Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2019) 27: 4220 – 4230
© TÜBİTAK
doi:10.3906/elk-1903-112

Defect detection of seals in multilayer aseptic packages using deep learning

Kemal ADEM[1*], **Cemil KÖZKURT**[2]
[1]Department of Management Information Systems, Faculty of Economics and Business Administration, Aksaray University, Aksaray, Turkey
[2]Department of Mechanical Engineering, Faculty of Engineering, Tokat Gaziosmanpaşa University, Tokat, Turkey

Received: 19.03.2019 • **Accepted/Published Online:** 19.06.2019 • **Final Version:** 26.11.2019

Abstract: Sealing in aseptic packages, one of the healthiest and cheapest technologies to protect food from parasites in the liquid food industry, requires a detailed and careful control process. Since the controls are made manually and visually by expert machine operators, the human factor can lead to the failure to detect defects, resulting in high cost and food safety risks. Therefore, this study aims to perform a leak test in aseptic package seals by a system that makes decisions using independent deep learning methods. The proposed Faster R-CNN and the Updated Faster R-CNN deep learning models were subjected to training and testing with a total of 400 images taken from a real production environment, resulting in a correct classification rate of 99.25%. As a result, it can be said that the study is the second study that performs a computer-aided quality control process with promising results, having distinctive features such as being the first study that conducts analysis using the deep learning method.

Key words: Multilayer aseptic packages, seal, Faster R-CNN

1. Introduction

In industrial societies, food safety is one of the most important criteria for human health due to the widespread consumption of industrial food products. The first of the five key rules for food safety as set by the World Health Organization (WHO) is to keep food clean, i.e. to protect food from rotting or disease-causing microorganisms[1]. Aseptic packaging is one of the healthiest and cheapest technologies to protect food from parasites in the industrial liquid food industry. However, sealing in aseptic packages requires a detailed and precise control process. Small changes in the parameters of aseptic packaging systems, such as temperature and pressure, lead to defective or leaking package sealing. Since these defects cannot be measured in production at effective speeds, samples are taken from the production line and destructive detection-based quality controls are performed. Since the controls are made manually and visually by expert machine operators, the human factor can lead to the failure to detect defects, resulting in high cost and food safety risks [1]. In order to reduce these risks, an autonomous defect-detection method, independent of people in the decision phase, is needed. Despite the use of machine-learning based methods to recognize visual patterns for the classification of images in the computer environment [2], images must be passed through image processing methods such as edge detection, color space transformations, morphological separators, noise filters, and threshold algorithms to make them distinguishable

*Correspondence: kemaladem@aksaray.edu.tr

[1]World Health Organization (2010). Prevention of foodborne disease: Five keys to safer food [online]. Website https://www.who.int/foodsafety/consumer/5keys/en/ [accessed 12 August 2018].

in machine learning algorithms [3]. In deep artificial neural networks, a convolutional artificial neural network (CNN) model can be created without the need for preprocessing and classifications can be made faster and more accurate than other machine learning methods [4].

1.1. Related works

The computer-aided testing approach for package seal quality is a rare method, especially in the liquid food industry. In [1], the authors converted seal images into binary format after thresholding in order to detect the defects in LS and TS regions, used the Canny method for edge detection, and classified the images by regression and support vector machine (SVM) methods. They concluded that the SVM method provides more successful results [1]. Estimation and detection of surface defects and properties using image processing and supervised and unsupervised learning methods are used in aseptic packaging as well as textile, marble, wood, and metal industries and agriculture and transportation [5–9]. In studies that use only image processing or computerized vision approaches, classification is performed based on statistics and signal processing, leading to the requirement of determining the correct parameters, such as threshold and window size [7]. In quality control studies using supervised artificial neural networks (ANNs) and the AdaBoost method, efficient classifications can be obtained after overcoming difficult stages such as pattern recognition, feature extraction, and determination of the number of hidden layers in the ANN [8–10]. Research on CNNs includes studies conducted with only the unsupervised learning-based stacked denoising autoencoder methods [6], as well as studies that used unsupervised learning for quick training of a deep learning model and then application of a supervised learning method for fine-tuning [11].

In this study, a CNN-based method for quality control tests in aseptic liquid food packages is discussed. Samples obtained from the DİMES Food Industry were used for CNN training in a computer system with software and hardware for industrial image acquisition. The CNN method was found to be more successful than other methods, and the success rates are presented in the Section 3. In another proposed approach, increases in success rates have been observed in line with updates on CNN parameters.

2. Materials and methods

2.1. Dataset used in the study

In liquid food production, impermeability tests are performed using the destructive examination approach by taking samples from the production line output. The package seals remaining on the inner surface of the package prevent these tests from being carried out in real-time, automated nondestructive tests. The location of the quality control phase in which the impermeability tests are performed is shown in Figure 1 in a block diagram.

Before the quality control phase, operators take samples from the production line according to the instructions of the packaging system manufacturer, unpack and empty the product, and then prepare the inside surface in a clean and dry form, as shown in Figure 1. The production and sampling process continues when the quality control result is positive; however, when it is negative, maintenance is performed in the packaging system according to the type of defect in the package. This maintenance includes changing the control system parameters or the sealing materials.

Aseptic packages generally have a 7-layer structure consisting of materials such as aluminum foil, cardboard, and polyethylene (PE). The PE material provides sealing and adherence functions to the package through the induction heating process. The strip, which is obtained by the combination of other materials, forms the transverse and longitudinal PE–PE seal regions of the package. These seal regions are shown in Figure 2.

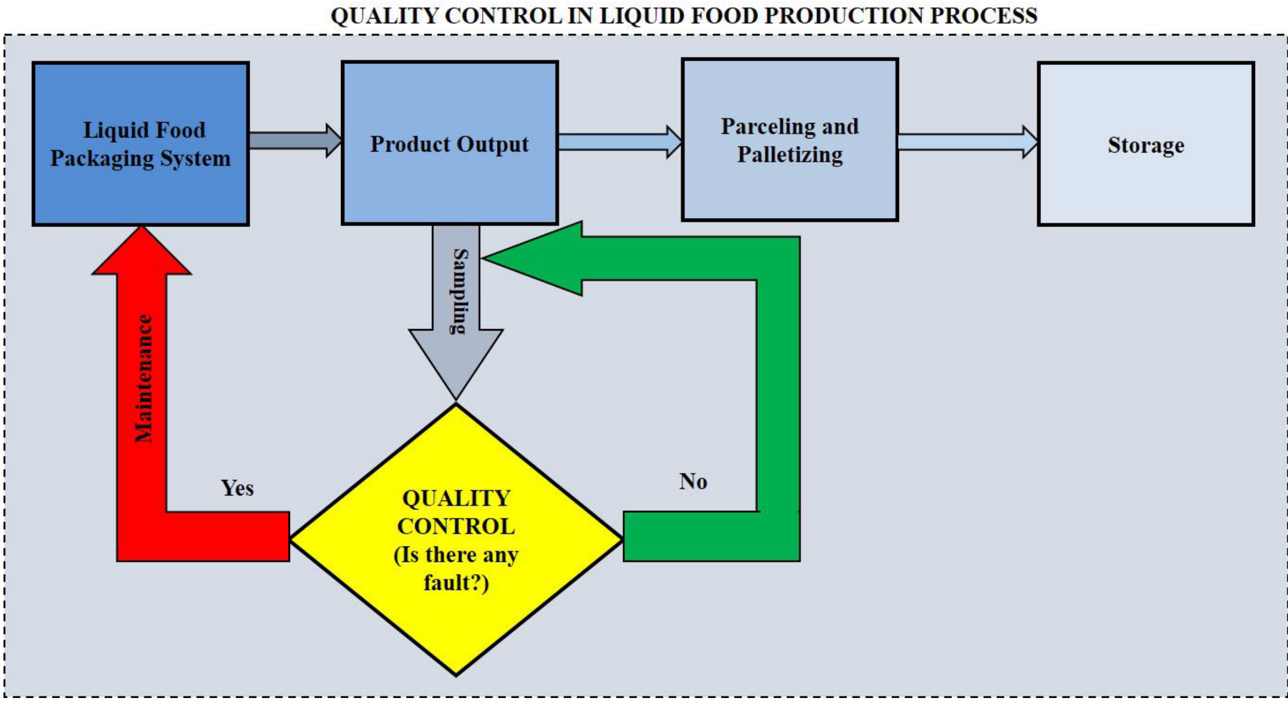

Figure 1. Impermeability tests in the production process.

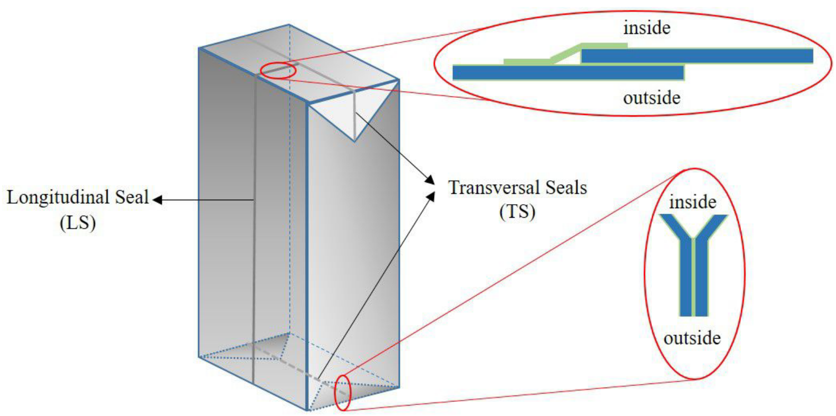

Figure 2. Transverse and longitudinal seal regions.

In the longitudinal seal (LS), an inner PE strip is adhered internally to block out the external environment. In high-temperature, high-pressure (HTHP) LS defects, aseptic package materials are exposed to high temperature and high pressure caused by the machine. Figure 3a shows the fluctuation-free image of the seamless package while Figure 3b shows the fluctuations in the seals of the material due to excessive pressure. Another defect on the LS is low-temperature low-pressure (LTLP). The LTLP defects are caused by the failure of the polyethylene layer in the seal region and by the application of wrong pressure by the sealing machines on the box junctions. In these two types of defects, the desired level of seal adherence cannot be achieved due to lack of desired temperature and pressure values. In the LTLP LS defect shown in Figure 3c, nonadhered seal areas are more matte than they should be. In a transverse seal (TS), the mutual PE coatings on the inner surface of the package adhere to each other. In TS formation, HTHP defects do not occur since induction sealing jaws do not have direct contact with PE material. The only LTLP defect is examined on the TS. In the TS defect given in Figure 3d, it is seen that the nonadhered seal areas are brighter than they should be.

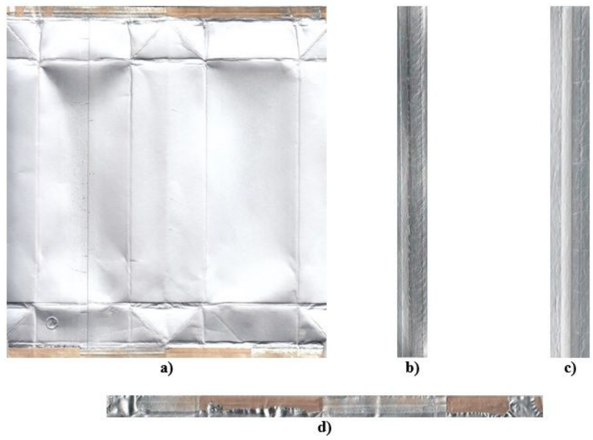

Figure 3. Sample package images: a) Defect-free package, b) HTHP LS, c) LTLP LS, d) LTLP TS.

In the dataset consisting of the sample package images shown in Figure 3, a total of 400 packages were used, including 100 defect-free packages, 100 HTHP LS defective packages, 100 LTLP LS defective packages, and 100 TS defective packets. The number of packages used is given in Table 1.

Table 1. Number of package samples used in the study.

Types of seal error	Number of packages
Defect-free package	100
HTHP LS	100
LTLP LS	100
LTLP TS	100

In addition, the block diagram of the proposed system in our study as an alternative to the traditional quality control process given in Figure 1 is shown in Figure 4. In the proposed method, the quality control process consists of sample preparation, digital image acquisition, classification, decision-making, and result stages performed by the operator using image-taking devices and calculation environments. After the operator prepares the image taken from the production line, images taken from a digital image acquisition device, consisting of a CCD array scanner, are transferred to the computer, and a pretrained deep learning model running on the computer performs classification and decision-making processes to reach a conclusion as to whether to continue or stop the production.

Figure 5 shows the components of the proposed quality control system. The system consists of a standard PC, deep learning model interface, scanner, and package samples.

2.2. Method

2.2.1. Faster R-CNN

Faster R-CNN is a combination of the RPN network [12] and the Fast R-CNN network [13]. Figure 6 shows the RPN and Fast R-CNN regions of the Faster R-CNN structure. The innovation brought by RPN is the ability

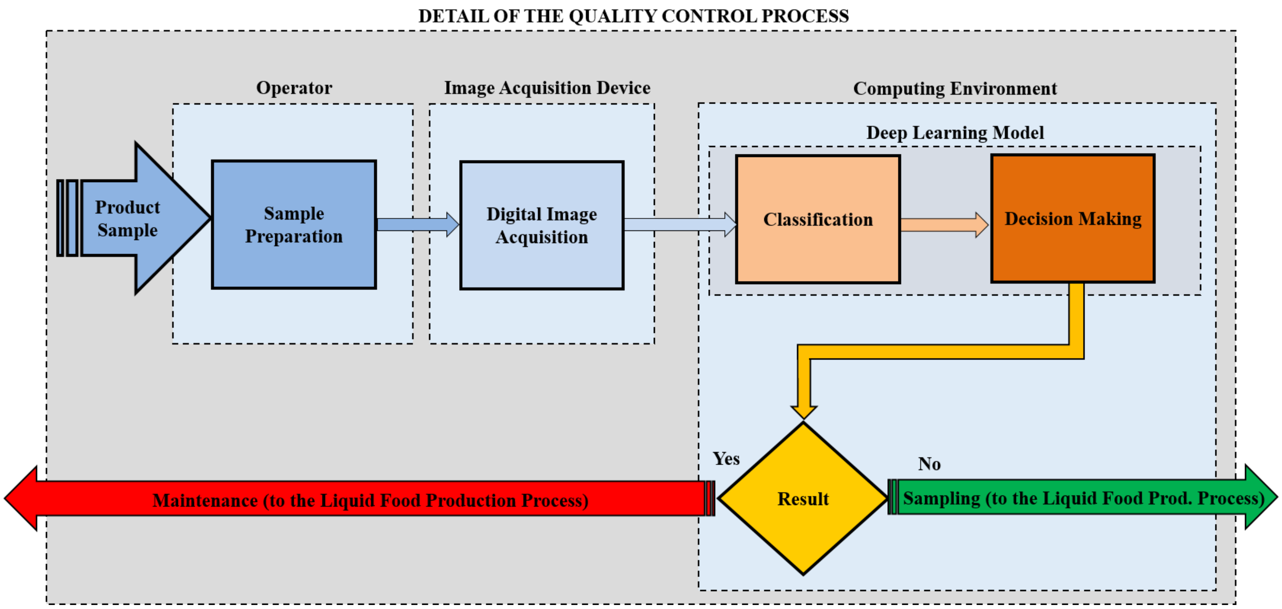

Figure 4. Block diagram of experimental setup.

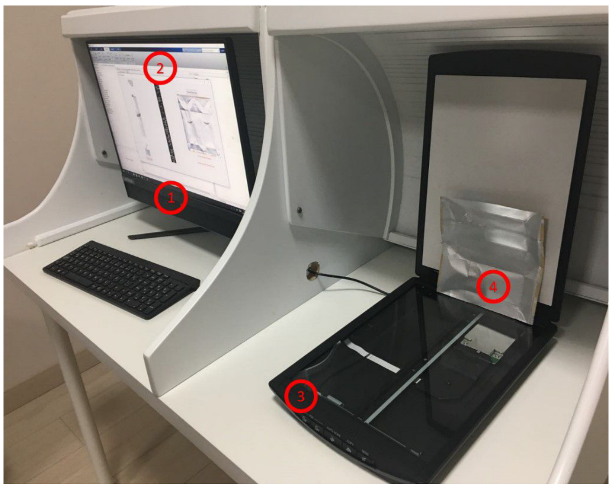

Figure 5. Experimental setup: 1- standard PC, 2- deep learning model interface, 3- CCD array scanner, 4- aseptic package sample.

to connect directly to the sampling layer. In this way, Faster R-CNN offers a working environment to perform object detection thoroughly with its strong structure [12].

RPN is a convolutional neural network. It is used for extracting proposed areas from the image at the input, and proposed areas are scored (prediction accuracy). The classification layer and scores of the proposed areas are combined in the Fast R-CNN network at the estimation layer stage. The Faster R-CNN network also has two output layers. The first one is the Softmax classifier layer and the other is the regression layer that gives the accuracy of the detected area [14].

The input image is calculated only once in Faster R-CNN during the classification process, and then the boundaries of the boxes, which point out the location of the areas to be detected later, are corrected.

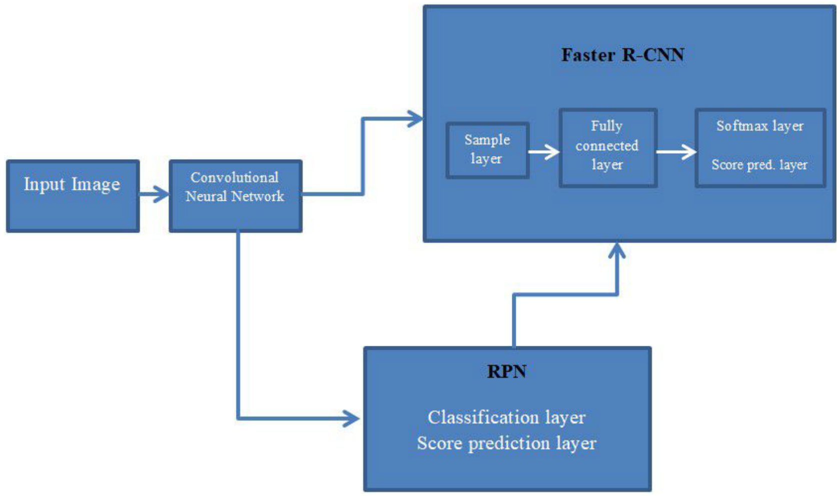

Figure 6. Faster R-CNN architecture used in [14].

Moreover, by sharing the convolutional layers, a very deep convolutional network can be trained to improve the performance of object detection.

2.2.2. Convolutional neural network (CNN)

In the first layers of the CNN architecture, influenced by the human image acquisition process, the features with low information content are learned in the first layers, whereas the features with high information content are learned in the last layers, including certain parts of the objects in the image [15]. A typical CNN architecture consists of input, convolution, ReLU, and fully connected layers. The input layer consists of a fixed-size image. If the size is small, the objects within the image cannot be distinguished well. When selected too large, hardware may become insufficient during the training of the architecture. Therefore, optimum outcomes should be determined as a result of experimental studies. The convolution layer is the layer where different features of the image are extracted. Size reduction is performed in the pooling layer by applying mathematical operations (averaging, taking the maximum) to neighborhood values in the eigenvalue matrices created during the convolution stage. In this way, the process time is reduced by reducing the learning time, but there may be information loss in this layer. In the CNN architecture, the weights are learned with functions such as Softmax in the fully connected layer, after obtaining the matrices following the cascaded connection of convolution and pooling layers [16]. It is observed that the success rate increases as a result of changes in CNN parameters according to the images analyzed and the objects to be detected in the image [17]. Table 2 shows the Faster R-CNN and the parameters used in the Faster R-CNN with updated CNN parameters.

As shown in Table 2, two different Faster R-CNN models were used to detect defects on the inner surfaces of liquid food packages. Considering the parameters used in these two models, in the Faster R-CNN model with updated CNN parameters, clear identification of the areas to be detected in the images was achieved using a 300 $\times$ 300 input and a filter number of 64. The hardware becomes insufficient and training time increases with increasing input image sizes, and it does not increase the success rate proportionally [18]. Therefore, as a result of experimental studies, the optimum input image size was determined as 300 $\times$ 300. The convolution layer, which is the first layer of the CNN model used for extracting features, takes its input from the inner surface images of the packages. In the Faster R-CNN model, the convolution layers have 1 stride, 1 padding, and

Table 2. Faster R-CNN models used in the study.

	Faster R-CNN		Updated Faster R-CNN	
Input image size	32 × 32 × 3		300 × 300 × 3	
Number of filter	32		64	
Size of filter	3x3		3x3	
Conv1	Stride=1	Padding=1	Stride=3	Padding=2
Conv2	Stride=1	Padding=1	Stride=3	Padding=2
Max pooling	Pool size=3	Stride=2	Pool size=3	Stride=1
Fully connected	64		8	

3 × 3 pool size, whereas the convolution layers in the Updated Faster R-CNN model use 3 strides, 2 paddings, and convolution cores with a 3 × 3 pool size. In the convolution layers, smaller filter size, stride, and pool size increase the complexity of the extracted features and challenge the hardware. If these values are selected too large, it is not possible to detect the objects in the image well, decreasing the classification success of the model. Therefore, selecting the most suitable parameters is very important to increase the classification success of the model as a result of experimental studies [4,13]. In the Faster R-CNN model, the pooling layer has 3 pooling sizes and 3 strides, whereas the updated Faster R-CNN model has a pooling layer with 2 pooling sizes and 1 stride. Selecting the scale size and the number of stride values too high causes the attribute map sizes to be reduced very quickly, which in turn causes the loss of attributes to be detected in the image [19]. The CNN model optimizes weights by updating the filters in each layer with the backpropagation method. In this way, the features that best exemplify the objects to be detected in the image are extracted [16]. During the optimization of the weights, training was carried out by taking the values of heap size 64, momentum 0.85, and weight reduction 0.001.

3. Experimental studies

The experiments were performed on a computer with MATLAB 2018b in a Windows 10 64-bit operating system environment, on an Intel i7 8550U, 16 GB RAM, with Nvidia GTX 960M hardware. In the study, 75% of the images were used for training, and the remaining 25% were used for testing. The training phase lasted about 30 h for 150,000 iterations. In order to evaluate the performance of the Faster R-CNN model with updated CNN parameters, comparisons were made by performing defect-type detection in packages using the original Faster R-CNN model. Prior to the training of the deep learning model, the labeling and the defect seal areas are determined using expert opinion. As a result of the training of the CNN model using these labels, the test images not encountered during the training phase are given as inputs to the model and checked for defective seals. In the test image, the location of the relevant area and the accuracy value for the defect seal are retained when regions similar to the different defect seal areas are detected. In our study, as seen in Figure 7 in the test images, defective seals can be detected in more than one region. In this case, all zones with a defect seal accuracy value of over 70% shall be marked on the image. This value was determined as a result of experimental studies. Areas with lower accuracy values are not shown on the test image and are not classified as defective packages in order to avoid misclassification. The images obtained by applying both models to the sample package images are shown in Figure 7.

It is seen in Figure 7a that the seal defect areas cannot be sufficiently segmented when the Faster R-CNN

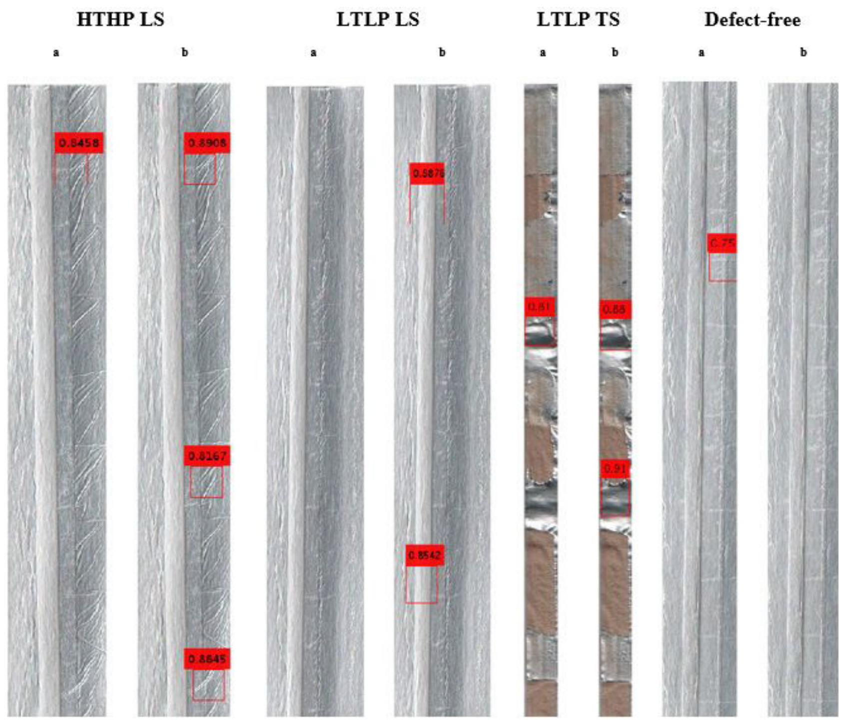

Figure 7. Results of the application of the proposed methods to strip seal images of the packages: a) Faster R-CNN model, b) Updated Faster R-CNN model.

model is applied to the inner images of liquid food packages. It can be seen that no seal defect was found in some images, and there were missing seal defects in other images. The Faster R-CNN model with updated CNN parameters was found to detect the seal defect areas better, as shown in Figure 7b. This shows that it is very important to adjust the parameters in the Faster R-CNN model according to the images, and the morphological structures of the objects within. Tables 3 and 4 show the confusion matrices of the original Faster R-CNN model and the Faster R-CNN model with updated parameters, and Tables 5 and 6 show the sensitivity, specificity, and accuracy values.

Table 3. Confusion matrix of the original Faster R-CNN model.

		Predict			
		0 (Defect- free)	1 (HTHP LS)	2 (LTLP LS)	3 (LTLP TS)
Actual	0 (Defect- free)	98	0	2	0
	1 (HTHP LS)	1	98	1	0
	2 (LTLP LS)	3	1	96	0
	3 (LTLP TS)	2	0	0	98

As shown in Table 4, 298 out of 300 inner surface images of packages that contain seal defects were correctly classified by the Faster R-CNN model with updated CNN parameters. There was only 1 incorrect classification in 100 images without seal defects. This shows that the specificity values of the proposed approach are higher than the sensitivity values as seen in Tables 5 and 6. Examination of incorrect classifications shows that the LTLP longitudinal seal defects are very similar to the faultless seal regions. In addition, Table 7 shows

Table 4. Confusion matrix of the Faster R-CNN model with updated CNN parameters.

		Predict			
		0 (Defect- free)	1 (HTHP LS)	2 (LTLP LS)	3 (LTLP TS)
Actual	0 (Defect- free)	99	0	1	0
	1 (HTHP LS)	0	100	0	0
	2 (LTLP LS)	2	0	98	0
	3 (LTLP TS)	0	0	0	100

Table 5. Evaluation of the success of the original Faster R-CNN model.

	Sensitivity	Specificity	Accuracy
0 (Defect-free)	98	98	98
1 (HTHP LS)	98	99.7	99.25
2 (LTLP LS)	96	99	98.25
3 (LTLP TS)	98	100	99.5
Overall	97.5	97.5	97.5

Table 6. Evaluation of the success of the Faster R-CNN model with updated CNN parameters.

	Sensitivity	Specificity	Accuracy
0 (Defect-free)	99	99.33	99.25
1 (HTHP LS)	100	100	100
2 (LTLP LS)	98	99.66	99.25
3 (LTLP TS)	100	100	100
Overall	99.25	99.25	99.25

the comparison of the success rates of the methods we have proposed and recent studies in the literature on image processing-based quality control systems in the industry.

In Table 7, the classification performance of the Updated Faster R-CNN model, developed by changing the parameters in the CNN architecture, is compared with the results of the original Faster R-CNN approach and the results of machine learning methods with image processing in the literature. As a result of the application of the updated Faster R-CNN model to the dataset we used in the study, the classification of the defects in the strip seals in the packages was carried out with a 99.25% accuracy rate. Image processing, machine learning methods, and the original Faster CNN model were not able to achieve the performance of the updated Faster R-CNN model we proposed in the study. This shows that it is very important to adjust the parameters in the CNN architecture according to the images to be analyzed and the morphological structures of the regions to be detected.

4. Conclusion

This is the second study in the literature to perform quality control of strip seals in multilayer aseptic packages through computer-aided systems, and it is the first study to perform analysis using the deep learning method. In practice, various experiments were performed on the defect controls of strip seals by using Faster R-CNN

Table 7. Comparison of success rates of the proposed methods and studies in the literature on image processing-based quality control systems in industry.

Authors	Year	Objective	Number of images	Method	Sens.	Spec.	TCC
Li et al. [6]	2017	Textile fabric defect detection	2600	FCSDA	100	87.88	99.2
Bennamoun and Bodnarova [7]	2003	Textile quality control	50	STFT SGLS	-	-	96 88
Zuñiga et al. [8]	2014	Grape maturity estimation	257	Neural network	-	-	86
Cord and Chambon [9]	2012	Road defect detection	6875	AdaBoost	-	-	95.2
Tiloca et al. [10]	2002	Textile fabric defect detection	2000	Neural network	-	-	83.6
Zhang et al. [11]	2016	Halftone image classification	28000	Stacked sparse autoencoders / softmax regression	-	-	98.69
Adem et al/ [1]	2015	Detection of faulty seals in liquid food packages	204	Canny edge, thresholding, SVM	-	-	99.2
Proposed method-1	2019	Detection of faulty seals in liquid food packages	400	Faster R-CNN	97.5	97.5	97.5
Proposed method-2	2019			Updated Faster R-CNN	99.25	99.25	99.25

models, which were updated by changing the parameters of the CNN model, and the results were compared with different studies on image processing and machine learning-based quality control. Defective seals rarely occur depending on the state of the machine producing liquid food packs. Liquid food companies face high costs due to the time of detection in each faulty production. Therefore, the detection of faulty seals with a computer-aided self-learning system is very important in order to prevent human errors. In our study, a comparable number of samples was obtained for each defect in order to evaluate the accuracy of classification objectively. Although the results obtained are satisfactory in terms of classification, further research is needed to support the study due to the vital impact of liquid foods on human health. For this reason, the number of packages used in the experiments should be increased by hundreds of times for better estimations in the study. It can be said that the calculated success rate will likely be higher in this way.

Acknowledgment

This work was supported by the Research Fund of the TÜBİTAK-TEYDEB, Project Number 2150314.

References

[1] Adem K, Orhan U, Hekim M. Image processing based quality control of the impermeable seams in multilayered aseptic packages. Expert Systems with Applications 2015; 42 (7): 3785–3789. doi: 10.1016/j.eswa.2014.12.045

[2] Michalski R, Carbonell J, Mitchell T. Machine Learning: An Artificial Intelligence Approach. Berlin, Germany: Springer-Verlag, 2013.

[3] Gonzalez RC. Digital Image Processing Using MATLAB. Upper Saddle River, NJ, USA: Pearson-Prentice-Hall, 2004.

[4] Adem K. Exudate detection for diabetic retinopathy with circular Hough transformation and convolutional neural networks. Expert Systems with Applications 2018; (114): 289-295. doi: 10.1016/j.eswa.2018.07.053

[5] Xie X. A review of recent advances in surface defect detection using texture analysis techniques. Electronic Letters on Computer Vision and Image Analysis 2008; 7 (3): 1-22.

[6] Li Y, Zhao W, Pan J. Deformable patterned fabric defect detection with Fisher criterion-based deep learning. IEEE Transactions on Automation Science and Engineering 2017; 14 (2): 1256-1264. doi: 10.1109/TASE.2016.2520955

[7] Bennamoun M, Bodnarova A. Digital image processing techniques for automatic textile quality control. Systems Analysis Modelling Simulation 2003; 48 (1): 1581-1614. doi: 10.1080/0232929032000115083

[8] Zuñiga A, Mora M, Oyarce M, Fredes C. Grape maturity estimation based on seed images and neural networks. Engineering Applications of Artificial Intelligence 2014; (35): 95-104. doi: 10.1016/j.engappai.2014.06.007

[9] Cord A, Chambon S. Automatic road defect detection by textural pattern recognition based on AdaBoost. Computer-Aided Civil and Infrastructure Engineering 2012; 4 (27): 244-259. doi: 10.1111/j.1467-8667.2011.00736.x

[10] Tilocca A, Borzone P, Carosio S, Durante A. Detecting fabric defects with a neural network using two kinds of optical patterns. Textile Research Journal 2002; 6 (72): 545-550. doi: 10.1177/004051750207200614

[11] Zhang Y, Zhang E, Chen W. Deep neural network for halftone image classification based on sparse auto-encoder. Engineering Applications of Artificial Intelligence 2016; (50): 245-255. doi: 10.1016/j.engappai.2016.01.032

[12] Ren S, He K, Girshick R, Sun J. Faster R-CNN: Towards real-time object detection with region proposal networks. IEEE Transactions on Pattern Analysis and Machine Intelligence 2015; 39 (6): 91-99.

[13] Girshick R. Fast R-CNN. In IEEE International Conference on Computer Vision; Santiago, Chile; 2015. pp. 1440-1448.

[14] Yang S, Fang B, Tang W, Wu X, Qian J et al. Faster R-CNN based microscopic cell detection. In: Security, Pattern Analysis, and Cybernetics; Shenzhen, China; 2017. pp. 345-350.

[15] Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems; Lake Tahoe, NV, USA; 2012. pp. 1097-1105.

[16] LeCun Y, Bengio Y. Convolutional networks for images, speech, and time series. Handbook of Brain Theory and Neural Networks 1995; 3361 (10): 1-14.

[17] Lawrence S, Giles CL, Tsoi AC, Back AD. Face recognition: a convolutional neural-network approach. IEEE Transactions on Neural Networks 1997; 8 (1): 98-113.

[18] Huang G, Liu Z, Van Der Maaten L, Weinberger KQ. Densely connected convolutional networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; Honolulu, HI, USA; 2017. pp. 4700-4708.

[19] Hanson J, Paliwal K, Litfin T, Yang Y, Zhou Y et al. Accurate prediction of protein contact maps by coupling residual two-dimensional bidirectional long short-term memory with convolutional neural networks. Bioinformatics 2018; 34 (23): 4039-4045. doi: 10.1093/bioinformatics/bty481