Intelligent Methods in Engineering Sciences 3(2): 063-069, 2024

IMIENS

INTELLIGENT METHODS
IN ENGINEERING SCIENCES

https://www.imiens.org

International Open Access

June, 2024

e-ISSN 2979-9236

*Research Article*

https://doi.org/10.58190/imiens.2024.100

# Detecting Industrial Potato Chips Defects with Machine Learning Methods Using Deep Features

***Gulsen TASPINAR*** [a] ***, Murat KOKLU*** [b,*]

[a] *Graduate School of Natural and Applied Sciences, Selcuk University, Konya, Türkiye*
[b] *Department of Computer Engineering, Faculty of Technology, Selcuk University, Konya, Türkiye*

ARTICLE INFO

*Article history:*
Received 03 April 2024
Accepted 29 June 2024

*Keywords:*
potato chips,
computer vision,
defective products,
convolutional neural network.

ABSTRACT

Detection of production defects in industrial foods is vital to protect consumer health. Early detection of these errors can minimize the economic losses of manufacturers by reducing the costs of recalls and production stoppages. Additionally, continuous monitoring and improvement of product quality can increase brand reliability and customer satisfaction. Image processing can detect product defects, minimize human error and increase efficiency by performing uninterrupted inspection on the production line. Based on these reasons, this study aimed to detect potato chip errors with image processing. PepsiCo Lab Potato Chips Quality Control image dataset was used in the study. There are two classes in the dataset: defective and not defective. There are 967 images in total. SqueezeNet Convolutional Neural Network (CNN) architecture was used to extract the features of the images. With this architecture, 1000 features obtained for each image were classified with Artificial Neural Network (ANN), K Nearest Neighbor (KNN), Random Forest (RF) machine learning methods. As a result of the classifications, 0.986 classification accuracy was obtained from the ANN model, 0.927 from the KNN model, and 0.962 from the RF model. F1 Score, precision, recall and specificity metrics were used to compare the models in detail. According to the data obtained from the experimental results, it is predicted that the proposed feature extraction and classification models can detect industrial production errors occurring in potato chips.



## 1. INTRODUCTION

Food processing is the conversion of raw materials, such as natural animals and plants, into food or one form of food into other forms more suitable to the dietary habits of modern humans. Therefore, food processing is closely related to the quality of life of modern people and the economic development of the whole society. Food processing involves various aspects (e.g., food production, modification, and production) that require a series of physical and chemical changes in raw materials [1]. However, due to the increase in environmental pollution, people are concerned about the safety of both food sources and food processing procedures. During the process, it is necessary to ensure that the nutritional properties of raw materials are preserved and that toxic and harmful substances do not enter the food. Therefore, food processing has high value for food scientists, the food industry and consumers [2]. After years of rapid development, machine vision has become widespread in various sectors, including agriculture, medical care, transportation and communications. Its high efficiency and accuracy can reduce labor costs and even outperform humans [3]. Specifically, in food processing, a machine vision system can collect a number of parameters of the food, such as its size, weight, shape, texture and color, and even a large number of details that cannot be observed by the human eye. Thanks to the monitoring and control of food processing, errors caused by humans in repetitive tasks are prevented [4].

Potato (Solanum tuberosum L.) is one of the world's most important crops, considered a staple food in many developing countries [5]. The importance of this crop also stems from the fact that potatoes can be used in many ways as a staple food, commercial crop, animal feed, and as a starch source for many industrial uses [6]. The quality of potatoes and potato products is determined by various attributes that determine their final acceptance in the market. Both potato consumers and the retail sector prefer quality potatoes; therefore, the potato industry faces an ever-increasing demand for quality products [7]. For this reason, it is necessary to quickly detect defects or the quality of products obtained from potatoes. Thanks to computer vision, such problems can be solved quickly.

Computer vision is widely used for classification and

*** Corresponding Author:** mkoklu@selcuk.edu.tr

object detection in military applications, automation, security, biometrics and medical fields. Recently, imaging systems made with computers that are low-cost, harmless and capable of high calculations are used in packaging and wrapping systems as well as in the agriculture and food industry. It is noteworthy that image processing and computer vision applications are increasing in agriculture due to decreasing equipment costs, increasing computational power and increasing interest in non-destructive food evaluation methods [8]. The use of these techniques offers advantages compared to traditional methods based on manual work, but there are still a number of challenges to overcome [9]. Manual methods for grain evaluation are challenging even for people trained to perform these tasks. However, one of the main challenges is the training of these assessors. There are scarce places prepared to produce people of the required quality. Another challenge is the time required to conduct such assessments, hindering rapid decision-making and large-scale evaluation [10].

There are studies in the literature to detect defects in industrial products. Villalba-Diez et al. have demonstrated how a high-resolution optical quality inspection camera and a Deep Learning-based software sensor can be combined to increase the accuracy of the industrial visual inspection process and reduce costs in printing Industry 4.0. In the production process of gravure cylinders, errors such as holes are inevitable. In their paper, they proposed a Deep Neural Network (DNN) software sensor that compares the scanned surface with the used scratch file and learns features by exposure to training data. The developed DNN sensor achieved a fully automatic classification accuracy rate of 98.4% [11].

In their article, Wang et al. focused on machine vision-based product inspection methods, which are widely researched to improve product quality and reduce labor costs. In this study, a new deep learning-based machine vision inspection method is presented to identify and classify defective products without loss of precision. Specifically, random noise is limited by using a Gaussian filter on the resulting image. Then, region of interest (ROI) extraction is performed based on the Hough transform to eliminate irrelevant background, thereby reducing the computational burden of the subsequent identification process. The identification module is based on convolutional neural network, and inverse resolution block is used to achieve a good balance between identification accuracy and computational efficiency. The proposed method achieves superior inspection performance by using a large data set consisting of defective and perfect bottle images.

Considering these studies in the literature, the motivation of this study was determined. The aim of the study was to detect potato chips errors. The contributions of the study to the literature and the procedures performed are as follows:

• A two-class dataset containing a total of 967 images was used in the study.

• SqueezeNet CNN model was used to extract the features of the images in the dataset.

• 1000 features obtained for each image from the SqueezeNet model were classified with ANN, SVM and KNN machine learning methods.

• The performance of machine learning models was analyzed and the most successful model was determined.

The rest of the article is planned as follows. In the second part, the dataset used in the study, SqueezeNet CNN model, ANN, SVM and KNN machine learning methods are explained. In addition, explanations of the confusion matrix and performance metrics used to evaluate the performance of the models are also given in this section. In the third section, the results of the classifications made in the Experimental results section are included. The last section, Conclusion, includes the results of the study and recommendations.

## 2. Material and Methods

In the study, SqueezeNet model was used to extract the features of the images. 1000 image features were obtained for each image. The obtained features are given as input to ANN, KNN and RF models. The results obtained as a result of the classifications were analyzed. The flow chart of the study describing these processes is given in Figure 1.

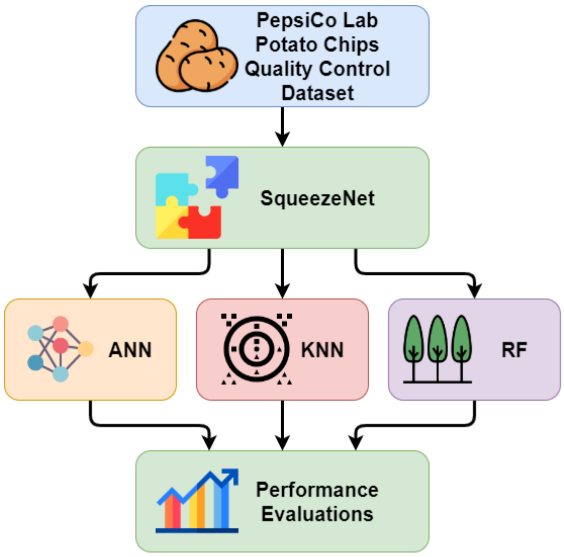



**Figure 1.** Flow chart of study

In this section, information about the dataset in Figure 1, feature extraction method, machine learning methods and performance evaluations is given.

### *2.1. PepsiCo Lab Potato Chips Quality Control Dataset*

PepsiCo Lab Potato Chips Quality Control dataset was used [12]. There are two classes in the dataset: defective and not defective. There are a total of 965 images in two classes. The dataset is divided into train and test. There are 771 images in the Train section and 194 images in the test section. Sample images of the classes in the dataset are given in Figure 2.

PepsiCo Lab Potato Chips Quality Control dataset was used [12]. There are two classes in the dataset: defective and not defective. There are a total of 965 images in two classes. The dataset is divided into train and test. There are 771 images in the train section and 194 images in the test section. There are 771 images in the train section and 194 test section. There are 370 images in the defective class and 401 images in the non-defective class in train section. There are 93 images in the defective class and 101 images in the non-defective class. Sample images of the classes in the dataset are given in Figure 2.

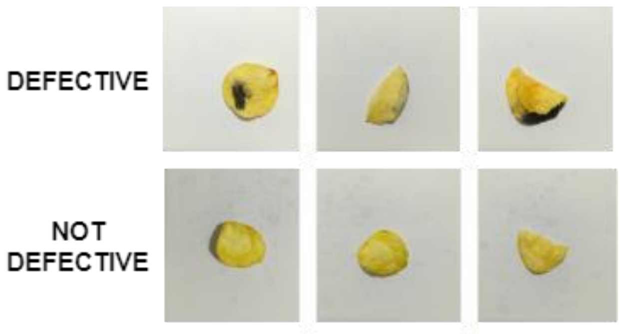



**Figure 2.** Sample images of the PepsiCo Lab Potato Chips Quality Control dataset

### *2.2. Convolutional Neural Network (CNN) and SqueezeNet*

Convolutional Neural Networks (CNN) are deep learning architectures that enable revolutionary developments, especially in the fields of image processing and computer vision [13]. CNNs use local connections and shared weights on data input to create feature maps and thus learn spatial hierarchies [14]. Convolution layers extract low-level features such as edges, corners, and textures in the image, while deep layers learn more complex and abstract representations [15]. These networks increase the information density and improve the generalization capacity of the model with techniques such as nonlinear activation functions and maximum pooling. In particular, by training on large data sets, they demonstrate superior performance in areas such as object recognition, face recognition and medical image analysis. CNNs occupy an important position in the field of artificial intelligence, offering a wide range of applications in deep learning research [16]. In this study, SqueezeNet architecture was used to extract features from images. 1000 features are obtained for each image from the SqueezeNet model.

SqueezeNet is a lightweight and efficient convolutional neural network (CNN) architecture and was developed in 2016 by Forrest N. Iandola, Song Han, Matthew W. Moskewicz, Khalid Ashraf, William J. Dally, and Kurt Keutzer. Its purpose is to obtain smaller model sizes by reducing the number of parameters and at the same time maintain high accuracy rates. Although SqueezeNet has similar accuracy rates to AlexNet, it has managed to reduce the number of parameters by 50 times. This achievement allows the network to run faster using less memory and to be especially effective on devices with limited resources (mobile devices, embedded systems).

Using SqueezeNet in feature extraction is very effective. When an image is given to the input of SqueezeNet, the network processes this image through layers and extracts various features. In particular, the features obtained from the final layers contain a high-level representation of the input image. These extracted features are usually in the form of vectors and can be used with other machine learning algorithms. For example, as in this study, 1000 features obtained from SqueezeNet can be given as input to classification models such as ANN, KNN and RF. Thus, SqueezeNet performs the basic task of image processing and feature extraction, while other models complete the classification process using these features. This method enables effective and efficient feature extraction and classification in complex image datasets.

### *2.3. Artificial Neural Network (ANN)*

Artificial Neural Networks (ANN) are computational systems that imitate the functioning of biological neural networks and aim to model the learning and problem-solving abilities of the human brain [17]. Thanks to its multi-layered structures, ANN is highly effective in extracting meaningful patterns from complex and multi-dimensional data sets. These networks take input data, process this data through weights and activation functions, and ultimately produce an output [18]. ANNs supported by deep learning techniques have provided significant innovations in various fields such as image recognition, natural language processing and voice recognition. Especially in the era of big data, the flexibility and learning capacity of ANNs have brought them to the forefront of artificial intelligence research. In this direction, the potential of ANNs to solve complex problems and facilitate human life is constantly increasing [19].

### *2.4. K Nearest Neighbor (KNN)*

K Nearest Neighbor (KNN), one of the supervised learning algorithms, has a wide range of use in classification and regression problems. When determining the class of a data point, the KNN algorithm takes into account the K neighbors near this point. The neighbors in question are typically determined using the Euclidean distance, and the majority class of the nearest neighbors is assigned as the class of the target data point. The main advantage of the KNN algorithm is that it has a simple and understandable structure; Since it does not require any learning process during the model creation phase, it is considered in the category of "lazy learning" algorithms. However, in large data sets and high-dimensional data spaces, the computational cost may increase and the performance of the algorithm may decrease. Despite this, the KNN algorithm is considered an effective and useful method, especially in small-scale data sets and certain applications [20].

### *2.5. Random Forest (RF)*

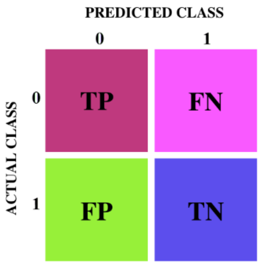
Random Forest is a flexible and powerful supervised learning algorithm used in both classification and regression problems. This method consists of a combination of multiple decision trees, and each tree is trained on different subsamples of the data set. Random sampling and random feature selection ensure that the trees are diverse and independent, increasing the generalization ability of the model and reducing the risk of overlearning. The results of decision trees are combined by majority vote in classification problems and by averaging in regression problems. Random Forest is widely preferred, especially in large data sets and complex problems, due to its high accuracy rate, balanced error rates and insensitivity to parameter settings. Additionally, this algorithm plays an important role in determining which features contribute more to the predictive power of the model by ranking variable importance [21].

### *2.6. Performance Evaluations*

Evaluating the performance of machine learning models is of great importance in determining the effectiveness and reliability of these models in real-world applications [22, 23]. Performance evaluation is performed using a variety of metrics to measure the model's accuracy, generalization ability, and consistency across different data sets. For classification problems, metrics such as accuracy, precision, sensitivity (recall) and F1 score, Specificity are frequently preferred. These metrics are used to evaluate how accurately the model predicts positive and negative classes, the rate of false positive and false negative predictions, and the overall performance of the model [24]. Correct selection and application of performance metrics plays a critical role in the process of developing and improving models and makes a significant contribution to predicting how they will perform in different scenarios [25, 26]. An example confusion matrix and performance metrics formulas are given in Figure 3.

## 3. Experimental Results

PepsiCo Lab Potato Chips Quality Control dataset was used in the study. There are a total of 965 images in the dataset. SqueezeNet model was used to extract the features of the images. 1000 images were obtained for each image.




| Metrics | Equation |
|---|---|
| Accuracy | $\frac{TP+TN}{TP+TN+FP+FN}x100$ |
| Precision | $\frac{TP}{TP+FP}$ |
| Recall | $\frac{TP}{TP+FN}$ |
| F-1 Score | $2x\frac{Precision\ x\ Recall}{Precision+Recall}$ |
| Specificity | $\frac{TP}{TP+FN}$ |

**Figure 3.** Confusion matrix and performance metrics

A total of 965 images were used for training and testing of ANN, KNN and RF models. A computer with Intel® Core i7™ 12700K 3.61 GHz, NVIDIA GeForce RTX 3080Ti, and 64GB RAM was used in the training and testing of the models. The dataset is divided into train and test. There are 771 images in the Train section and 194 images in the test section. As a result of the training and testing of ANN, KNN and LR models, a confusion matrix was obtained for each model. Confusion matrices of ANN, KNN and RF models are given in Figure 4.

(a) ANN

| Actual \ Predicted | Defective | Non-Defective | Σ |
|---|---|---|---|
| Defective | 360 | 9 | 369 |
| Non-Defective | 2 | 398 | 400 |
| Σ | 362 | 407 | 769 |

(b) KNN

| Actual \ Predicted | Defective | Non-Defective | Σ |
|---|---|---|---|
| Defective | 314 | 55 | 369 |
| Non-Defective | 1 | 399 | 400 |
| Σ | 315 | 454 | 769 |

(c) RF

| Actual \ Predicted | Defective | Non-Defective | Σ |
|---|---|---|---|
| Defective | 357 | 12 | 369 |
| Non-Defective | 21 | 379 | 400 |
| Σ | 378 | 391 | 769 |

**Figure 4.** Confusion matrix of ANN, KNN and RF models

In Table 1, performance metrics of the models calculated according to the data obtained from the confusion matrices are given.

**Table 1.** Performance metrics of all models

| | Accuracy | F1 Score | Precision | Recall | Specificity |
|---|---|---|---|---|---|
| ANN | 0.986 | 0.986 | 0.986 | 0.986 | 0.985 |
| KNN | 0.927 | 0.927 | 0.935 | 0.927 | 0.921 |
| RF | 0.962 | 0.962 | 0.962 | 0.962 | 0.962 |

The accuracy value of the ANN model was calculated as 0.986. This value expresses the proportion of examples that the model classifies correctly. An accuracy value of 0.986 indicates that the model has a very high level of accuracy overall. That is, it indicates that the model correctly classified most of the examples in the dataset. Precision value was calculated as 0.986. This value expresses how many of the examples that the model predicts as positive are actually positive. A sensitivity value of 0.986 indicates that the majority of the model's positive predictions are correct. In other words, it indicates that the model keeps the false positive rate quite low. The recall value is calculated as 0.986. This value expresses how much of the true positives are correctly recognized by the model. A sensitivity value of 0.986 indicates that the model correctly recognizes all true positives. That is, it indicates that the model does not miss positive examples. Specificity value was calculated as 0.985. This value expresses how many of the examples that the model predicts as negative are actually negative. A specificity value of 0.985 indicates that the majority of the model's negative predictions are correct. In other words, it indicates that the model keeps the false negative rate quite low. F1 score was calculated as 0.986. This value provides the balance between sensitivity and sensitivity. A high F1 score indicates that the model performs well in terms of both precision and sensitivity.

The accuracy value of the KNN model was calculated as 0.927. This value expresses the proportion of examples that the model classifies correctly. An accuracy value of 0.927 indicates that the model has a very high level of accuracy overall. That is, it indicates that the model correctly classified most of the examples in the dataset. Precision value was calculated as 0.935. This value expresses how many of the examples that the model predicts as positive are actually positive. A sensitivity value of 0.935 indicates that the majority of the model's positive predictions are correct. In other words, it indicates that the model keeps the false positive rate quite low. The recall value was calculated as 0.927. This value expresses how much of the true positives are correctly recognized by the model. A sensitivity value of 0.927 indicates that the model correctly recognizes all true positives. That is, it indicates that the model does not miss positive examples. Specificity value was calculated as 0.921. This value expresses how many of the examples that the model predicts as negative are actually negative. A specificity value of 0.921 indicates that the majority of the model's negative predictions are correct. In other words, it indicates that the model keeps the false negative rate quite low. F1 score was calculated as 0.927. This value provides the balance between sensitivity and sensitivity. A high F1 score indicates that the model performs well in terms of both precision and sensitivity.

The accuracy value of the RF model was calculated as 0.962. This value expresses the proportion of examples that the model classifies correctly. An accuracy value of 0.962 indicates that the model has a very high level of accuracy overall. That is, it indicates that the model correctly classified most of the examples in the dataset. Precision value was calculated as 0.962. This value expresses how many of the examples that the model predicts as positive are actually positive. A sensitivity value of 0.962 indicates that the majority of the model's positive predictions are correct. In other words, it indicates that the model keeps the false positive rate quite low. The recall value was calculated as 0.962. This value expresses how much of the true positives are correctly recognized by the model. A sensitivity value of 0.962 indicates that the model correctly recognizes all true positives. That is, it indicates that the model does not miss positive examples. Specificity value was calculated as 0.962. This value expresses how many of the examples that the model predicts as negative are actually negative. A specificity value of 0.962 indicates that the majority of the model's negative predictions are correct. In other words, it indicates that the model keeps the false negative rate quite low. F1 score was calculated as 0.962. This value provides the balance between sensitivity and sensitivity. A high F1 score indicates that the model performs well in terms of both precision and sensitivity. Train and test times for ANN, KNN and RF models are given in Table 2.

Table 2 Train and Test time of all models (second)

| | Train Time | Test Time |
|---|---|---|
| ANN | 9.849 | 2.553 |
| KNN | 1.918 | 1.331 |
| RF | 2.543 | 1.175 |

The Artificial Neural Network (ANN) model spends 9,849 seconds during training and 2,553 seconds during testing. ANN models generally take a long time in training due to their complex structure and large number of parameters. However, the testing time is shorter compared to the training time because it takes less time to make predictions on new data once the model is trained. The K-Nearest Neighbor (KNN) model spends only 1.918 seconds during training. The training time for the KNN model can be quite short, because the training phase of

KNN actually consists of storing the data, and this process is very fast. However, the testing time is 1.331 seconds, which is relatively high because the KNN model performs similarity calculations over the entire training dataset for each new data point. The Random Forest (RF) model spends 2,543 seconds during training and 1,175 seconds during testing. Because RF models involve building and training multiple decision trees, training time can be moderately long. However, the testing time is shorter as it involves the trained model making predictions, as in the ANN model. As a result, the ANN model takes the longest time in terms of training time, while the testing time is shorter. While the KNN model has the shortest training time, its testing time is longer compared to other models. The RF model, on the other hand, exhibits a balanced performance in both training and testing periods. Considering these times, KNN and RF models can be preferred in cases where processing time is critical, but the complexity and prediction accuracy of the model should also be taken into account.

## 4. Conclusions

In this study, defects in potato chips, an industrial product, were detected. PepsiCo Lab Potato Chips Quality Control image dataset downloaded from Kaggle.com was used. SqueezeNet CNN architecture was used to extract the features of images belonging to two classes in the dataset. ANN, KNN and RF classification models were used to classify 1000 features obtained for each image. Classification accuracy of 0.986 was obtained from the ANN model, 0.927 from the KNN model, and 0.962 from the RF model. It is seen that the highest classification accuracy value belongs to the ANN model.

This study has some limitations. First, the data set used may be of limited variety and the ability to generalize to larger data sets has not been tested. Additionally, the computational costs of the SqueezeNet CNN architecture and other models can be high, especially in complex models such as ANN, which can pose a challenge for real-time applications. The performance of the models may be specific to the data set used and may not produce similar results in different data sets. Finally, the imbalance between classes and the lack of hyperparameter optimization may not fully reflect the potential performance of the models.

The generalization ability of the model can be increased by using larger and more diverse data sets. For usability in real-time applications, the computational costs of the models must be optimized. The performances of ANN, KNN and RF models can be further improved by performing hyperparameter optimization. By eliminating possible class imbalances in the data set, models can be provided with consistent performance in all classes. Finally, existing results can be surpassed and higher accuracy rates can be achieved by trying different machine learning and deep learning techniques.

## Acknowledgements

This study is part of Gulsen Taspinar's Master Thesis and Murat Koklu is her advisor.

## References

[1] Smith, P.G. and P.G. Smith, An introduction to food process engineering, Springer US, 2011. p. 1-3, Online ISBN 978-1-4419-7662-8. DOI: 10.1007/978-1-4419-7662-8_1

[2] Augustin, M.A., et al., Role of food processing in food and nutrition security. Trends in Food Science & Technology, 2016. 56: p. 115-125. DOI: 10.1016/j.tifs.2016.08.005

[3] Patel, K.K., et al., Machine vision system: a tool for quality inspection of food and agricultural products. Journal of food science and technology, 2012. 49: p. 123-141. DOI: 10.1007/s13197-011-0321-4

[4] Cubero, R. and I.V. Hollar, Equity and fiscal policy: income distribution effects of taxation and social spending. Economic Progress and Reforms, 2008: p. 62.

[5] Alva, A., et al., Improving nutrient-use efficiency in Chinese potato production: experiences from the United States. Journal of Crop Improvement, 2011. 25(1): p. 46-85. DOI: 10.1080/15427528.2011.538465

[6] López, A., et al., A review of the application of near-infrared spectroscopy for the analysis of potatoes. Journal of agricultural and food chemistry, 2013. 61(23): p. 5413-5424. DOI: 10.1021/jf401292j

[7] Peña, R., et al., Authentication of Galician (NW Spain) quality brand potatoes using metal analysis. Classical pattern recognition techniques versus a new vector quantization-based classification procedure. Analyst, 2001. 126(12): p. 2186-2193. DOI: 10.1039/B107114A

[8] Mahajan, S., A. Das, and H.K. Sardana, Image acquisition techniques for assessment of legume quality. Trends in Food Science & Technology, 2015. 42(2): p. 116-133. DOI: 10.1016/j.tifs.2015.01.001

[9] Barbedo, J.G.A., A review on the main challenges in automatic plant disease identification based on visible range images. Biosystems engineering, 2016. 144: p. 52-60. DOI: 10.1016/j.biosystemseng.2016.01.017

[10] Zareiforoush, H., et al., Potential applications of computer vision in quality inspection of rice: a review. Food engineering reviews, 2015. 7(3): p. 321-345. DOI: 10.1007/s12393-014-9101-z

[11] Villalba-Diez, J., et al., Deep learning for industrial computer vision quality control in the printing industry 4.0. Sensors, 2019. 19(18): p. 3987. DOI: 10.3390/s19183987

[12] Pedreschi, F., D. Mery, and T. Marique, Quality evaluation and control of potato chips, in Computer vision technology for food quality evaluation. 2016, Elsevier. p. 591-613. DOI: 10.1016/B978-0-12-802232-0.00022-0

[13] Gencturk, B., et al., Detection of hazelnut varieties and development of mobile application with CNN data fusion feature reduction-based models. European food research and technology, 2024. 250(1): p. 97-110. DOI: 10.1007/s00217-023-04369-9

[14] Cinar, I., et al. Identification of corneal ulcers with pre-trained AlexNet based on transfer learning. in 2022 11th Mediterranean conference on embedded computing (MECO). 2022. IEEE. DOI: 10.1109/MECO55406.2022.9797218

[15] Feyzioglu, A. and Y.S. Taspinar, Beef quality classification with reduced E-nose data features according to beef cut types. Sensors, 2023. 23(4): p. 2222. DOI: 10.3390/s23042222

[16] Kursun, R., et al. Flower recognition system with optimized features for deep features. in 2022 11th Mediterranean Conference on Embedded Computing (MECO). 2022. IEEE.

[17] Koklu, M., et al. Identification of sheep breeds by CNN-based pre-trained InceptionV3 model. in 2022 11th Mediterranean Conference on Embedded Computing (MECO). 2022. IEEE. DOI: 10.1109/MECO55406.2022.9797214

[18] Dağlı, E., M. Büber, and Y.S. Taspınar, Detection of accident situation by machine learning methods using traffic announcements: the case of metropol Istanbul. International journal of applied mathematics electronics and computers, 2022. 10(3): p. 61-67. DOI: 10.18100/ijamec.1145293
[19] Isik, M., et al., Automated classification of hand-woven and machine-woven carpets based on morphological features using machine learning algorithms. The Journal of The Textile Institute, 2024: p. 1-10.
[20] Kishore, B., et al., Computer-aided multiclass classification of corn from corn images integrating deep feature extraction. Computational Intelligence and Neuroscience, 2022. 2022(1), 2062944. DOI: 10.1155/2022/2062944
[21] Butuner, R., et al., Classification of deep image features of lentil varieties with machine learning techniques. European Food Research and Technology, 2023. 249(5): p. 1303-1316. DOI: 10.1007/s00217-023-04214-z
[22] Isik, H., et al., Maize seeds forecasting with hybrid directional and bi-directional long short-term memory models. Food Science & Nutrition, 2024. 12(2): p. 786-803. DOI: 10.1002/fsn3.3783
[23] Unal, Y., et al., Application of pre-trained deep convolutional neural networks for coffee beans species detection. Food Analytical Methods, 2022. 15(12): p. 3232-3243. DOI: 10.1007/s12161-022-02362-8
[24] Dogan, M., et al., Dry bean cultivars classification using deep cnn features and salp swarm algorithm based extreme learning machine. Computers and Electronics in Agriculture, 2023. 204: p. 107575. DOI: 10.1016/j.compag.2022.107575
[25] Kursun, R., K.K. Bastas, and M. Koklu, Segmentation of dry bean (Phaseolus vulgaris L.) leaf disease images with U-Net and classification using deep learning algorithms. European Food Research and Technology, 2023. 249(10): p. 2543-2558. DOI: 10.1007/s00217-023-04319-5
[26] Singh, D., et al., Classification and analysis of pistachio species with pre-trained deep learning models. Electronics, 2022. 11(7): p. 981. DOI: 10.3390/electronics11070981