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e-ksper: A Convolutional Neural Network Based System for Seedless Raisin Quality Grading

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ABSTRACT

Seedless raisins are graded according to their quality which is determined based on several features such as color, size, texture, and humidity. Currently, most of the raisin grading process is performed by human experts manually, which is laborious and subjective work. Therefore, an automated system that enables objective evaluation of the raisins would be helpful for both producers and experts during this process. In this study, we propose a simple machinery prototype that takes images of raisins under standard background and illumination conditions and an automated system that performs quality grading of raisins using convolutional neural networks. The proposed model not only targets color classes but also aims to identify foreign matters and defected raisins. The model achieves about 88.2% average classification accuracy on five classes including four color classes and a defected raisin class; whereas the model's accuracy becomes 98.6% if defected raisins are excluded. Hence, the proposed model is very successful in differentiating color classes and has also considerable success in detecting foreign matters and defected raisins. We provide a comprehensive analysis and discussion on these results.

e-ksper: Çekirdeksiz Kuru Üzüm Kalite Değerlendirmesi için Evrişimsel Sinir Ağları Temelli Sistem

ÖZ

Çekirdeksiz kuru üzümler, renk, boyut, doku ve nem gibi çeşitli özelliklere göre belirlenen kaliteler doğrultusunda değerlendirilir. Mevcut şartlarda kuru üzüm sınıflandırma işleminin çoğu insan uzmanlar tarafından manuel olarak gerçekleştirilmektedir. Bu işlemin manuel olarak yapılması insan gücü açısından zahmetli olmakla birlikte öznel sonuçlar ortaya çıkarmaktadır. Bu nedenle, kuru üzümlerin objektif bir şekilde değerlendirilmesini sağlayan otomatik bir sistem, bu süreçte hem kuru üzüm üreticilerine hem de uzmanlara yardımcı olacaktır. Bu çalışmada, standart arka plan ve aydınlatma koşulları altında kuru üzümlerin görüntülerini alan basit bir makine prototipi ve evrişimsel sinir ağları kullanarak kuru üzümlerin kalite derecelendirmesini yapan otomatik bir sistem öneriyoruz. Önerilen model sadece renk sınıflarını değil, aynı zamanda yabancı maddeleri ve kusurlu çekirdekleri de tespit etmeyi amaçlamaktadır. Model, dört renk sınıfı ve bir kusurlu çekirdek sınıfı dahil olmak üzere beş sınıf üzerinde ortalama %88,2 sınıflandırma doğruluğu elde ederken, kusurlu çekirdekler hariç tutulduğunda modelin doğruluğu %98,6 olmaktadır. Dolayısıyla, önerilen model renk sınıflarını ayırt etmede çok başarılıdır ve ayrıca yabancı maddeleri ve kusurlu kuru üzümleri tespit etmede de önemli bir başarıya sahiptir. Bu çalışmada elde edilen sonuçlar üzerine kapsamlı bir analiz ve tartışma sunuyoruz.

Anahtar Kelimeler: Kuru üzüm değerlendirme, kuru üzüm sınıflandırma, evrişimsel sinir ağları, yabancı madde tespiti

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1. Introduction

In today's world, applying technological tools and techniques in agriculture has become vital to survive in the competitive world market and ensure sustainable agriculture. The continuous increase in population and prosperity comes with a food demand that agricultural production is struggling to meet. Although agricultural mechanization has come close to meeting this demand in the past centuries, artificial intelligence (AI) applications can produce sustainable solutions to the ever-increasing demand for food [1]. The progress in the field of internet-of-things and machine learning (ML) has enabled many applications of smart systems in food and agriculture sectors. Recently, AI started to reform the processes in the agricultural sector as well as other sectors. The use of AI can be seen throughout the food supply chain, starting from crop planting scheduling [2], irrigation management [3], pest monitoring [4], autonomous harvesting [5] to product quality evaluation [6] and food logistics [7].

Seedless raisin is one of the main agricultural products in the world and the main exporters are Turkey, USA, China, India, and Iran. It is one of the major agricultural products in Turkey, especially for the Aegean Region. Turkey, which realizes 27% of seedless raisins in the world, is the biggest seedless raisin producer and exporter (32%) in the world [8]. The price of a bulk of raisins is determined based on its quality grade which depends on factors such as color, texture, size, and humidity. Currently, most raisin grading is done manually by human experts under daylight, which is a labor-intensive, subjective and error-prone process due to varying light conditions and the human factor in general. Thus, an AI-powered automated system that enables objective evaluation of the raisins would be helpful for both producers and experts during this process. Such a system would pave the way for the validation of the process in terms of ethical concerns such as fairness, transparency, and explainability.

The main objective of this study is to develop an automated process for classifying seedless raisins according to their quality. Within the scope of this work, we only consider image-based features like color, size, and texture by omitting humidity and mass. In this work, we propose a hardware prototype and a software methodology for classifying raisins into one of four color classes or defected raisins. The current system targets Turkish standards for raisin grading; though, it is possible to adapt and calibrate the system for other countries' standards.

The hardware component is constructed for taking photos of raisins under standard illumination conditions since color is the main factor in determining the quality and it is highly affected by illumination. Yet, the hardware is designed to be used for materials other than raisins. For the software part, we employ convolutional neural networks (CNN) as one of the state-of-the-art machine vision techniques to obtain a mapping between the input raisin images and expert labels. We named our automatic raisin grading system as "e-ksper".

The rest of the paper is organized as follows: Section 2 reviews the literature in the field of food and raisin grading. Section 3 includes the details about our data, hardware prototype, and software methodology. Quantitative and qualitative results are elaborated in Section 4; and Section 5 wraps up the study.

2. Related Work

In the literature, computer vision techniques are widely employed for quality inspection of agricultural products such as fruits and grains. Some examples include grain classification [9, 10], quality assessment of cocoons [11], and fruit maturity grading [12]. Surveys on the application of computer vision techniques for agricultural product grading and characterization can also be found [13, 14, 15, 16].

Although there are a number of studies on raisin or grape variety classification using machine vision and deep learning methods [17, 18, 19], in different wavelengths [20], these studies do not take raisin quality into account. The studies on raisin quality grading can be analyzed based on their methodologies, extracted features, or classes. Omid et al. [21] proposed a simple algorithm to identify good and bad raisins on a given image, by analyzing their color and size features. Wang et al. [22] proposed a machine vision system based on hybrid image features of color, texture, and morphological properties to classify raisins into four varieties produced in China. They compared several classifiers including partial least squares (PLS), linear discriminant analysis (LDA), soft independent modeling of class analogy (SIMCA), and least squares support vector machine (LS-SVM) with linear and radial basis function (RBF) kernels. They achieved up to 99% accuracy using LDA. Yu et al. [23] combined HSI color space and texture features and utilized LS-SVM classifier. They showed that integrating texture features to the system improves the classification accuracy when compared to using color features solely. Pawar and Sarkar [24] proposed a fuzzy classification system using hue, saturation, and intensity features. The main difference of their study from the others is that the classification is done based on the whole image, instead of dealing with individual raisins.

Li and Liu [25] proposed an artificial neural network (ANN) architecture to classify raisins into three grading classes, based on color and size features. Another grading algorithm that uses ANN was developed by Angadi and Hiregoudar [26] and employs color and size features such as RGB mean, RGB variance, RGB moment, area, aspect ratio, etc. They achieved about 95% average classification accuracy on seven industrial classes. Mollazade et al. [27] compared the performance of several data mining classifiers such as ANN, SVM, Bayesian networks, and decision trees (DT) on raisin classification. They obtained up to 96% classification accuracy using ANN. Karimi et al. [28] used a Principle Components Analysis (PCA)-reduced subset of texture features such as gray-level co-occurrence matrix (GLCM), gray-level run-length matrix (GLRM), and local binary patterns (LBP); and then compared the performance of ANN and SVM classifiers. Their purpose is to classify mixtures of raisins based on 10 mixture percent. They achieved about 93% classification accuracy with SVM. Similarly, a machine vision system for classifying bulk raisins was developed using several texture features including GLCM, GLRM, and LBP [29]. They compared the performance of SVM and LDA classifiers and obtained about 86% and 70% classification accuracy for six classes and fifteen classes of good and bad raisin, respectively. Zhao et al. [30] trained a neural network by extracting waveform resolution features on hyperspectral images of raisin samples, to classify raisins into eight categories produced in China region and obtained about 93% classification accuracy.

Several machines were also developed for automatically sorting raisins using conveyor belts. Shinde and Patil [31] used average color values to classify and sort raisins into four categories; namely green, golden, brown, and black. Abbasgholipour et al. [32] developed a machine vision system to segment image pixels into desired and undesired raisin regions under varying luminance conditions, using genetic algorithm on HSI color space.

As the literature review indicates, the studies on automatic raisin grading are very limited. Most of them classify raisins into just two categories as good and bad. The rest are generally proposed for region-specific grading criteria. The standards used in Turkey differ from those criteria. For example, possible defects on raisins have a significant effect on the Turkish standard for grading raisins. Detecting foreign matters and defections is a challenging task compared to just color classification. Furthermore, most of the proposed methods require a hand-crafted feature extraction process, which is labour-intensive. Instead, the application of modern machine vision techniques such as CNN would remove the necessity for manual feature extraction and explore descriptive features and their hierarchical and non-linear interactions automatically.

3. Materials and Methods

In this section, we explain the hardware/software methods and algorithms that are employed in the study. We have developed a simple hardware prototype that takes images of raisin samples under standard illumination conditions. These images are then fed into a CNN model to be classified according to their quality. The details are explained in the subsequent sections.

3.1. Data

In the development process, Sultana-1 seedless raisins were used. The origin of this variety is Asia Minor and commercially it is very popular around the world and commonly cultivated in the Aegean Region of Turkey. Raisin samples were classified and labeled by experts into five classes according to the Seedless Raisin Quality Grading Standard of Turkish Standards Institute [33]. These classes are shown in Figure 1 and shortly explained below.

- Class1: raisins of light yellow or similar color.

- Class2: raisins of light brown or similar color. Raisins of light yellow-light brown mottled color are also included in this class.
- Class3: raisins of dark brown or similar color. Raisins of dark brown-black mottled color are also included in this class.
- Class4: raisins of black color.
- Class5: Defected raisins and foreign matters:
    - Capstems: The small stems that attach the raisins to the branches of the bunch.
    - Immature raisin: Raisins with a very small mass, with no sugared tissue indicating that growing is incomplete, completely wrinkled, with almost no flesh, hard structure, and raisins of less than 5 mm diameter.
    - Moldy raisin: Raisins with visible mold filaments.
    - Defected raisin: Raisins with significant defects in appearance, consumption, quality, transport, and storage due to visible sunburn, mechanical injury, insect defeat, and so on.
    - Sugared raisin: Raisins with sugar crystals inside and outside, which affect the appearance.
    - Conjoint raisin: Raisins stuck together, usually due to exocarp injury.
    - Foreign matters: Any other material than raisins.

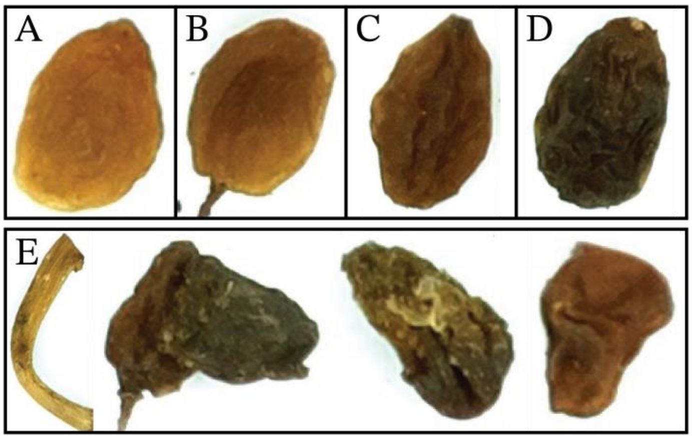

Figure 1. Samples for four color classes and the class of defected raisins and foreign matters. A) Class1, B) Class2, C) Class3, D) Class4, E) Class5: Defected raisins and foreign matters.

In this study, our main aim is to cover five classes including defected raisins. However, we also compare the prediction performance when only four color classes are targeted. For five classes, a total of 1751 sample raisin images were captured and labeled by experts. There are 409 Class1, 300 Class2, 314 Class3, 410 Class4 and 318 Class5 raisin images in the dataset. For four classes, defected raisin class is excluded and 1433 raisin images were used. The datasets were divided into three sets: Training (70%), validation (15%), and testing sets (15%). All images were resized to 64 x 64 pixels and online data augmentation techniques were used to mitigate overfitting by randomly rotating and flipping the raisin images. Unlike offline data augmentation, which generates images once before training, online data augmentation generates images randomly for each batch based on the predefined augmentation rules during the training.

In Figure 2, the distribution of class samples in RGB and HSV color spaces are plotted. Each datapoint in the figure represents the average color for a raisin image in a color space. The plots show that the classes are not trivially separable in both spaces. Instances of Class5 (purple) are spread over the whole samples and they are especially intertwined with Class3 and Class4 instances. Thus, it is not straightforward to classify the samples using just a rule-based system.

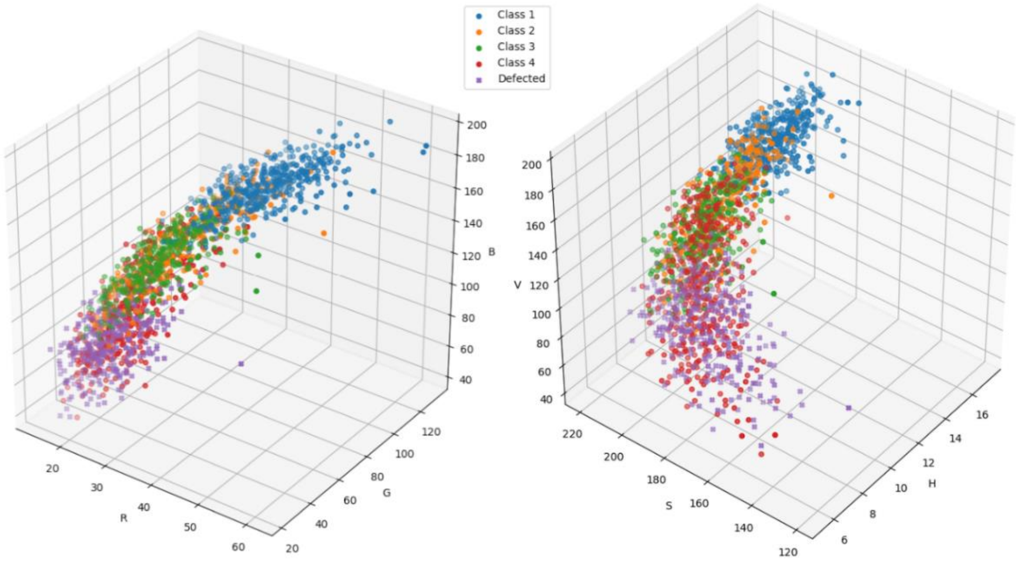

Figure 2. Distribution of the samples in RGB space (left), in HSV space (right).

3.2. Hardware

Since raisin quality is mainly determined by the color which is highly affected by illumination conditions; we have developed a machine prototype (Figure 3) which takes images of raisin samples under standard illumination conditions. A white fiberglass tray is used as a background. The tray is illuminated with two LED panels. The color temperature of those panels was selected as 3000K. The panels were placed at a 45° angle with the tray to reduce the shadows. To capture the RGB images of the raisins, a Raspberry Pi Camera Rev 1.3 which is placed 28 cm above the tray was employed. The resolution of the captured images was 1920x1200 pixels.

Figure 3. The hardware in which the photos of raisin samples to be evaluated are taken and processed.

Raisins were manually placed on the tray, and then each of tem was separated from each other; similar to the process during human expert evaluation. Defected raisin clusters such as twin raisins were not separated because those raisins are defined as defected in the standards. After distributing the raisins, images were captured by the integrated Raspberry Pi camera.

Due to its small size, Raspberry Pi 3 Model B is used as a micro-computer. It has a quad-core 64-bit ARM Cortex-A53 (1.2 GHz) processor and a dual-core Videocore IV (400Mhz) multimedia processor. Its 1 GB of LPDDR2 memory is sufficient for image processing. This micro-computer was not used for the training of the CNN model, it is just used for test queries. Raspberry Pi compatible LCD touch screen, which is 5-inch in size and 800x480 resolution, is used to facilitate the image acquisition process and display the results.

3.3. Methodology

The raisin quality classification process is illustrated in Figure 4. All the raisins are annotated by human experts according to their quality class and their images are taken. After capturing the images of randomly distributed raisins on the tray, images of individual raisins are obtained through several preprocessing steps. The constructed dataset is randomly split into train, test, and validation sets. A CNN model is trained to produce predictions of quality classes based on color and texture properties. Lastly, the size analysis of the raisins is performed and the user is presented with a report on the quality of the sample being tested.

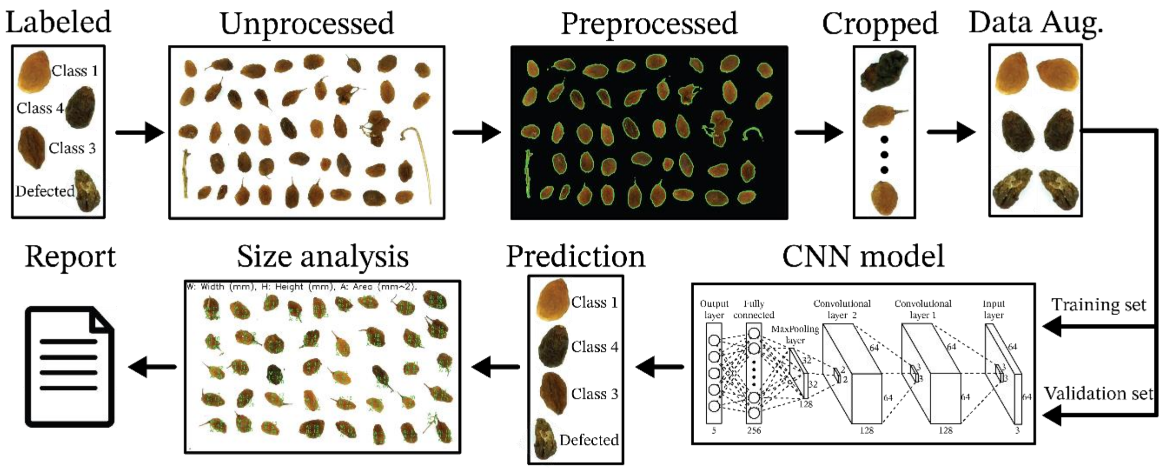

Figure 4. Raisin quality classification process.

3.3.1. Preprocessing

After capturing RGB images of raisins as described above, the images go through several preprocessing stages before the CNN model. The main objective of the preprocessing is to crop the individual raisin images from the overall picture. The preprocessing stages operate on the greyscale version of the input image.

Although we take the images in a box under standard lighting, they are still exposed to some noise. We first remove this noise by applying a 5x5 median filter. Afterwards, to segment the image into background (tray) and foreground (raisin) pixels, we apply Otsu's thresholding algorithm [34]. As in other thresholding methods, the image pixels with intensity values lower than a threshold value are labeled as foreground. Otsu determines the optimum threshold value which separates two classes so that their inter-class variance is maximal, using the histogram of the image. Thresholding segments the image into two classes but the result may contain some gaps or surplus pixels. Therefore, the exact boundaries of the raisins are extracted by morphological operations using erosion and dilation. Then the foreground images were cropped from the overall image and resized to 64x64 pixels.

3.3.2. Classification

Although the characteristics of the quality classes are outlined in the standard, the expressions used such as "light yellow", "similar", etc. are vague expressions. The fact that the color and size ranges are not clearly defined makes it difficult to use a rule-based approach. In addition, there is no clear definition of defected raisins and foreign matters. In this case, the best way is to learn the quality classes from the data labeled by experts. Therefore, at this stage, modern machine learning techniques have been utilized.

Convolutional neural networks, a class of deep learning methods, have been developed with inspiration from the interconnection of neurons in the visual cortex. One of the most important advantages of the CNN model is that it creates spatial and hierarchical relationships in the image through hierarchical filters without the need for manual feature extraction. Today, this method, which has become the basis of computer vision, gives very successful results in fields such as image/video classification and object recognition [35].

In our study, cropped raisin images feed a CNN model. The input to the model is the cropped RGB image in the shape of 64x64x3 and the output is the class label to which the corresponding image belongs with the highest probability. Since our problem is not as complex as standard image categorization problems, we have not used a standard CNN architecture such as AlexNet [36] or GoogLeNet [37] pre-trained on the ImageNet dataset [38]. Instead, we have constructed the simple CNN architecture shown in Figure 5 and trained it from scratch.

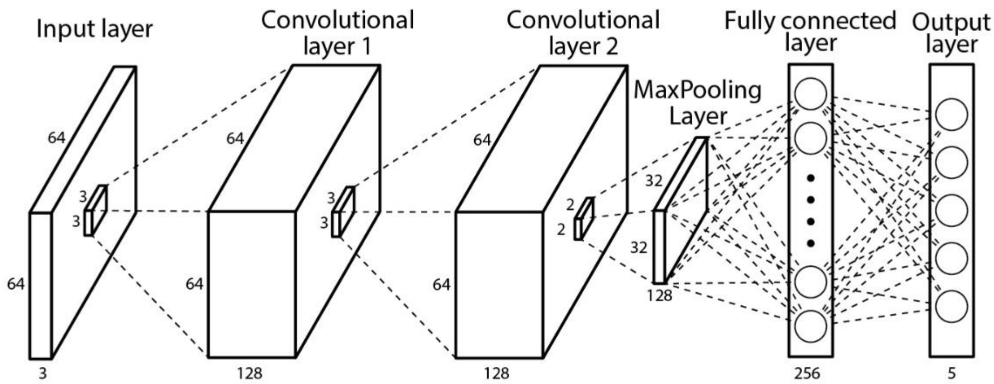

Figure 5. The CNN architecture developed for raisin quality classification.

There are six layers in this CNN model. The first layer is the input layer including the raisin images. After that, there are two convolutional layers, both of which apply 128 filters on the given image. The properties obtained with these layers are condensed with the MaxPooling layer and transmitted to a fully connected layer of 256 artificial neurons. The last layer is the output layer which predicts the class of the raisin. The application was implemented using Python. OpenCV libraries were used for the preprocessing steps and Keras was used for the development of the CNN model.

3.3.3. Reporting Application

Our hardware prototype and software methodology were designed to be flexible enough to be used even for the classification of objects other than raisins. However, our primary concern in this study is to grade seedless raisins according to the Turkish grading standards. Therefore, we demonstrate the sample application of our system in this section. Please note that all the parameters and thresholds used here can be calibrated for different grading standards and preferences of different corporations.

According to the Turkish standards, the proportion of each color class must be in a certain range and based on these proportions, the type of the raisin sample is determined as one of Type 7 through 11. These proportions are given in Table 1 for each type. These values have a 10% tolerance. One drawback of the manual grading process occurs at this stage. Counting the total number of raisins and calculating the proportions of each class is a tedious work for human experts. Thus, our automated system is also effective at objectively determining the type number of the whole sample, in addition to identifying color classes of the individual raisins.

Table 1. Type properties of raisin groups.

Type	Class1	Class2	Class3	Class4
7	10%	20%	55%	15%
8	26%	34%	32%	8%
9	45%	11%	12%	2%
10	64%	30%	6%	0%
11	75%	25%	0%	0%

Besides the color properties, size is also a key factor in determining the quality of raisins. For this reason, the size of each raisin on the tray is also calculated. Size of each object is first determined in pixels using OpenCV functions. Then the values in pixels are converted to millimeters according to the focal length of the camera. Width, height, and area of each raisin is displayed on the screen.

Finally, all these results regarding the test sample are reported to the user in a simple text file format. In the report, the number and proportion of each color class, the total number of raisins, type number, minimum, maximum, and average area, and size category of the sample based on the preferences of the client are listed.

4. Results

In this section, we present the quantitative results of the proposed method and discussion on these results.

4.1. Quantitative Results

Although we aim to develop a method for predicting five classes including defected raisins, we compare our results to just predicting four color classes. The annotated datasets were split into three sets as training (70%), validation (15%), and test (15%) sets. Table 2 lists the parameters used in the training of the CNN model. Training of the model was performed on an NVIDIA GeForce GTX 1060 3GB GPU and it took about one hour to train for 650 epochs.

Table 2. Parameters of the CNN architecture.

Parameter Name	Value
Loss function	Categorical crossentropy
Optimizer	RMSProp
Learning rate	0.0005
Decay	0.000001
Activation function (middle layers)	ReLu
Activation function (last layer)	Softmax

The results were evaluated according to the following metrics: *prediction accuracy, precision, recall*, and *F1 score*. Prediction accuracy is the correct classification rate and it is the primary metric to evaluate the overall success. Metrics are calculated for each class according to the following equations.

$$Precision \quad = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{1}$$

Precision (Eq. 1) for a class x, measures how many of the objects that are predicted as class x actually belong to that class

$$Recall \quad = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{2}$$

Recall (Eq. 2) calculates how many of the class x objects are correctly predicted as class x by our model.

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

F1 score (Eq. 3) is the harmonic mean of precision and recall metrics. It measures the balance between them.

4.1.1. Results for 5-Class Prediction

Accuracy and loss plots are given in Figure 6 for 5-class prediction case. According to the plots, one can observe that overfitting starts after about epoch 160 since training and validation curves move away from each other. For this reason, we evaluate the accuracy of the test set for five classes based on the model which is trained for 156 epochs.

Feature maps for the convolutional layers were analyzed to determine the number of filters as we preferred to keep the architecture simple by not adding new layers after this stage to avoid overfitting. In the first convolutional layer, shape, color, and texture properties of the raisin image are extracted using 128 filters. In the second layer, 128 filters extract high-level features based on those previous low-level features.

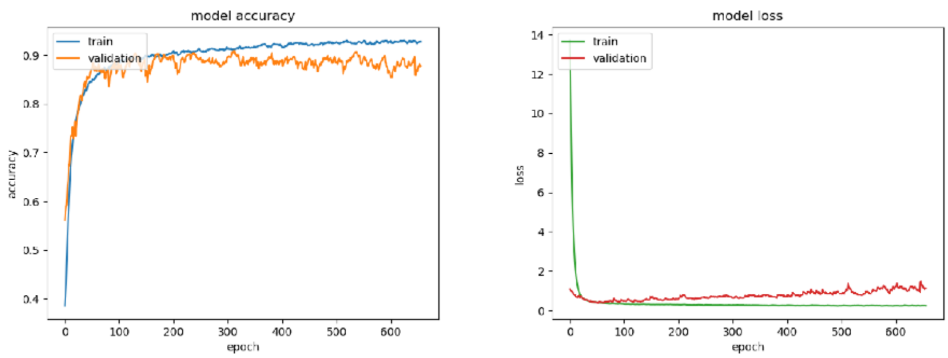

Figure 6. Accuracy (left) and loss (right) plots for 5-class training and validation sets.

The average prediction accuracy is measured as 88.21% and the confusion matrix is given in Figure 8. The confusion matrix shows that the Class5 is confused with all other, as the defected raisins can originally belong to any other class before a defect occurs. It is also clear that the Class1 and Class4 can be easily classified as those classes consist of the brightest and the darkest raisins, respectively. Based on the confusion matrix values; precision, recall, and F1 score metrics were also calculated for each class and listed in Table 3.

Table 3. Precision, recall, and F1 Score (5-class).

Class	Precision	Recall	F1 Score
Class1	98.21%	94.83%	96.49%
Class2	88.64%	88.64%	88.64%
Class3	93.02%	86.96%	89.89%
Class4	85.48%	84.13%	84.80%
Class5	77.59%	86.54%	81.82%

4.1.2. Results for 4-Class Prediction

Figure 7 shows the accuracy and loss plots for the 4-class prediction case. Based on these plots, the test set for four classes was evaluated according to the model trained for 637 epochs. Similar to 5-class scenario, confusion matrix for the 4-class prediction (Figure 8) also shows that the model can successfully classify the brightest and darkest raisins while struggling for the Class2 and Class3. Performance of the 4-class model is shown in Table 4 with the evaluation metrics. In this case, the overall prediction accuracy is calculated as 98.60%.

Table 4. Precision, recall, and F1 Score (4-class).

Class	Precision	Recall	F1 Score
Class1	100.00%	100.00%	100.00%
Class2	95.56%	100.00%	97.73%
Class3	97.37%	94.87%	96.10%
Class4	100.00%	98.44%	99.21%

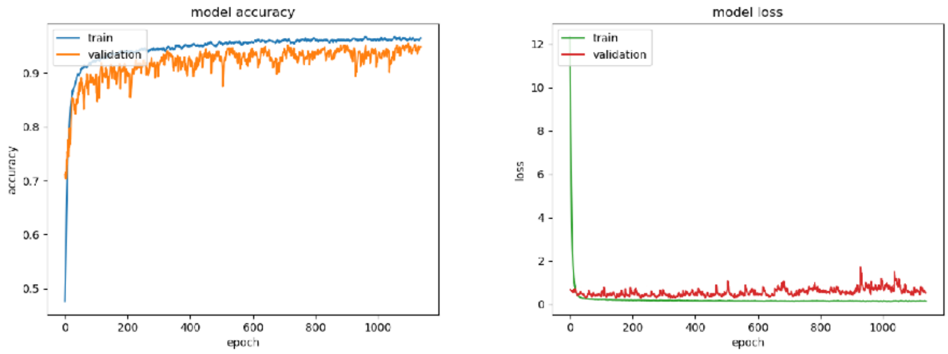

Figure 7. Accuracy (left) and loss (right) plots for 4-class training and validation sets.

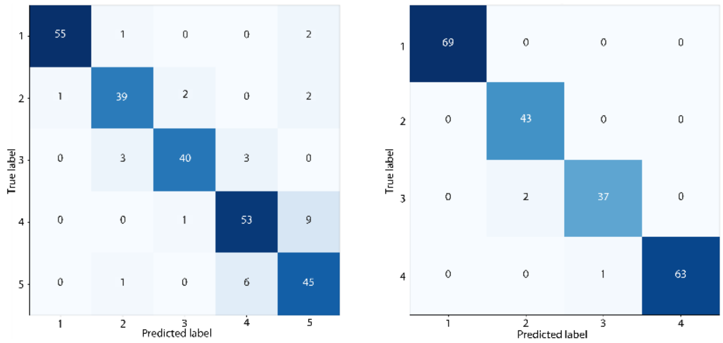

Figure 8. Confusion matrices for 5-class model (left) and 4-class model (right).

4.2. Discussion

The most prominent observation from the results given in Section 4.1 is that detecting defected raisins is a demanding task compared to identifying color classes. This is validated by both the significant improvement in the prediction accuracy and relatively low values for precision, recall, and F1 scores of the defected raisins class (Class5) in Table 3. The reason behind this may be two-fold: First, Class5 is a complex class that comprises many different categories like stems, foreign matters, immature raisins, etc. Considering such kind of items are not common in the market, it is difficult to collect a sufficient number of samples in the dataset to let the model learn the characteristic patterns of each category. Expanding the dataset with more samples could alleviate this problem to some extent. Secondly, using 2D images from a single viewpoint may not capture all the characteristics of the raisins. This second reason will be scrutinized in the next section with some examples.

Correctly classified instances of Class5 in our test set are displayed in Figure 9. As seen from the figure, our test set has sufficient diversity to encompass different categories of Class5 such as stems, foreign matters, and immature/defected/conjoint raisins. The proposed model correctly recognizes apparent instances of Class5. The only misclassified instances are the raisins that are difficult to differentiate by just inspecting visual features from a single viewpoint. These failure cases will be discussed in the next section.

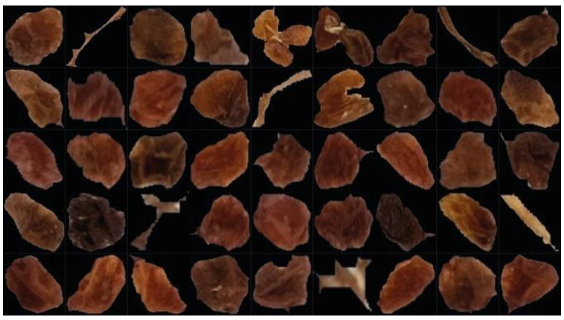
Figure 9. Correctly classified instances of Class5 in the test set.

4.2.1. Limitations

As one can observe in the confusion matrix given in Figure 8, there are incorrect predictions in the first four color classes which are predicted as one of the neighboring classes. This is plausible since their colors are close. It can be tackled by increasing the number of samples per class in the dataset. Nevertheless, there are also a notable amount of misclassified raisins that are predicted as defected raisins although they belong to a color class. Furthermore, most of the false positives and false negatives in Class5 are in Class4. As the color of the raisins in Class4 is black, it is possible to confuse them with foreign matters or defected raisins (See Figure 1). It can also be explained by the fact that since black color reveals any dust or similar defects clearly, Class4 raisins are more prone to be recognized as defected raisins compared to other color classes.

We see that metric values are very close to 100% (Table 4) and prediction accuracy is very high for the 4-class case. Therefore, we speculate that foreign matters and defected raisins deteriorate the prediction performance and one reason behind this is using 2D images of the raisins from a single viewpoint. Raisins that are practically lacking in flesh with a very small mass are typical members of Class5. We refer such kind of raisins as "empty raisins" in the rest of the paper. In Figure 10, sample misclassifications because of empty raisins are shown. Raisins in the first row are predicted as Class5, although they are not empty. Conversely, in the second row, there are actually empty raisins but predicted as one of the color classes. As seen from the figure, their color properties are very similar to each other but their mass is different. In such cases, 2D images are not sufficient to detect defected raisins and alternative methods are needed such as taking images from several views, using infrared cameras, or incorporating mass information into the prediction algorithm.

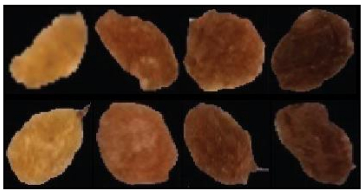

Figure 10. Samples of misclassification due to empty raisins. First row: Actually not empty but predicted as empty. Second row: Actually empty but predicted as Class1, Class2, Class3, and Class4 respectively.

Another typical misclassification reason is illustrated in Figure 11. These raisins look mottled from this view. They are predicted worse than their labels and assigned to the neighboring class. In this respect, our system may be considered as low-tolerant to mottles. We also think that different sides of raisins may produce different class predictions. It is even possible that experts would annotate raisins differently if they checked them from opposite sides.

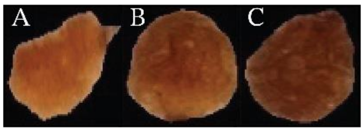

Figure 11. Samples of misclassification due to mottled raisins. A) Label: Class1, Prediction: Class2. B) Label: Class2, Prediction: Class3. C) Label: Class3, Prediction: Class4.

At this point, it is pertinent to note that an inherent problem of supervised machine learning algorithms is their high dependency on the dataset which is eventually annotated by human experts. Although experts perform the annotation according to the standards, vague expressions such as "light yellow, brownish, etc." in the standards lead to subjective annotations. We are planning to suppress this problem and improve the prediction accuracy by increasing the size of our dataset to obtain better generalization for the model and the number of experts for labeling to reduce human factor. Nevertheless, updating the standards to make the terms more quantifiable would be a better solution. We believe that our machine prototype will also make way for such a good standardization in the medium term.

4.2.2. Comparison to Related Work

We also compare our results to the related studies in the literature and these results are tabulated in Table 5. By inspecting the table, we can say that our results are on par with the results of state-of-the-art studies in terms of prediction accuracy. However, it is not fair to directly compare these studies since their target classes and standards are quite different. Although the prediction accuracy for the 5-class case is relatively low, this is still a promising result since the model also includes foreign matters and defected raisin class. The superior aspects of our study can be summarized as follows:

- It covers defected raisins and foreign matters in addition to color classes. Therefore, it has a diverse dataset.
- It is the first study that applies deep learning methods in the problem of quality classification of raisins, as far as we know.
- It does not require manual feature extraction thanks to the CNN classification method.
- The size of the dataset is larger than most of the datasets in other studies.
- It has a general-purpose hardware component that can be used for taking images of other objects under standard illumination conditions.

Table 5. Comparison to other studies. The studies who used classes defined by a national standard are indicated with the issuing country in parentheses.

Study	Target classes	Method(s)	Accuracy
Omid et al. [8]	2 classes: Good and bad	Rule-based	96%
Wang et al. [9]	4 classes (China)	PLS, LDA, SIMCA, LSSVM	99%
Yu et al. [10]	4 classes (China)	LSSVM	95%
Angadi et al. [13]	7 classes (India)	ANN	95%
Mollazade et al. [14]	4 classes: Green and black (with and without stem)	MLP, SVM, Bayesian, DT	96%
Karimi et al. [15]	Classes based on mixture percentages	ANN, SVM	93%
Our (5-class)	5 classes: 4 color classes + defected raisins and foreign matters (Türkiye)	CNN	88%
Our (4-class)	4 color classes (Türkiye)	CNN	99%

5. Conclusion

In this paper, we propose a simple device and an algorithm for determining the quality class of seedless raisins. We have designed a hardware module that helps taking photos of raisins under standard illumination and background conditions. RGB images of raisins are cropped using several image processing operations and they are used for training a CNN model that predicts the quality class of the raisin. We obtain about 88% prediction accuracy for five classes including foreign matters and defected raisins. On the other hand, when foreign matters and defected raisins are excluded, the model achieves almost 99% prediction accuracy. Size features are also extracted to determine the overall quality of the sample and a summary report is provided to the user. We have used Sultana-1 seedless raisins and developed our system based on Turkish standards. However, it is possible to calibrate and train the model to operate on other varieties and standards.

For the future, our first objective is to improve the prediction accuracy by increasing the size and quality of the dataset and fine-tuning the parameters of the CNN architecture. We are also planning to integrate mass and humidity measurement sensors into the system since these are also important factors in determining raisin quality, especially for defected raisins. We have concluded that visual cues alone are not sufficient to detect some kind of defected raisins. Another future work can be designing a conveyor belt which sorts raisins based on detected quality class. In addition to these, a similar system can be developed for measuring the quality of other fruits and grains such as olives, dried figs, and apricots. Our hardware system is already designed flexible enough for general-purpose usage. A similar CNN architecture can be constructed and trained for this purpose.

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Conflict of Interest Statement

The authors declare that there is no conflict of interest.

References

[1] H. Ü. Evcim. A. Yazgı, E. Gülsoylu, E. Aykas, B. Çakmak, V. Demir, H. Yürdem, H. Güler, E. Urkan, F. Alayunt, H. Yalçın, H. Bilgen ve T. Günhan, "Tarimsal Mekanizasyonda Mevcut Durum ve Gelecek," *Türkiye Ziraat Mühendisliği IX. Teknik Kongresi, 2020, ss. 497-526.*

[2] S. S. Sajid and G. Hu, "Optimizing Crop Planting Schedule Considering Planting Window and Storage Capacity," *Frontiers in Plant Science*, vol. 13, pp. 762446, 2022. doi: 10.3389/fpls.2022.762446

[3] E. A. Abioye, O. Hensel, T. J. Esau, O. Elijah, M. S. Z. Abidin, A. S. Ayobami, O. Yerima and A. Nasirahmadi, "Precision irrigation management using machine learning and digital farming solutions," *AgriEngineering*, vol. 4, no. 1, pp. 70-103, 2022. doi: 10.3390/agriengineering4010006

[4] J. G. A. Barbedo, "Detecting and classifying pests in crops using proximal images and machine learning: A review," *AI*, vol. 1, no. 2, pp. 312-328, 2020. doi: 10.3390/ai1020021

[5] E. J. Van Henten, J. Hemming, B. A. J. Van Tuijl, J. G. Kornet, J. Meuleman, J. Bontsema and E. A. Van Os,. "An autonomous robot for harvesting cucumbers in greenhouses," *Autonomous robots*, vol. 13, no. 2, 241-258, 2002. doi: 10.1023/A:1020568125418

[6] X. Zhang, J. Yang, T. Lin, Y. Ying, "Food and agro-product quality evaluation based on spectroscopy and deep learning: A review," *Trends in Food Science & Technology*, vol. 112, pp. 431-441, 2021. doi: 10.1016/j.tifs.2021.04.008

[7] S. Jagtap, F. Bader, G. Garcia-Garcia, H. Trollman, T. Fadiji, K. Salonitis, Food logistics 4.0: Opportunities and challenges. *Logistics*, vol. 5, no. 1, 2020. doi: 10.3390/logistics5010002

[8] T. Halstead, "Raisins: World Markets and Trade," *Foreign Agricultural Service U.S. Department of Agriculture*, 2018. Available: https://www.fas.usda.gov/data/raisins-world-markets-and-trade. [Accessed: 20.01.2023].

[9] A. Kayabasi, A. Toktas, K. Sabanci and E. Yigit, "Automatic classification of agricultural grains: Comparison of neural networks," *Neural Network World,* vol. 28, no. 3, pp. 213–224, 2018. doi: 10.14311/nnw.2018.28.013

[10] K. Sabanci, A. Toktas and A. Kayabasi, "Grain classifier with computer vision using adaptive neuro-fuzzy inference system," *Journal of the Sicence of Food an Agriculture,* vol. 97, no. 12, pp. 3994–4000, September 2017. doi: 10.1002/jsfa.8264

[11] P. P. Prasobhkumar, C.R. Francis and S.S. Gorthi, "Automated quality assessment of cocoons using a smart camera based system," *Engineering in Agriculture, Environment and Food,* vol. 11, no. 4, pp. 202-210, 2018. doi: 10.1016/j.eaef.2018.05.002

[12] K. Rai, M. Dutta and S. Aggarwal, "A Grading System For Fruits Maturity Using Neural Networks Approach," *International Journal of Advanced Research in Computer Science,* vol. 2, no. 6, pp. 451-454, 2011. doi: 10.26483/ijarcs.v2i6.868

[13] J. A. Kodagali and S. Balaji, "Computer vision and image analysis based techniques for automatic characterization of fruits-a review," *International Journal of Computer Applications,* vol. 50, no. 6, pp. 451-454, 2012. doi: 10.5120/7773-0856

[14] M. P. Raj and P. Swaminarayan, "Applications of image processing for grading agriculture products," *International Journal on Recent and Innovation Trends in Computing and Communication,* vol. 3, no. 3, pp. 1194-1201, March 2015. doi: 10.17762/ijritcc.v3i3.4000

[15] D. Saha and A. Manickavasagan, "Machine learning techniques for analysis of hyperspectral images to determine quality of food products: A review," *Current Research in Food Science*, vol. 4, pp. 28-44, 2021. doi: 10.1016/j.crfs.2021.01.002

[16] H. Chopra, H. Singh, M. S. Bamrah, F. Mahbubani, A. Verma, N. Hooda, P. S. Rana, R. K. Singla and A. K. Singh, "Efficient fruit grading system using spectrophotometry and machine learning approaches," *IEEE Sensors Journal*, vol. 21, no. 14, pp. 16162-16169, 2021. doi: 10.1109/JSEN.2021.3075465

[17] I. Cınar, M. Koklu and S. Tasdemir, "Classification of Raisin Grains Using Machine Vision and Artificial Intelligence Methods," *Gazi Journal of Engineering Sciences*, vol. 6, no. 3, pp. 200-209, December, 2020, doi: 10.30855/gmbd.2020.03.03

[18] S. Kılıçarslan, "Kurum Üzüm Tanelerinin Sınıflandırılması İçin Hibrit Bir Yaklaşım", *Mühendislik Bilimleri ve Araştırmaları Dergisi*, cilt 4, sayı 1, ss. 62-71, 2022, doi:10.46387/bjesr.1084590

[19] I. Terzi, " Derin Öğrenme Teknikleri ile Üzüm Çeşitlerinin Belirlenmesi," Doktora Tezi, Biyosistem Mühenisliği, Tokat Gaziosmanpaşa Üniversitesi, Tokat, 2023.

[20] J. Guo, C. Chen, C. Chen, E. Zuo, B. Dong, X. Lv and W. Yang, "Near-infrared spectroscopy combined with pattern recognition algorithms to quickly classify raisins," *Scientific Reports*, vol. 12, no. 1, pp. 7928, 2022. doi: 10.1038/s41598-022-12001-1

[21] M. Omid, M. Abbasgolipour, A. Keyhani and S. S. Mohtasebi, "Implementation of an efficient image processing algorithm for grading raisins," *International Journal of Signal and Image Processing,* vol. 1, no. 1, pp. 31-34, 2010.

[22] S. Wang, K. Liu, X. Yu, D. Wu and Y. He, "Application of hybrid image features for fast and non-invasive classification of raisin," *Journal of Food Engineering,* vol. 109, no. 3, pp. 531-537, 2012. doi: 10.1016/j.jfoodeng.2011.10.028

[23] X. Yu, K. Liu, D. Wu and Y. He, "Raisin quality classification using least squares support vector machine (LSSVM) based on combined color and texture features," *Food and Bioprocess Technology,* vol. 5, no. 5, pp. 1552-1563, 2012. doi: 10.1007/s11947-011-0531-9

[24] S. P. Pawar and A. Sarkar, "Cost Effective Grading Process for Grape Raisins based on HSI and Fuzzy Logic Algorithms," *International Journal of Computer Applications,* vol. 67, no. 22, pp. 18-22, April 2013.

[25] X. Li and X. Liu, "Detection Level of Raisins Based on Neural Network and Digital Image," *2011 Third Pacific-Asia Conference on Circuits, Communications and System,* pp. 1-3, 2011. doi: 10.1109/PACCS.2011.5990209

[26] S. A. Angadi and N. Hiregoudar, "A Cost Effective Algorithm for Grading Raisins Using Image Processing," *International Journal of Recent Trends in Engineering & Research (IJRTER),* vol. 2, pp. 2455-1457, 2016.

[27] K. Mollazade, M. Omid and A. Arefi, "Comparing data mining classifiers for grading raisins based on visual features," *Computers and Electronics in Agriculture,* vol. 84, pp. 124-131, June 2012. doi: 10.1016/j.compag.2012.03.004

[28] N. Karimi, R. R. Kondrood and T. Alizadeh, "An intelligent system for quality measurement of Golden Bleached raisins using two comparative machine learning algorithms," *Measurement,* vol. 107, pp. 68-76, September 2017. doi: 10.1016/j.measurement.2017.05.009

[29] M. Khojastehnazhand and H. Ramezani, "Machine vision system for classification of bulk raisins using texture features," *Journal of Food Engineering,* vol. 271, no. 3, pp. 109864, April 2020. doi: 10.1016/j.jfoodeng.2019.109864

[30] Y. Zhao, X. Xu and Y. He, "A Novel Hyperspectral Feature-Extraction Algorithm Based on Waveform Resolution for Raisin Classification," *Applied Spectroscopy,* vol. 69, no. 12, pp. 1194-1201, 2015.

[31] K. G. Shinde and B. G. Patil, "Sorting of raisins using computer vision approach," *International Research Journal of Engineering and Technology,* vol. 4, no. 6, pp. 2540-2544, June 2017.

[32] M. Abbasgholipour, M. Omid and A. Keyhani, "Color image segmentation with genetic algorithm in a raisin sorting system based on machine vision in variable conditions," *Expert Systems with Applications,* vol. 38, no. 4, pp. 3671-3678, April 2011. doi: 10.1016/j.eswa.2010.09.023

[33] TSE Ziraat İhtisas Grubu, "Seedless raisin (TS 3411)," *Turkish Standards Institution,* vol. TR3411, 2011.

[34] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE Transactions on Systems, Man, and Cybernetics,* vol. 9, no. 1, pp. 62-66, January 1979.

[35] Y. LeCun, Y. Bengio and G. E. Hinton, "Deep learning," *Nature,* vol. 521, pp. 436-444, May 2015. doi: 10.1038/nature14539

[36] A. Krizhevsky, I. Sutskever and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Communications of the ACM,* vol. 60, no. 6, pp. 84-90, June 2017. doi: 10.1145/3065386

[37] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke and A. Rabinovich, "Going Deeper With Convolutions," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA, USA, June 7-12, 2015,* pp. 1-9.

[38] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich, "Imagenet: A large-scale hierarchical image database," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Miami, FL, USA, June 20-25, 2009,* pp. 248-255.