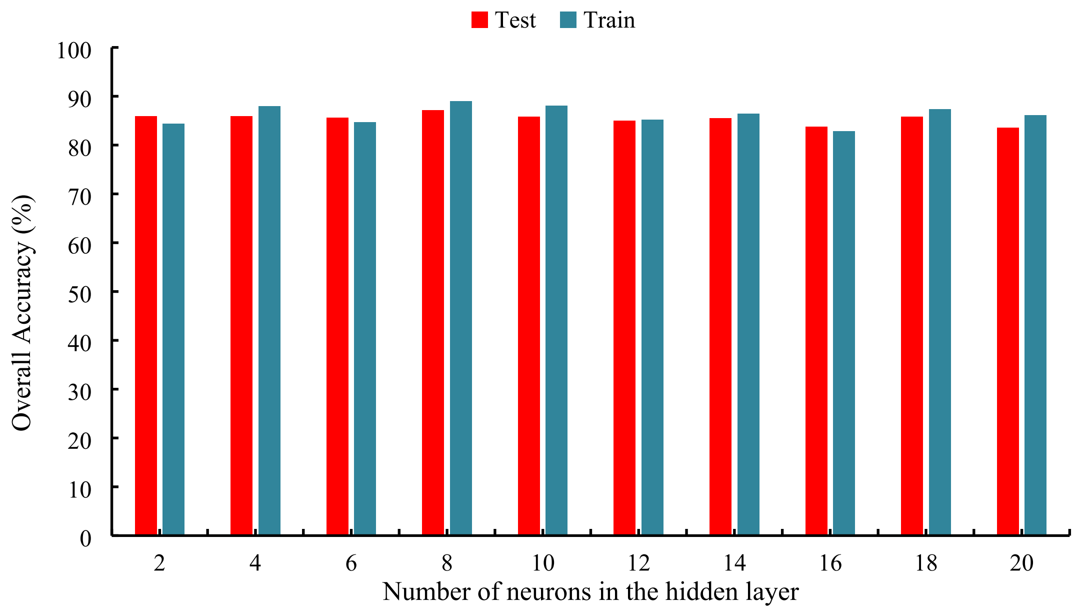


Fig. 5 – Overall accuracy values obtained from different MLP structures.

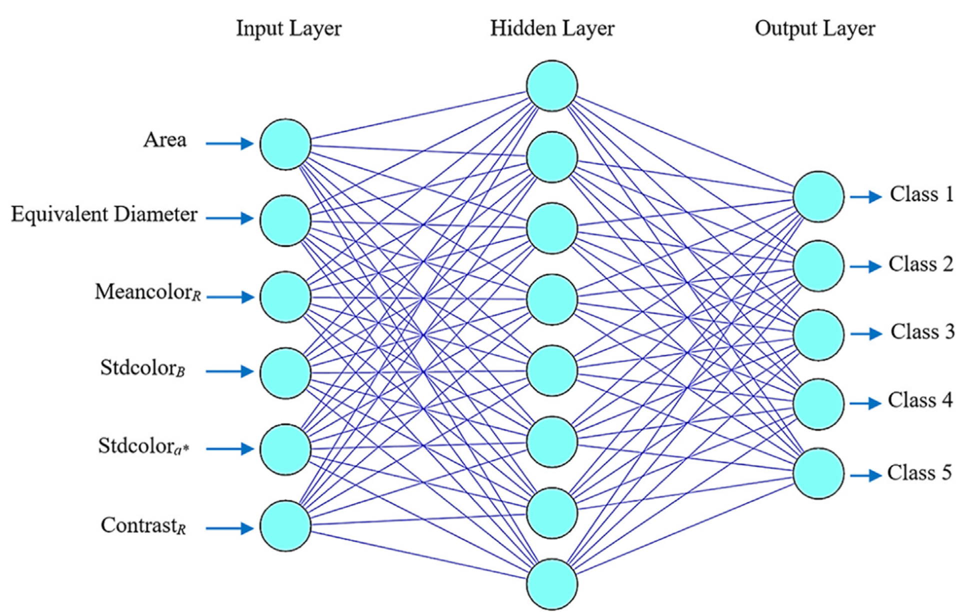


Fig. 6 – The optimal ANN model with MLP-6-8-5 structure.

line mode were 93.9%, 75.5%, 76%, and 96%, respectively. While, the average values of ACC, PR, SE, and SP parameters related to the optimum MLP model were 94.6%, 83.5%, 85.4%, and 96.7%, respectively (Table 3). Comparing these results reveals that the values of all performance parameters obtained from the optimum MLP classifier are higher than those of the LDA classifier. Accordingly, the optimum MLP classifier outperforms the LDA model.

The processing time is critical in real-time applications, so developing an accurate and efficient machine vision-based algorithm is highly preferred. During the in-line evaluation, and using the conveyor's maximum possible speed (0.2 m/s), the test samples were successively placed on the conveyor with a distance of 25 cm at various orientations; thus, every 1.25 s, one sample was passed in front of the camera. Therefore, the processing time of the classification algorithm needs to be less than 1.25 s, taking the accuracy into account. Despite the larger number of parameters compared to the LDA model, the processing time to classify each sample by the MLP technique (0.2 s/sample) is low enough for real-time application. Accordingly, the optimum MLP model was selected as a proposed classifier to be used in the MV-based bell pepper sorting machine.

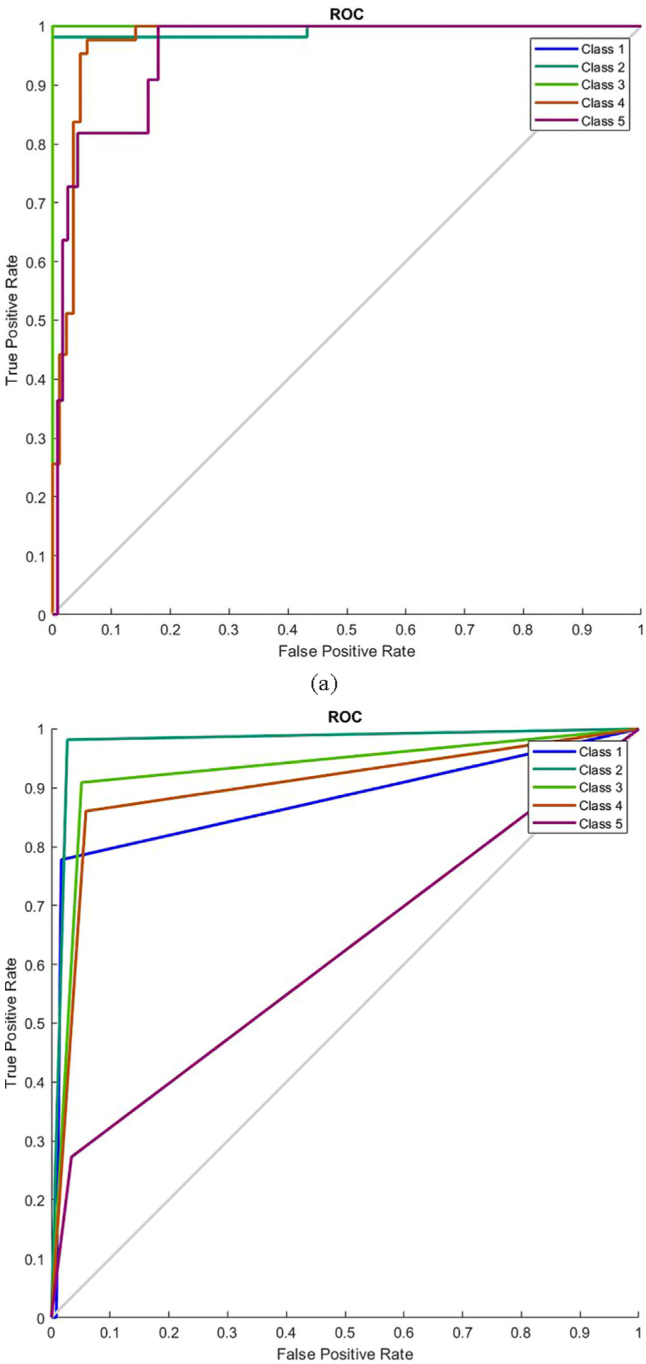


Fig. 7 – ROC curves for predicting of five bell pepper classes with developed classifiers: (a) MLP model and (b) LDA model.

3.4. *Quantitative classification by the proposed MLP classifier in in-line phase*

The developed sorting system was evaluated to separate 100 test bell pepper samples (20 samples for each class) using separating units in the in-line phase. To clarify more, during the in-line evaluation of the developed sorting machine, 100 samples from five several bell pepper types (including three different maturity stages with two different sizes) was prepared. All peppers were put together to be sorted at the same time by the proposed sorting system, as is the case in industrial applications. It is of note that depending on the type of the separating units (pneumatic jack cylinders) used in the developed machine and the distance between them, only one sample must pass in front of the pneumatic actuator to be correctly pushed out from the conveyor belt to the appropriate channel. So, the samples in the in-line evaluation were fed randomly and successively in the maximum speed of the conveyor belt (0.2 m/s). At the end of the test, the number and the type of peppers found in each separation channel was counted, and the results were analyzed and presented. The time taken by the developed sorting machine to separate all of the 100 bell pepper samples in the in-line phase was about 2 min. The resulting confusion matrix related to the proposed classifier is illustrated in Fig. 9 (a). Also, the prediction results as a percentage are shown in Fig. 9(b). The values of performance indices calculated from the confusion matrix in in-line phase were used to evaluate the classification results of the proposed classifier. The results for all bell pepper classes are listed in Table 4.

As seen from the confusion matrix and the normalized confusion matrix (Fig. 9), GS2, RS1, and RS2 classes were identified well by the proposed classifier. The highest performance has achieved in RS1 class with ACC = 100%, PR = 100%, SE = 100%, and SP = 100% (Table 4). However, one bell pepper sample was misclassified from RS2 class into the UR class (Fig. 9). The GS1 and GS2 classes are almost identical in color and texture features. So, size-based features only can play an important role in classifying the samples of these classes. Accordingly, it can be concluded that the extracted features related to the size of the crop (Area and Equivalent diameter) played a significant role in identifying and separating these classes in the proposed MLP classifier. For that, four bell pepper samples from the GS1 class were confused with GS2 and UR classes (Fig. 9). Another result is that classification of the UR class by the proposed MLP classifier did not provide satisfactory results. UR category with 11 errors showed the lowest performance level with ACC = 86.6%, PR = 81.8%, SE = 45%, and SP = 97.4% (Table 4). The results showed that only 45% of the UR samples were correctly graded (Fig. 9). Such a decrease in accuracy level is due to the high color similarities between UR, RS1, and RS2 classes. Only a small difference in the texture features makes a slight distinction in this class. Therefore, it is realistic that the classification of the UR class is less accurate than other classes of the bell peppers. The explanation is that, only the texture feature ($Contrast_R^{\theta=0,\ d=1}$) is effective in separating the UR class and the other selected features did not help the ANN model to classify this class. However, the average values of performance parameters including accuracy, precision, sensitivity, and specificity were 93.2%, 86.4%, 84%, and 95.7%, respectively. As can be seen, the prediction accuracy of all classes in the proposed MLP classifier was from 86.6% to 100% (Table 4), which are acceptable results for bell peppers sorting machine.

In the literature, Elhariri et al. proposed an algorithm for grading bell peppers into five different classes from green to fully ripened stage (red). The classification algorithm was developed based on the SVM technique as traditional intelligent modeling. The bell peppers were classified based on their

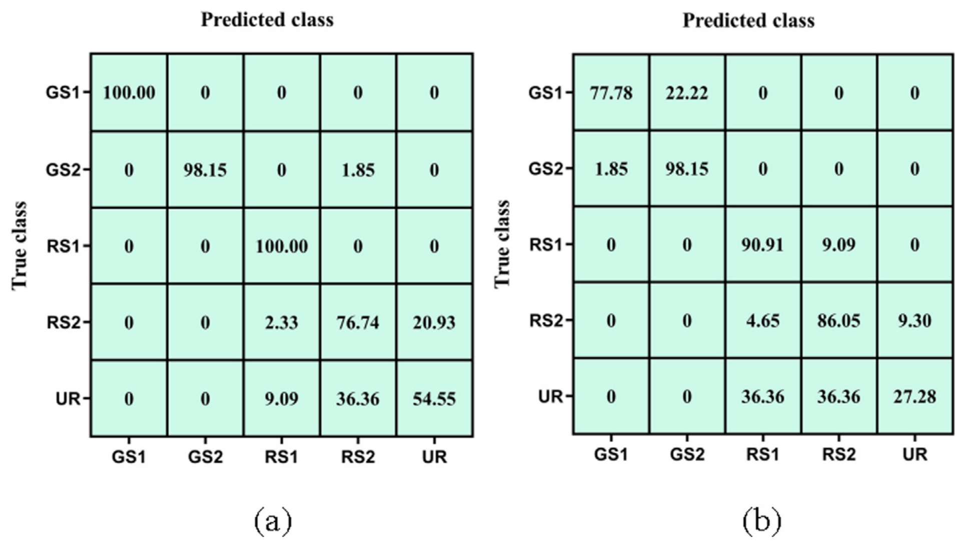


Fig. 8 – Predicted results related to testing data as a percentage in the off-line phase (the normalized confusion matrix): (a) MLP model and (b) LDA model.

Table 3 – The performance parameters based on optimum MLP and LDA models calculated from the confusion matrix on the test data set in off-line mode.

Class	Optimum MLP model				LDA model			
	ACC(%)	PR(%)	SE(%)	SP(%)	ACC(%)	PR(%)	SE(%)	SP(%)
GS1	100	100	100	100	97.3	87.5	77.8	99
GS2	99.1	100	98.1	100	97.3	96.4	98.1	96.6
RS1	97.6	85.8	98.2	97.5	94	62.5	90.9	94.3
RS2	88.1	69.9	76.2	94.3	90.9	88.1	86	93.6
UR	88.5	62	54.5	91.7	90.2	42.9	27.3	96.4
Average (%)	94.6	83.5	85.4	96.7	93.9	75.5	76	96

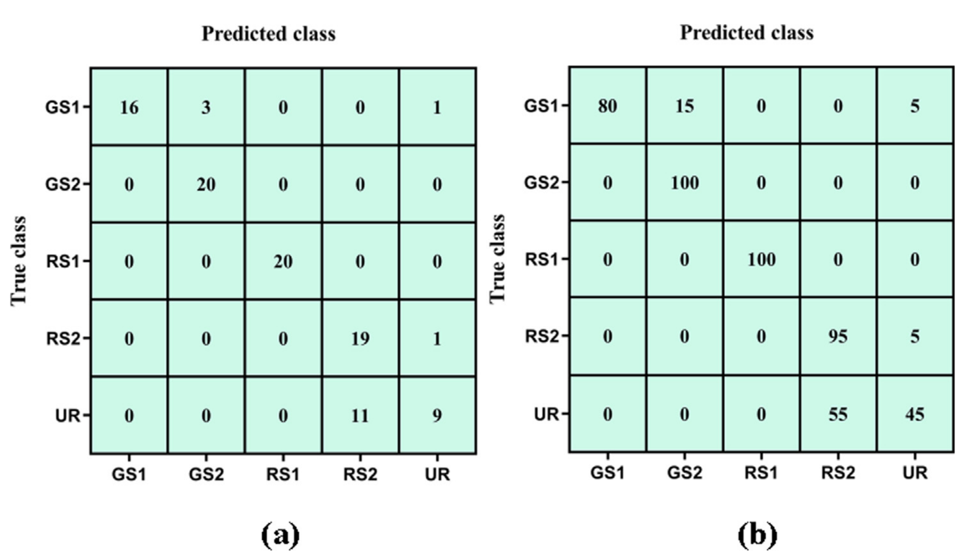


Fig. 9 – Predicted results related to MLP model on the test samples in the in-line phase: (a) The confusion matrix and (b) the normalized confusion matrix as a percentage.

Table 4 – The performance parameters based on the proposed classifier calculated from the confusion matrix on the test samples in in-line phase.

Class	ACC(%)	PR(%)	SE(%)	SP(%)
GS1	95.5	100	80	100
GS2	96.6	87	100	95.5
RS1	100	100	100	100
RS2	87.5	63.3	95	85.5
UR	86.6	81.8	45	97.4
Average /%	93.2	86.4	84	95.7

color in that research, but their size features were not considered. A total of 175 images, including different ripening classes, were used to train and test the SVM algorithm. The bell pepper grading accuracy in off-line mode was 93.9% [11]. In a similar study, Harel et al. did not investigate the critical quality factor, size of the bell peppers [31]. However, the current study also considered the size of bell pepper samples as a quality factor in the classification. The average accuracy of grading based on the maturity level and size was equal to 94.6% and 93.2% for off-line and in-line phases, respectively.

4. Conclusion

According to export standards, a machine vision (MV) system was developed in this research for sorting bell peppers into five classes. One of the achievements of this study was the grading of bell pepper based on size, in addition to the ripeness stage. Also, to improve the packaging quality of this crop, the not likable low-color bell peppers were detected and separated. The proposed MLP classifier was integrated with a MV-based sorting machine. Then, the developed system was evaluated in the in-line phase. Based on the results, the proposed MLP classifier has shown good ability in sorting the bell pepper crop. Also, compared to previous research, the obtained results are considered excellent and satisfying, and this system can be used in industrial applications. The immature bell pepper samples can be placed so the green part is not visible in the image, which is the limitation of the present research. As a result, further research is needed to develop a system capable of rotating bell peppers to take multiple images from different perspectives, so the performance of the system would be improved. A limitation of the current study is that each image must have a constant background with a controlled condition. So future work may include developing ANNs such as deep learning models for sorting bell peppers based on the maturity level and size through images with a non-standardized background and less controlled conditions.

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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REFERENCES

[1] Patel N, Gantait S, Panigrahi J. Extension of postharvest shelf-life in green bell pepper (Capsicum annuum L.) using exogenous application of polyamines (spermidine and putrescine). Food Chem 2019;275:681–7.
[2] Kader AA. Maturity, ripening, and quality relationships of fruit-vegetables. Acta Hortic 1996;434:249–56. Available from: https://doi.org/10.17660/actahortic.1996.434.30.
[3] Chen J, Lian Y, Li Y. Real-time grain impurity sensing for rice combine harvesters using image processing and decision-tree algorithm. Comput Electron Agric 2020;175. https://doi.org/10.1016/j.compag.2020.105591 105591.
[4] Mohi Alden K, Omid M, Rajabipour A, Tajeddin B, Soltani FM. Quality and shelf-life prediction of cauliflower under modified atmosphere packaging by using artificial neural networks and image processing. Comput Electron Agric 2019;163. https://doi.org/10.1016/j.compag.2019.104861 104861.
[5] Eizentals P, Oka K. 3D pose estimation of green pepper fruit for automated harvesting. Comput Electron Agric 2016;128:127–40. https://doi.org/10.1016/j.compag.2016.08.024.
[6] Singh A, Ganapathysubramanian B, Singh AK, Sarkar S. Machine learning for high-throughput stress phenotyping in plants. Trends Plant Sci 2016;21(2):110–24. https://doi.org/10.1016/j.tplants.2015.10.015.
[7] Miraei Ashtiani SH, Rohani A, Aghkhani MH. Soft computing-based method for estimation of almond kernel mass from its shell features. Sci Hortic (Amsterdam) 2020;262. https://doi.org/10.1016/j.scienta.2019.109071 109071.
[8] Utai K, Nagle M, Hämmerle S, Spreer W, Mahayothee B, Müller J. Mass estimation of mango fruits (Mangifera indica L., cv. 'Nam Dokmai') by linking image processing and artificial neural network. Eng Agric Environ Food 2019;12(1):103–10. https://doi.org/10.1016/j.eaef.2018.10.003.
[9] Vlontzos G, Pardalos PM. Assess and prognosticate greenhouse gas emissions from agricultural production of EU countries, by implementing, DEA Window analysis and artificial neural networks. Renew Sustain Energy Rev 2017;76:155–62. https://doi.org/10.1016/j.rser.2017.03.054.

[10] Omid M, Firouz MS, Nouri-Ahmadabadi H, Mohtasebi SS. Classification of peeled pistachio kernels using computer vision and color features. Eng Agric Environ Food 2017;10 (4):259–65. https://doi.org/10.1016/j.eaef.2017.04.002.
[11] Elhariri E, El-Bendary N, Hussein AMM, Hassanien AE, Badr A. Bell pepper ripeness classification based on support vector machine. ICET 2014–2nd Int. Conf Eng Technol 2014:1–6. https://doi.org/10.1109/ICEngTechnol.2014.7016802.
[12] Taofik A, Ismail N, Gerhana YA, Komarujaman K, Ramdhani MA. Design of smart system to detect ripeness of tomato and chili with new approach in data acquisition. IOP Conf Ser Mater Sci Eng 2018;288:012018.
[13] Mazen FMA, Nashat AA. Ripeness classification of bananas using an artificial neural network. Arab J Sci Eng 2019;44 (8):6901–10. https://doi.org/10.1007/s13369-018-03695-5.
[14] Yossy EH, Pranata J, Wijaya T, Hermawan H, Budiharto W. Mango fruit sortation system using neural network and computer vision. Procedia Comput Sci 2017;116:596–603. https://doi.org/10.1016/j.procs.2017.10.013.
[15] USDA, United States Standards for Grades of Sweet Peppers (United States Department of Agriculture, Agricultural Marketing Service. Fruit and Vegetable Program); 2005.
[16] Teimouri N, Omid M, Mollazade K, Mousazadeh H, Alimardani R, Karstoft H. On-line separation and sorting of chicken portions using a robust vision-based intelligent modelling approach. Biosyst Eng 2018;167:8–20. https://doi.org/10.1016/j.biosystemseng.2017.12.009.
[17] Otsu N. Threshold selection method from gray-level histograms. IEEE Trans Syst Man Cybern 1979;9:62–6. https://doi.org/10.1109/tsmc.1979.4310076.
[18] Jhawar J. Orange Sorting by applying pattern recognition on colour image. Procedia Comput Sci 2016;78:691–7. https://doi.org/10.1016/j.procs.2016.02.118.
[19] Gonzalez RC, Woods RE, Eddins SL. Digital image processing using Matlab. 2nd Ed. Gatesmark; 2004.
[20] Rovira Más F, Zhang Q, Hansen AC. Mechatronics and intelligent systems for off-road vehicles. Springer Science & Business Media; 2011. https://doi.org/10.1007/978-1-84996-468-5.
[21] Thendral R, Suhasini A. Automated skin defect identification system for orange fruit grading based on genetic algorithm. Curr Sci 2017;112(8):1704–11. Available from: https://doi.org/10.18520/cs/v112/i08/1704-1711.
[22] Hosseinpour S, Ilkhchi AH, Aghbashlo M. An intelligent machine vision-based smartphone app for beef quality evaluation. J Food Eng 2019;248:9–22. https://doi.org/10.1016/j.jfoodeng.2018.12.009.
[23] Chandrashekar G, Sahin F. A survey on feature selection methods. Comput Electr Eng 2014;40(1):16–28. https://doi.org/10.1016/j.compeleceng.2013.11.024.
[24] Gazeloğlu C. Prediction of heart disease by classifying with feature selection and machine learning methods. Prog Nutr 2020;22(2):660–70. Available from: https://doi.org/10.23751/pn.v22i2.9830.
[25] Al-Batah M, Zaqaibeh B, Alomari SA, Alzboon MS. Gene microarray cancer classification using correlation based feature selection algorithm and rules classifiers. Int J Online Biomed Eng 2019;15(08):62–73. https://doi.org/10.3991/ijoe.v15i08.10617.
[26] Senliol B, Gulgezen G, Yu L, Cataltepe Z. Fast correlation based filter (FCBF) with a different search strategy. In: 2008 23rd Int. Symp. Comput. Inf. Sci. Isc. 2008, 2008. https://doi.org/10.1109/ISCIS.2008.4717949.
[27] Omid M, Salehi A, Rashvand M, Firouz MS. Development and evaluation of an online grading system for pinto beans using machine vision and artificial neural network. Int J Postharvest Technol Innov 2020;7(1):1–14. https://doi.org/10.1504/IJPTI.2020.108740.
[28] Du YC, Stephanus A. Levenberg-marquardt neural network algorithm for degree of arteriovenous fistula stenosis classification using a dual optical photoplethysmography sensor. Sensors (Switzerland) 2018;18(7):2322. https://doi.org/10.3390/s18072322.
[29] Nasiri A, Taheri-Garavand A, Zhang YD. Image-based deep learning automated sorting of date fruit. Postharvest Biol Technol 2019;153:133–41. https://doi.org/10.1016/j.postharvbio.2019.04.003.
[30] Zheng YY, Kong JL, Jin XB, Wang XY, Su TL, Zuo M. Cropdeep: The crop vision dataset for deep-learning-based classification and detection in precision agriculture. Sensors 2019;19(5):1058. https://doi.org/10.3390/s19051058.
[31] Harel B, Parmet Y, Edan Y. Maturity classification of sweet peppers using image datasets acquired in different times. Comput Ind 2020;121. https://doi.org/10.1016/j.compind.2020.103274 103274.
[32] Farmer Today. Colored bell peppers, from planting to harvest. Link: https://alfallahalyoum.news/. 2020