Selcuk Journal of Agriculture and Food Sciences

http://sjafs.selcuk.edu.tr/sjafs/index

Research Article

SJAFS

(2022) 36 (3), 515-520

e-ISSN: 2458-8377

DOI:10.15316/SJAFS.2022.067

Classification and Analysis of Tomato Species with Convolutional Neural Networks

Yavuz Selim TASPINAR[1,*]

[1]Selcuk University, Doganhisar Vocational School, Department of Transport and Traffic Services, Konya, Türkiye

ARTICLE INFO

Article history:
Received date: 16.11.2022
Accepted date: 19.12.2022

Keywords:
Classification
Computer Vision
Food Quality
Nutrients
Tomato Varieties

ABSTRACT

Tomatoes are one of the most used vegetables. There are varieties that can grow in different climates. The taste, usage area and commercial value of each are different from each other. For this reason, identifying and sorting tomato species after the production stage is a problem. In addition, since tomato is a sensitive vegetable, it is extremely important to separate it from a distance. For this purpose, the classification of tomato images belonging to 9 different tomato species was carried out in the study. In total, a dataset containing 6810 tomato images in 9 classes was used. Three different pre-trained Convolutional Neural Network (CNN) models were used with the transfer learning method to classify the images. AlexNet, InceptionV3 and VGG16 models were used for classification. As a result of the classifications made, the highest classification belongs to the AlexNet model with 100%. Evaluation of the performances of the models was also made with precision, recall, F1 Score and specificity performance metrics. It is foreseen that the proposed methods can be used for the separation of tomatoes.

1. Introduction

The main food sources of humans are protein, carbohydrates and fats. They can get these nutrients directly or indirectly from various fruits and vegetables. From past to present, vegetable and fruit cultivation has developed rapidly. As a result, different species emerged. The genetics of the seeds have been changed to meet the demands of people and increase the yield. As a result of these changes, different species emerged. Many different types have emerged in tomato from vegetable varieties. There are differences in color, texture, odor and flavor according to the species. For this reason, the differentiation of tomato species has therefore become important. In the literature, there are studies on the identification of tomato species and other vegetable and fruit species with image processing methods.

Jhaawar has differentiated oranges according to their size, quality and type using image processing methods. Using pattern recognition techniques, he classified oranges on a single color basis. He carried out his work using 160 orange images. He used only 4 image features to classify oranges into four classes based on maturity level and 3 classes based on size. It has achieved classification accuracies of up to 905 and 98% from Multi Seed Nearest Neighbor and Linear Regression methods, respectively (Jhawar, 2016). Arakeri et al. have proposed an automatic tomato grading system. The proposed method consists of two steps. In the first step, the software identifies the defects in the tomato. In the second stage, the maturity of the tomatoes was analyzed by image processing techniques. They achieved 96.47% classification accuracy with the method they suggested (Arakeri, 2016). Ramos et al. proposed a non-destructive method in order to estimate the number of fruit on the branches of the coffee tree with one-sided images of the branch. A total of 1018 coffee branch images were used. The images were collected in different numbers of trees, branches and times. In their experiments, they obtained an R2 result of over 0.93 (Ramos, Prieto, Montoya, & Oliveros, 2017). Sofu et al. have proposed an automatic apple grading and quality control system. They classified apples according to color, weight and size. With the method they recommend, they can also detect stains, crusts and rot. They used an industrial camera placed on a conveyor in a closed cabinet to analyze the image properties of apples. As a result, they were able to extract an average of 15 apples per second with the method they proposed. As a result of experimental studies, they achieved an average of 73%-96% separation accuracy (Sofu, Er, Kayacan, & Cetişli, 2016).

* Corresponding author email: *ytaspinar@selcuk.edu.tr*

Elhariri et al. proposed an image processing-based system to monitor the ripening processes of tomatoes. The proposed approach consists of three stages. They determined that it was tomato with pre-processing, feature extraction and classification stages. Since color is the most important feature in maturity, they used a colored histogram. They used Support Vector Machine and Principal Component Analysis (PCA) for classification. There are 230 images in total in the dataset they use. They divided the images into 5 classes according to their maturity stage. As a result of the experiments, they obtained 92.72% classification accuracy with the SVM method (Elhariri et al., 2014). Ohali proposed an image-processing-based system to rate the quality of dates by date. They identified a set of external quality characteristics that they identified. According to the features extracted from the date images, the dates are divided into 3 quality grades by experts. They achieved 80% classification accuracy in their classification with the back propagation neural network (Al Ohali, 2011). Zhang et al. proposed a hybrid classification model based on artificial bee colony and feedforward neural network to classify fruits. By removing the background of the fruit images they used, they extracted the color histogram, shape and texture properties of the images. They used PCA to reduce the number of features. They achieved the highest classification accuracy of 88.72% with a dataset of 1653 images in 18 classes (Zhang, Wang, Ji, & Phillips, 2014). Muhammad used a feature extraction based SVM classifier to classify palm images in his study. Local Binary Pattern (LBP) and Weber Local Descriptor (WLD) were used to extract features from images. It combined the obtained features. Fisher used the Discrimination Ratio (FDR) to reduce the dimensionality of the feature set. As a result of the classifications made with SVM, it has achieved more than 98% classification accuracy (Muhammad, 2015). Moallem et al. proposed a six-step computer vision-based apple classification method. As a result of all operations, they extracted statistical, geometric and textural properties of apples. Finally, SVM, Multilayer Perceptron (MLP) and k Nearest Neighbor (kNN) were used for classification. In their classifications, they achieved the highest classification accuracy of 92.5% with SVM (Moallem, Serajoddin, & Pourghassem, 2017).

Oo et al. proposed a simple and efficient image processing method for estimating strawberry shape and size. In their proposed method, diameter, apex angle and length properties are used for estimation. They achieved classification accuracy between 94% and 97% in their classification with artificial neural networks (Oo & Aung, 2018). Mim et al. classified mango fruits according to six maturity levels. They used more than 100 mango images in the experiments. 24 image features were classified by the decision tree method. As a result of the classifications, they achieved classification accuracy of up to 96% (Mim, Galib, Hasan, & Jerin, 2018). Wang et al. classified fungi according to their diameters by image processing methods. With the algorithms they proposed, they eliminated the effect of shadow and stem on the image. They achieved 97.42% classification accuracy in their experimental studies with OpenCV (Wang et al., 2018). Wan et al. used color values and ANN to determine the maturity level of fresh tomatoes. The diameter and color of the tomatoes were used to determine the maturity level. As a result, they achieved 99.31% classification accuracy (Wan, Toudeshki, Tan, & Ehsani, 2018).

When the studies in the literature are examined, it is seen that the types, ripe levels and quality of vegetables and fruits can be classified by image processing methods. Although there are studies on tomato, there are not many studies on the classification of the species. For this reason, in this study, the subject of classification of tomato species was studied. The steps in the article are as follows:

- A dataset containing a total of 6810 images of 9 different tomato species was used.
- For classification of tomato images, the dataset is divided into 5103 trains and 1707 test images.
- AlexNet, InceptionV3 and VGG16 pre-trained models were used for classification with transfer learning method.
- Confusion matrix tables were used to compare the classification performances of the models.
- Performance metrics were calculated using confusion matrix data for the detailed analysis of the performances of the models.

When other studies in the literature are examined, the contributions of this study to the literature are listed as follows:

- A 9-class tomato dataset, which is not included in other studies in the literature, was used.
- Classification of tomato images was made with 3 different CNN models and compared.
- Performance evaluation of AlexNet, InceptionV3 and VGG16 pre-trained models was made.

The study includes the material and method used in the 2nd section, the 3rd section experimental results and the 4th section results and recommendations.

2. Materials and Methods

In this section, the dataset used in the study, CNN, pre-trained CNN models and the methods used in performance evaluation are explained.

2.1. Tomato Dataset

The dataset used in the study includes images of 9 tomato species (Mureşan & Oltean, 2017; "Tomato Dataset,"). 5103 tomato images are reserved for train, 1707 tomato images are reserved for testing. The total number of images is 6810. Each image in the dataset is 100x100 pixels. The names and image numbers of the tomato classes in the dataset are given in Table 1. Example images according to the classes in the dataset are given in Figure 1.

Table 1
Data counts by classes in the dataset

Class	Number of Images	
	Train	Test
Tomato 1	738	246
Tomato 2	672	225
Tomato 3	738	246
Tomato 4	479	160
Tomato Cherry Red	492	164
Tomato Heart	684	228
Tomato Maroon	367	127
Tomato Yellow	459	153
Tomato Not Ripened	474	158

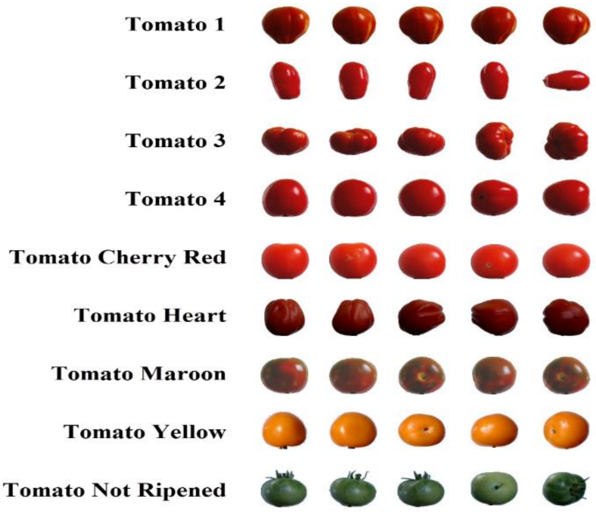

Figure 1
Example images of classes in the dataset

2.2. Convolutional Neural Network (CNN)

CNN is a deep learning model used in object detection, pattern recognition and image classification problems. There are different layers in the CNN structure. End-to-end classification processes can be performed with convolutional, pooling, activation and fully connected layers (Koklu, Kursun, Taspinar, & Cinar, 2021). Convolution is the layer where feature extraction operations are performed from the image. Feature maps are output from this layer (Singh et al., 2022). The pooling layer is used to get rid of data clutter in feature maps. This layer reduces the size of feature maps. Activation layers, on the other hand, ensure that the data is kept within a certain range. Classification operations of feature maps are performed with the fully connected layer. The number of layers in CNN may differ according to the problem (Unal, Taspinar, Cinar, Kursun, & Koklu, 2022). AlexNet, InceptionV3 and VGG16 architectures were used in this study.

2.3.Transfer Learning and AlexNet, InceptionV3, VGG16 Pre-trained Models

It is the use of machine learning methods to solve other problems. Pre-trained CNN models are trained with a large number of images. The information obtained as a result of the training can be stored in the network and used in the classification of new images (Taspinar et al., 2022). The advantage of transfer learning is that high accuracy can be achieved using less training data. At the same time, the model tends to be trained quickly with new images since it has been run on images before. A large amount of data may be needed to train models from scratch (Kishore et al., 2022). At the same time, high hardware features may be required. The models used in this study are proven models. The AlexNet pre-trained model has a depth of 8. The AlexNet pre-trained model includes 61M parameters. The Inception V3 model has a depth of 48 and contains 23.9M parameters. The VGG16 model has a depth of 16 and includes 138M parameters. For classification of all pre-trained models and images, the input layer and the penultimate layer, the fully connected layer, are set for this study. The number of fully connected layer outputs is set to 9, which is the number of classes in the dataset.

2.4. Confusion matrix and performance metrics

It is a table used to evaluate the performance of models used in solving confusion matrix classification problems (Taspinar, Cinar, & Koklu, 2021). There are True positive, True negative, False positive and False negative values on the table (Cinar & Koklu, 2022). The 9x9 confusion matrix used in the study and the calculation of these values are shown in Figure 2.

ACTUAL CLASS

PREDICTED CLASS	Tomato 1	Tomato 2	Tomato 3	Tomato 4	Tomato Cherry Red	Tomato Heart	Tomato Maroon	Tomato Yellow	Tomato Not Ripened
Tomato 1	TN	FN	TN	TN	TN	TN	TN	TN	TN
Tomato 2	FP	TP	...	...	...	...	...	...	FP
Tomato 3	TN	...	TN	TN	TN	TN	TN	TN	TN
Tomato 4	TN	...	TN	TN	TN	TN	TN	TN	TN
Tomato Cherry Red	TN	...	TN	TN	TN	TN	TN	TN	TN
Tomato Heart	TN	...	TN	TN	TN	TN	TN	TN	TN
Tomato Maroon	TN	...	TN	TN	TN	TN	TN	TN	TN
Tomato Yellow	TN	...	TN	TN	TN	TN	TN	TN	TN
Tomato Not Ripened	TN	FN	TN	TN	TN	TN	TN	TN	TN

Figure 2
9x9 confusion matrix

With these values, some metrics can be calculated to measure the performance of the models (Taspinar, Koklu, & Altin, 2021). The metrics used in the study are Accuracy, precision, recall, specificity and F1 Score. Accuracy is the rate of correct prediction. Precision shows how many of the predicted samples are actually correct. Recall is the metric that shows how many of the samples belonging to the positive class are correct. Specificity is the ratio of false positives to false positives and true negatives. F1 Score is the harmonic mean of precision and recall. This metric is an important metric that shows the strength of the model (Al-Doori, Taspinar, & Koklu, 2021). The formulas of these metrics used in the study are shown in Table 2.

Table 2
Performance metrics equations

Metrics	Equation
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}x100$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1 Score	$2x\frac{Precision\ x\ Recall}{Precision+Recall}$
Specificity	$\frac{FP}{FP+TN}$

3. Experimental Results

In this section, classification results and analyzes made with tomato dataset are given. AlexNet, InceptionV3 and VGG16 pre-trained models were used to classify tomato images. As a result of the training and tests, a confusion matrix was obtained for each model. Performance metrics of the models were calculated with the obtained confusion matrix data. In the study, a computer with Intel® Core i7™ 12700K 3.61 GHz, NVIDIA GeForce RTX 3080Ti, and 64GB RAM was used. For training and testing the models, the dataset is divided into train 75% - test 25%. The classification processes of the images in the tomato dataset in the study are shown in Figure 3.

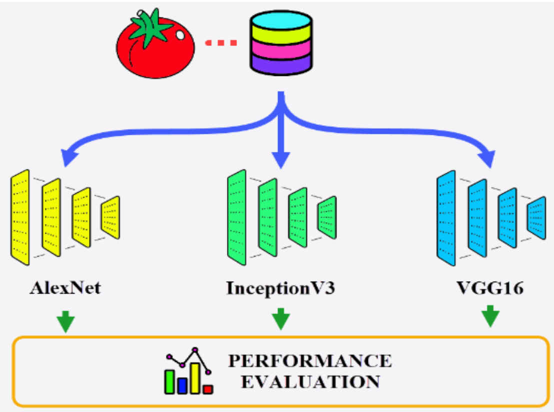

Figure 3
Tomato dataset classification process

Table 3
Confusion matrix of AlexNet model

PREDICTED CLASS \ ACTUAL CLASS	Tomato 1	Tomato 2	Tomato 3	Tomato 4	Tomato Cherry Red	Tomato Heart	Tomato Maroon	Tomato Yellow	Tomato Not Ripened
Tomato 1	246	0	0	0	0	0	0	0	0
Tomato 2	0	225	0	0	0	0	0	0	0
Tomato 3	0	0	246	0	0	0	0	0	0
Tomato 4	0	0	0	160	0	0	0	0	0
Tomato Cherry Red	0	0	0	0	164	0	0	0	0
Tomato Heart	0	0	0	0	0	228	0	0	0
Tomato Maroon	0	0	0	0	0	0	127	0	0
Tomato Yellow	0	0	0	0	0	0	0	153	0
Tomato Not Ripened	0	0	0	0	0	0	0	0	158

As a result of training and testing the images given as input to the AlexNet model, the confusion matrix in Table 3 was obtained. The confusion matrix of the InceptionV3 model is given in Table 4, and the confusion matrix of the VGG16 model is given in Table 5.

Table 4
Confusion matrix of InceptionV3 model

PREDICTED CLASS \ ACTUAL CLASS	Tomato 1	Tomato 2	Tomato 3	Tomato 4	Tomato Cherry Red	Tomato Heart	Tomato Maroon	Tomato Yellow	Tomato Not Ripened
Tomato 1	242	0	0	0	0	1	0	0	0
Tomato 2	0	225	0	0	0	0	0	0	0
Tomato 3	0	0	246	0	0	21	0	0	0
Tomato 4	0	0	0	160	0	0	0	0	0
Tomato Cherry Red	0	0	0	0	164	0	0	0	0
Tomato Heart	0	0	0	0	0	206	0	0	0
Tomato Maroon	0	0	0	0	0	0	127	0	0
Tomato Yellow	0	0	0	0	0	0	0	153	0
Tomato Not Ripened	0	0	0	0	0	1	0	0	157

Table 5
Confusion matrix of VGG16 model

PREDICTED CLASS \ ACTUAL CLASS	Tomato 1	Tomato 2	Tomato 3	Tomato 4	Tomato Cherry Red	Tomato Heart	Tomato Maroon	Tomato Yellow	Tomato Not Ripened
Tomato 1	246	0	2	0	0	0	0	0	0
Tomato 2	0	225	0	0	0	12	0	0	0
Tomato 3	0	0	244	0	0	35	0	0	0
Tomato 4	0	0	0	160	0	7	0	0	0
Tomato Cherry Red	0	0	0	0	164	1	0	0	0
Tomato Heart	0	0	0	0	0	170	0	0	0
Tomato Maroon	0	0	0	0	0	0	127	0	0
Tomato Yellow	0	0	0	0	0	3	0	153	6
Tomato Not Ripened	0	0	0	0	0	0	0	0	152

According to the confusion matrix data obtained from the AlexNet model given in Table 3, FP, FN and TP values in all classes are zero. All classes have been classified with 100% accuracy. In the confusion matrix of the InceptionV3 model given in Table 4, the FP value of the Tomato 1 class is 1, the FP value of the Tomato 3 class is 21 and the FP value of the Tomato Not Ripened class is 1. The FN value of the Tomato Heart class is 24. According to these data, Tomato 3 and Tomato Heart are classes that are confused with each other by the model. In the confusion matrix of the VGG16 model given in Table 5, the FP value of Tomato 1 class is 2, Tomato 2 class FP value is 12, Tomato 3 class FP value is 35, Tomato 4 class FP value is 7, Tomato Cherry Red class FP value is 1 and Tomato Yellow FP value is 9. The high FN value of Rn belongs to the Tomato Heart class and is 58. The most confused class in InceptionV3 and VGG16 models are Tomato Heart and Tomato 3 classes. Performance metrics calculated using confusion matrix data of all models are shown in Table 6.

Table 5
Performance metrics of AlexNet, InceptionV3 and VGG16 models

	Accuracy (%)	F1 Score	Precision	Recall	Specificity
AlexNet	100	1	1	1	1
InceptionV3	98.4	0.984	0.985	0.984	0.997
VGG16	96.1	0.96	0.965	0.961	0.994

When the data in Table 6 is examined, it is seen that the model with the highest classification accuracy is AlexNet. It is seen that the model with the lowest classification accuracy is the VGG16 model. Accuracy metric values show parallelism with other metric values. Although the model with the lowest depth was Alexnet, the highest classification accuracy was obtained from this model. In Figure 4, the column chart of the classification accuracy of all models is shown in Figure 4.

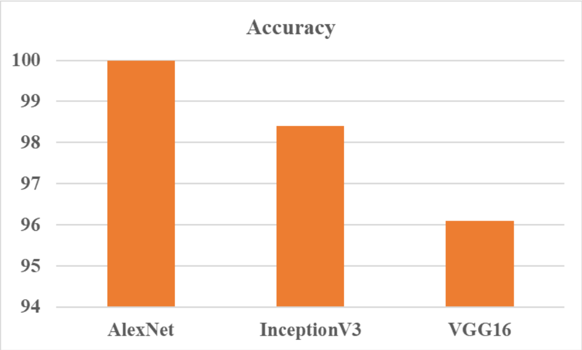

Figure 4
Comparison of classification accuracy of models

According to the graph in Figure 4, the AlexNet model with the smallest model size showed the highest classification accuracy. VGG16 with the highest model size showed the lowest classification accuracy. Image

4. Conclusions

Three different values were obtained as a result of the classification of images of nine different tomato species with AlexNet, InceptionV3 and VGG16 models. AlexNet model achieved 100% classification accuracy, InceptionV3 model 98.4% and VGG16 model 96.1% classification accuracy. In measuring the performance of the models, the dataset was divided into train-test at a rate of 75%-25%. It has been determined that the number of images in the dataset is sufficient for training and testing the models. Although the AlexNet model has the smallest size, it has achieved the highest classification accuracy. Although the VGG16 model has the largest size, it has the lowest classification accuracy. From these results, it has been seen that models with high depth and complexity cannot achieve high accuracy in every dataset. This situation may vary according to the datasets. For this reason, detailed analyzes are required in image classification problems regardless of the size and depth of the models. This also applies to the training and testing times of the models.

The usability of the proposed models in the classification of tomatoes is high. Tomato types can be separated from each other by image processing in automatic sorting machines. In addition, more detailed classification analyzes can be made by increasing the number of tomato species and creating new datasets. With all these developments, tomatoes will be able to be sorted non-destructively and quickly.

5. Acknowledgements

This project was supported by the Scientific Research Coordinator of Selcuk University with the project number 22111002. No funding was received for this study.

6. References

Al-Doori SKS, Taspinar YS, Koklu M (2021). Distracted Driving Detection with Machine Learning Methods by CNN Based Feature Extraction. *International Journal of Applied Mathematics Electronics and Computers, 9*(4), 116-121.

Al Ohali Y (2011). Computer vision based date fruit grading system: Design and implementation. *Journal of King Saud University-Computer and Information Sciences, 23*(1), 29-36.

Arakeri MP (2016). Computer vision based fruit grading system for quality evaluation of tomato in agriculture industry. *Procedia Computer Science, 79*, 426-433.

Cinar I, Koklu M (2022). Identification of Rice Varieties Using Machine Learning Algorithms. *Journal of Agricultural Sciences*, 9-9.

Elhariri E, El-Bendary N, Fouad MMM, Platoš J, Hassanien AE, Hussein AM (2014). Multi-class SVM based classification approach for tomato ripeness. In *Innovations in Bio-inspired Computing and Applications* (pp. 175-186): Springer.

Jhawar J (2016). Orange sorting by applying pattern recognition on colour image. *Procedia Computer Science, 78*, 691-697.

Kishore B, Yasar A, Taspinar YS, Kursun R, Cinar I, Shankar VG, Koklu M, Ofori I (2022). Computer-Aided Multiclass Classification of Corn from Corn Images Integrating Deep Feature Extraction. *Computational Intelligence and Neuroscience, 2022*.

Koklu M, Kursun R, Taspinar YS, Cinar I (2021). Classification of date fruits into genetic varieties using image analysis. *Mathematical Problems in Engineering, 2021*.

Mim FS, Galib SM, Hasan MF, Jerin SA (2018). Automatic detection of mango ripening stages–An application of information technology to botany. *Scientia horticulturae, 237*, 156-163.

Moallem P, Serajoddin A, Pourghassem H (2017). Computer vision-based apple grading for golden delicious apples based on surface features. *Information processing in agriculture, 4*(1), 33-40.

Muhammad G (2015). Date fruits classification using texture descriptors and shape-size features. *Engineering Applications of Artificial Intelligence, 37*, 361-367.

Mureşan H, Oltean M (2017). Fruit recognition from images using deep learning. *arXiv preprint arXiv:1712.00580*.

Oo LM, Aung NZ (2018). A simple and efficient method for automatic strawberry shape and size estimation and classification. *Biosystems engineering, 170*, 96-107.

Ramos P, Prieto FA, Montoya E, Oliveros CE (2017). Automatic fruit count on coffee branches using computer vision. *Computers and Electronics in Agriculture, 137*, 9-22.

Singh D, Taspinar YS, Kursun R, Cinar I, Koklu M, Ozkan IA, Lee HN (2022). Classification and Analysis of Pistachio Species with Pre-Trained Deep Learning Models. *Electronics, 11*(7), 981.

Sofu MM, Er O, Kayacan M, Cetişli B (2016). Design of an automatic apple sorting system using machine vision. *Computers and Electronics in Agriculture, 127*, 395-405.

Taspinar YS, Cinar I, Koklu M (2021). Prediction of Computer Type Using Benchmark Scores of Hardware Units. *Selcuk University Journal of Engineering Sciences, 20*(1), 11-17.

Taspinar YS, Dogan M, Cinar I, Kursun R, Ozkan IA, Koklu M (2022). Computer vision classification of dry beans (Phaseolus vulgaris L.) based on deep transfer learning techniques. *European Food Research and Technology, 248*(11), 2707-2725.

Taspinar YS, Koklu M, Altin M (2021). Classification of flame extinction based on acoustic oscillations using artificial intelligence methods. *Case Studies in Thermal Engineering, 28*, 101561.

Tomato Dataset. Retrieved from https://github.com/Horea94/Fruit-Images-Dataset

Unal Y, Taspinar YS, Cinar I, Kursun R, Koklu M (2022). Application of Pre-Trained Deep Convolutional Neural Networks for Coffee Beans Species Detection. *Food Analytical Methods, 15*(12), 3232-3243.

Wan P, Toudeshki A, Tan H, Ehsani R (2018). A methodology for fresh tomato maturity detection using computer vision. *Computers and electronics in agriculture, 146*, 43-50.

Wang F, Zheng J, Tian X, Wang J, Niu L, Feng W (2018). An automatic sorting system for fresh white button mushrooms based on image processing. *Computers and electronics in agriculture, 151*, 416-425.

Zhang Y, Wang S, Ji G, Phillips P (2014). Fruit classification using computer vision and feedforward neural network. *Journal of Food Engineering, 143*, 167-177.