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Apricot Position Determination Using Deep Learning for Apricot Stone Extraction Machine

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ABSTRACT

Despite the developing technology, extraction of Sulfured Dried Apricot (Prunus armeniaca) (SDA) stones is still done manually and thus requires a significant amount of labor and time and also causes serious problems in terms of hygiene. According to International Food Standards (CXS 130-1981) and Turkish Standard 485, the SDA stones must be extracted from the peduncle side of the apricot. Therefore, the correct position of the apricot peduncle and style side must be determined. In this study, a deep learning architecture was improved for the first time to determine the position of SDA stones as a component of the agricultural machine developed to extract SDA stones. In this study, a new Capsule Network architecture was used. With the original capsule network, SDA images were classified with 86.23% accuracy, while it increased to 94.47%with the improved capsule network. Also, the processing time of the developed network architecture was about twice as fast as the original. The result clearly demonstrates that the SDA stone positions are easily determined. Therefore, the designed agricultural machine can extract the SDA stones hygienically and rapidly, without any need for human power.

Keywords: Capsule networks, Deep features, *Prunus armeniaca*, Sulfured dried apricots.

INTRODUCTION

Apricot is a fruit as well as an important food source. Apricot production in Turkey is performed in various regions, primarily including Malatya, Elazig, and Erzincan (MEE) regions, where the apricots grown contain a substantially high content of sugar and dry matter and are mostly dried as whole fruit. Additionally, a significant amount of the world's Sulphured Dried Apricot (SDA) need is met from this region (Karabacak and Uzundumlu, 2020). According to the statistics of the International Nut and Dried Fruit Council, Turkey ranks first in the world in dried apricot production with a global market share of 54% as of 2020/21 (INC, 2021). In addition, according to the Food and Agriculture Organization of the United Nations (FAO) statistical database, 833398 tonnes of apricots were produced in Turkey in 2020, of which 88062 tonnes were exported as dried apricots (FAO, 2021). A significant labor is needed for tonnes of apricots, which have an average harvest time of 60-75 days and are processed as SDA. To date, various consumption and preservation techniques have been developed in order to benefit from apricots in longer time periods, which are produced in large quantities in short periods.

One of preferred methods that is predominantly utilized to extend the shelf life of fresh apricots is using drying methods with sulphur treatment (Özdemir *et al*., 2018). All dried apricot products are

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described according to International Food Standards (IFS) (CXS 130-1981) and Turkish Standard (TS) 485 (IFS, 2022; TS, 2022). According to these standards, the products classified as *extra category* are divided as whole and pitted. In order to preserve the integrity of the dried apricot, the seed must be removed from the peduncle side of the dried apricot (Figure 1). For this purpose, it is necessary to determine the correct position of the peduncle and style of the apricot. After the application of sulphur dioxide and sun drying treatment, an ergonomic thrust is applied by labor from the style of the apricot towards its peduncle using the thumb procedure, which delicately leads to the removal of the apricot stone from the peduncle side. According to the IFS and TS, it is a quality standard requirement that the stone is extracted from the peduncle side without damaging the integrity of the apricot and causing mesocarp reduction. Figure 1 shows the gradual extraction of SDA stones by labor. Despite the developing technology, the extraction of SDA (Prunus armeniaca) stones is still performed manually with human power and, therefore, requires a significant amount of manpower and time and also causes serious problems in terms of hygiene.

Today, numerous processes that require manpower are solved in a relatively shorter period time and less manpower due to the use of machine learning methods (Zhu *et al*., 2021). Of these, for instance, Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) have been used in the determination of the volume and maturity level of apricots based on apricot images (Khojastehnazhand *et al*., 2019). Additionally, LDA and other methods including Decision Tree (DT), K-Nearest Neighbour (KNN), naive Bayes, Support Vector Machine (SVM), and feedback Artificial Neural Networks (ANN) have been used in the classification of apricots according to their shapes (Yang *et al*., 2019). In some others, this classification was made based on fuzzy logic (Mirnezami *et al*., 2020) or a Convolutional Neural Network (CNN) (Mureşan and Oltean, 2018; Shamim Hossain *et al*., 2019). On the other hand, a CNN-based model has been proposed for the classification of apricot diseases (Türkoğlu *et al*., 2020) and another CNN-based approach has been proposed for fixing the weights of apricots (Zhang and Chan, 2019). Due to the increase in data sizes over the last decades, deep learning methods have emerged as popular approaches in the field of machine learning. Of note, fruit classification has been made with the help of deep learning and computer vision, and smart harvesting systems have been proposed (da Costa *et al*., 2020; Faisal *et al*., 2020; Mao *et al*., 2020; Naik and Patel, 2017; Wu *et al*., 2021; Singh *et al*. 2022; Örnek and Örnek, 2020; Ropelewska *et al*. 2022; Örnek and Hacıseferoğulları, 2020). In addition to agricultural applications, deep learning architectures are frequently used in engineering, medicine, etc. (Toraman *et al*. 2021; Tang *et al*. 2022).

Today, extraction of apricot stone is performed one by one by using labor. One of the most important steps for the developed automatic apricot stone extracting machine is the correct determination of the peduncle part of the apricot stone with image processing techniques.

In this study, we aimed to develop an improved automated image processing for the determination of the position of the apricot stone in the apricot stone extraction machine. To the best of our knowledge, this

Figure 1. Apricot stone extraction process by human power.

study is the first for automatic determination of apricot direction using capsule networks.

MATERIALS AND METHODS

This section presents information about the designed apricot stone extraction machine, the recognition of apricot images (including the image processing and orientation process of the apricot stone extraction machine), data pre-processing, CapsNet, and the performance evaluation parameters of the improved method.

In the improved method, SDA images were obtained under LED light and the captured images were classified with a deep learning model known as Capsule Networks (CapsNet). As is commonly known, traditional feature extraction methods conduct operations such as classification/recognition using the features obtained from images. In these methods, various factors such as the features to be extracted from the images and the selection of the most effective of these features and the experience of the operator selecting the features can have a positive or negative effect on the performance of the system. Accordingly, in this study, a deep learning method that was not affected by the above-mentioned parameters was used.

Motivation

Since the processing of SDA is a sensitive process, today it is still manually processed one by one, which causes several problems. The first of these problems is hygiene. In particular, considering that various epidemic diseases such as COVID-19 are transmitted via human-human or human-object interaction, avoidance of human contact is vital for production processes. The other problem is that it requires substantial labor in a short time period. The employment, accommodation, and subsistence of thousands of daily workers in short time periods (average 75 days) impose a serious burden on the producer. The third problem is increased production costs, which lead to reduced motivation levels. Taken together, these factors implicate the importance of automatic removal of an apricot stone. Although there have been various applications in the classification of apricot species in the literature, to our knowledge, there is no application used for the determination of the direction of SDA stones, which is an important stage in the extraction process (Naik and Patel, 2017; Shamim Hossain *et al*., 2019).

Flowchart of the Study

Figure 2 shows the flow chart of the study.

Dataset and Pre-Processing

For the dataset used in the study, 600 SDA images (300 style and 300 peduncle side of the apricots) were used. The images were taken with Flir Blackfly USB3 Vision Camera by holding a LED light source under the conveyor, which allowed the visualization of the position of the apricot stone. Table 1 presents the specifications of Flir Blackfly USB3 Vision Camera. Figure 3 presents the images of raw and pre-processed (under LED light) SDAs.

In the pre-processing stage, images were resized to 64×64 pixels to be used as input to CapsNet. In addition, data augmentation was applied to increase the number of data.

Data Augmentation

Since the SDA images were limited in number, data augmentation strategies were applied to avoid overfitting problems, including width shift (0.2), rotate (5), height shift (0.2), shear (0.2), zoom (0.2), and horizontal flip parameters. As a result, the total number of SDA images was increased from 600 to 9,000. Figure 4 shows examples of data augmentation processes applied to SDA images.

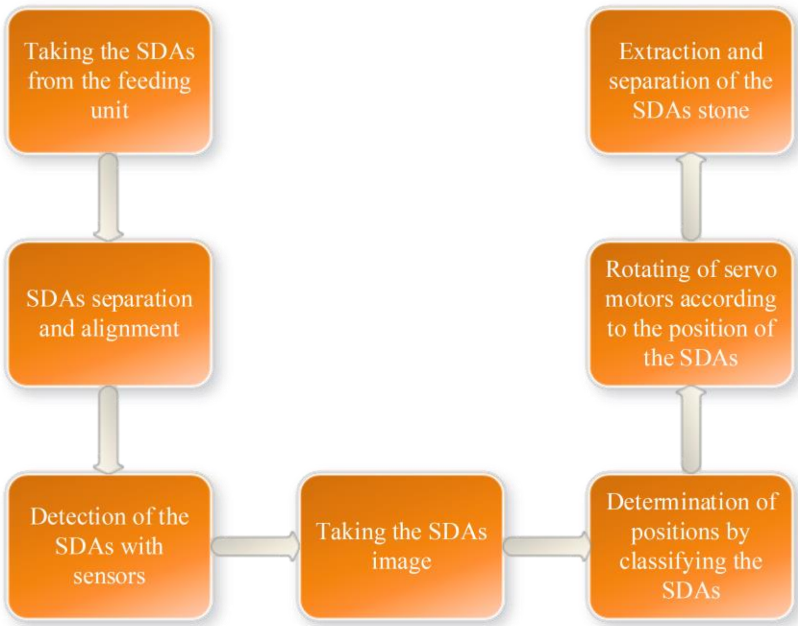

Figure 2. Flow-chart of the study

Table 1. Flir Blackfly USB3 Vision Camera specifications using for apricot image.

Model	Version	Megapixels	Imaging sensor
BFLY- U3- 50H5C-C	Color	5.0 MP	Sharp RJ32S3AA0DT, 2/3”, 3.45 µm Global shutter 7.5 FPS at 2448x204

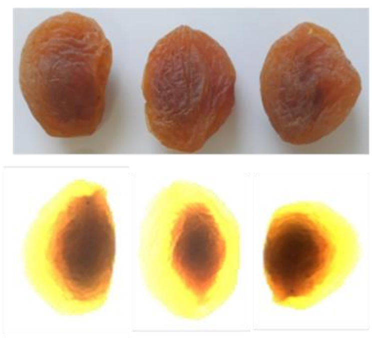

Figure 3. Raw SDA images are at the top, images exposed the LED light are below.

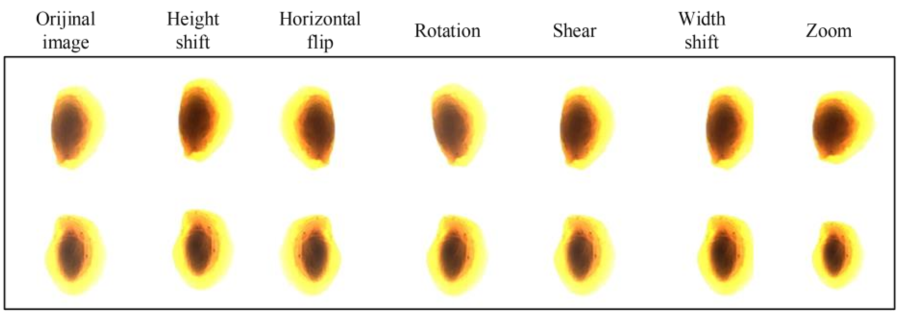

Figure 4. Data augmentation processes applied to SDA images

Convolutional Neural Networks

Artificial Neural Networks (ANN) is a widely used machine learning method in the field of image/signal, data processing (Toraman and Türkoğlu, 2020; Parviz, 2020). ANN can classify the features extracted from the image or signal. In fact, the quality and impact of extracted features are highly important in classification/recognition. There have been developments in neural networks in line with the advancements in technology over the last ten years, particularly in hardware technologies. On the other hand, deep learning architectures that began with AlexNet have increased the demand for neural networks and these architectures do not require feature extraction as in all ANN architectures and can extract features from the image/signal itself, thus leading to higher classification/recognition performances (Daş *et al*., 2020; Toraman *et al*., 2020). CNNs are one of the most preferred deep learning architectures and many CNN architectures have been successfully applied in numerous fields via the training of various datasets. However, CNN architectures have several shortcomings. For example, CNNs can find the features of the object in the image, but they cannot provide information about the relationship between the features. Scientists proposed a different neural network model to address these shortcomings (Sabour *et al*., 2017, Dombetzki, 2018).

Capsule Networks

As stated in the previous section, CNN cannot reveal the relationship between objects in the image. Capsule networks were proposed by Sabour *et al*. (2017) to address this deficiency and this structure hold a certain group of neurons together. Since the capsules consist of a group of neurons, it calculates an output vector from the input vectors. In this way, the output vector represents a set of parameters such as orientation, skew, thickness, etc. (Dombetzki, 2018; Lukic *et al*., 2019; Sabour *et al*., 2017). In this study, capsule networks were utilized to determine the position and orientation information of apricots in the images and the capsule networks architecture used in this study was different from that of the original capsule networks architecture. In the original capsule networks architecture, there is only one convolutional layer before the primary capsule layer and it is tested on the 28×28 MNIST dataset, and the data of this size is easier to process than those of large images. In our model, on the other hand, there were three convolutional layers before the primary wedge, which allowed for obtaining a better feature map. Moreover, the size of the input image was 64×64×3 and this large size significantly increased the processing load. To reduce this load, pooling was applied after the first two convolutional layers. Although the pooling process caused the loss of minor distinctions in the image, the results showed that the improved architecture was successful in processing SDA images. Figure 5 illustrates the structure of the improved network architecture and Table 2 provides further details about the improved architecture.

The Designed Apricot Stone Extraction Machine

A machine was designed and manufactured to enable the apricots subjected to sulphur treatment to be automatically pitted in a hygienic environment without physical damage and human contact. The machine consisted of four central units (Figure 6) including:

1. Product feeding unit.
2. Product separation and alignment unit.
3. Image processing and routing unit.
4. Apricot stone extraction and separation unit.

The first process in the apricot stone extraction machine was to wash and purify the apricots from foreign materials by discharging them into the product feeding-

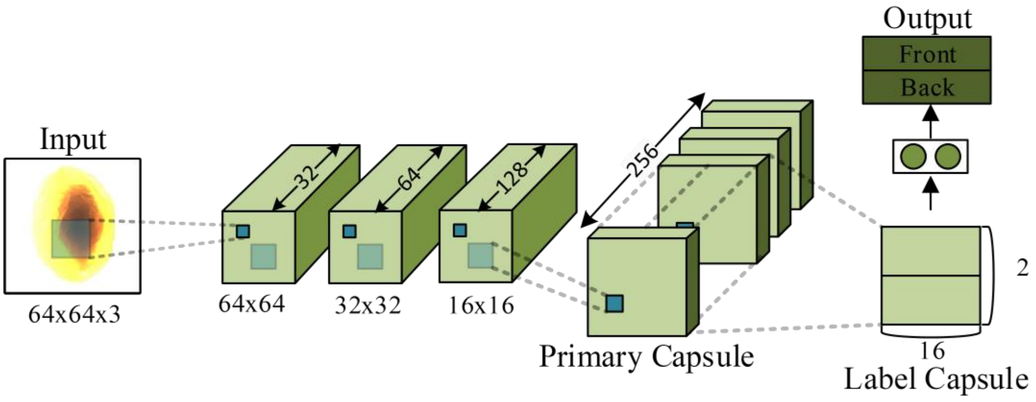

Figure 5. Improved CapsNet architecture.

Table 2. Structure of the improved architecture.

Layers	Kernel size	Filter size	Stride	Output size
Input				64, 64,3
Convolution1	7x7	32	1	64, 64, 32
Maxpooling	2x2	-	2	32, 32, 32
Convolution2	5x5	64	1	32, 32, 64
Maxpooling	2x2	-	2	16, 16, 64
Convolution3	9x9	128	1	16, 16, 128
Primary capsule	9x9	256	1	16, 16, 256
Label capsule	-	-	-	16, 2
Output	-	-	-	2

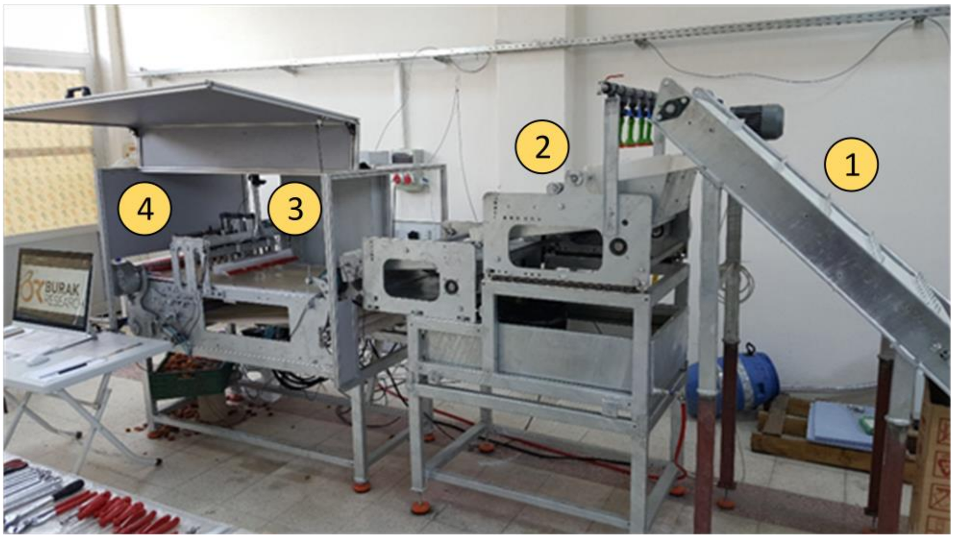

Figure 6. The units of the machine. 1. Product feeding unit, 2. Product separation and alignment unit, 3. Image processing and routing unit, 4. Apricot stone extraction and separation unit.

unit. The purified SDAs were transported to the product separation and alignment unit by means of an elevator.

Subsequently, the SDAs that fell on the straw walker were lined up in a single row on the conveyor. SDAs detected by sensors were stopped on LED lights. In Figure 7, the main parts of the dried apricots are shown in longitudinal section.

Afterwards, they were rotated by servo-motors and their positions were determined based on the angle of their longitudinal axis

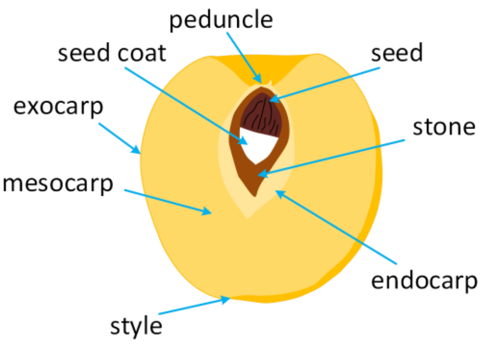

Figure 7. Longitudinal section of an apricot.

with regard to the reference axis. The position angle of the apricots was calculated according to the maximum and minimum axis lengths. However, when the peduncle side of the apricot was in two different positions, as shown in Figure 8, the correct position angle could not be calculated with this approach. In order to calculate the correct position angle, the positioning of the peduncle side was classified by a deep learning.

The apricot stone was extracted from the peduncle side by applying an ergonomic pressure simultaneously with the rotation of the apricot. Figure 9 presents a view of the image processing and orientation unit of the machine.

Classification and Performance Evaluation

For the performance evaluation of the proposed method, a 5-fold cross-validation method was applied. Figure 10 presents the usage rates of training and test data.

Accuracy, sensitivity, specificity, precision and F1 indicators were used to evaluate the performance of the method (Toraman and Dursun, 2021).

Sensitivity = TP / (TP+FN) (1)

Specificity =TN / (TN+FP) (2)

Precision = TP / (TP+FP) (3)

Accuracy = (TP+TN) / (TP+FP+TN +FN) (4)

F1-score=2TP / (2TP+FP+FN) (5)

True Positive (TP)= Number of peduncle that the system correctly identifies

False Positive (FP)= Number of peduncle that the system incorrectly identifies

True Negative (TN)= Number of style that the system correctly identifies

False Negative (FN)= Number of style that the system incorrectly identifies

Results and Discussion

In the study, a total of 9,000 SDA images (4,500 style and 4,500 peduncle side of the apricots) were used. The images were photographed under special light and were

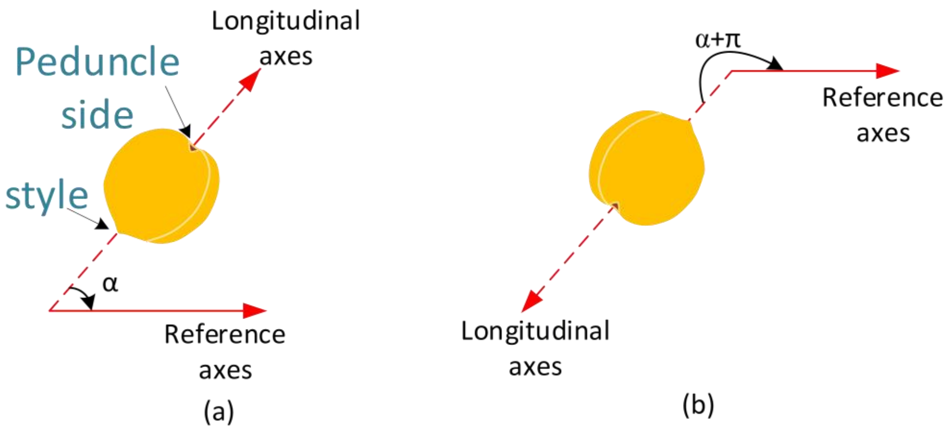

Figure 8. Two different positions of the peduncle side of the apricot: (a) The position where the apricot peduncle side makes an α angle with the reference axis, (b) The position where the apricot peduncle side makes an α+π angle with the reference axis.

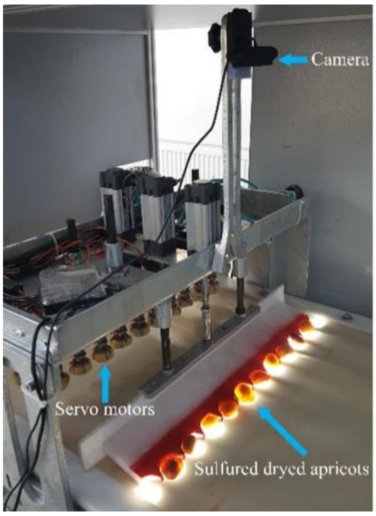

Figure 9. Prototype automatic apricot stone extraction machine image processing unit.

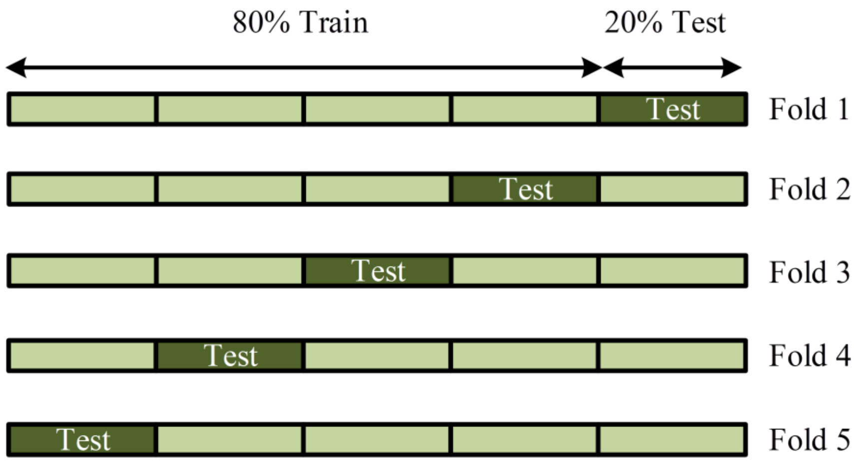

Figure 10. Graphical representation of the test and training data.

resized to 64×64 pixels. The resized images were given as input to the CapsNet and a 5-fold cross-validation method was used to evaluate the accuracy performance of the results obtained. The accuracy, sensitivity, specificity, precision, and F1 score obtained as a result of the classification processes conducted by the original CapsNet architecture and by the improved CapsNet architecture are presented in Table 3 and 4, respectively. As seen in Figure 11, the original CapsNet architecture learned more slowly compared to the proposed method. In addition, in terms of the point of uptime, the improved network architecture was faster than the original CapsNet architecture. Table 5 presents the hyper-parameters and run times. Brute force method was used to determine hyper parameters. All the experiments were developed using Keras library in Python environment. RTX 2060 Graphics card was used for the application.

Confusion matrix is one of the methods used to measure the performance of the proposed method. Figure 12 presents the confusion matrices that were administered to assess the ability of the proposed method in separating the style and peduncle side of the apricots.

As can be seen in Figure 12, the improved method correctly classified 8,502 (94.47%) out of 9,000 SDA images, and classified only 498 (5.53%) images incorrectly. In contrast, the original CapsNet architecture correctly classified 7,761 (86.23%) images and classified 1,239 (13.77%) images

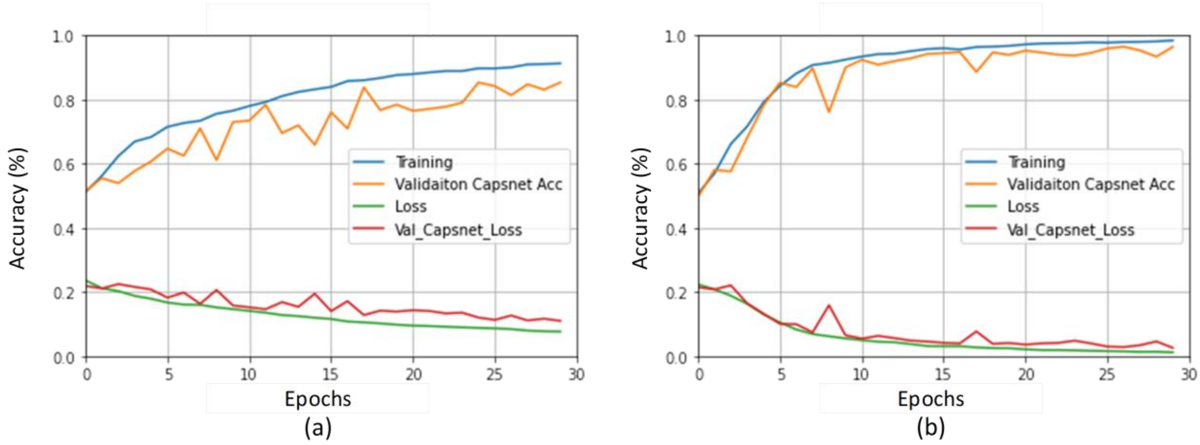

Figure 11. Training and loss plots of the (a) Original CapsNet and (b) Improved architecture for one fold.

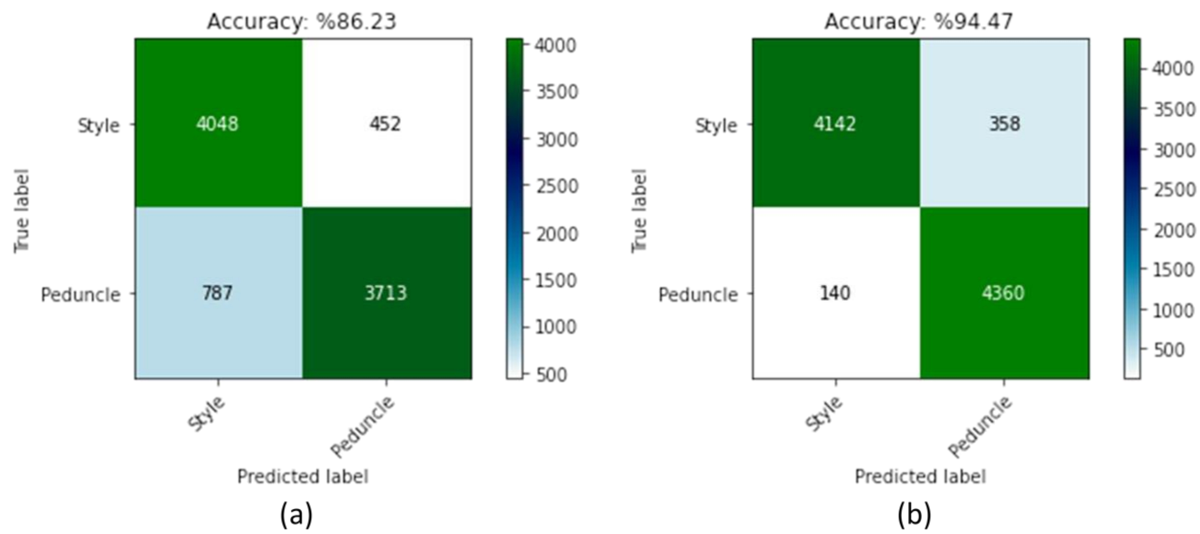

Figure 12. Confusion matrices for (a) Original CapsNet and (b) Improved architecture.

incorrectly. The data processing times of the improved architecture and the original CapsNet architecture are given in Table 5. Example images for classification results are given in Figure 13.

The contributions of the improved method to the literature can be listed as follows:

- Apricot processing can be performed under hygienic conditions.
- The process of determining the direction of apricot stone, which is currently performed manually, can be carried out automatically through a computer-aided system.
- The production speed, which varies depending on manpower, will become more stable and economical with the help of machine learning.
- To our knowledge, the present study, for the first time in the literature, indicated that the determination of the peduncle side of an apricot stone can be performed with deep learning methods.

The limitations of the study are stated below.

• Low number of original apricot pictures
• Using LED as light source

Table 3. Classification results for original CapsNet.[a]

Fold	Acc (%)	Pre (%)	Sen (%)	Spe (%)	F1 score (%)
Fold 1	85.33	91.19	78.22	92.44	84.21
Fold 2	82.33	97.24	66.56	98.11	79.02
Fold 3	86.22	89.85	81.67	90.78	85.56
Fold 4	86.67	81.49	94.89	78.44	87.68
Fold 5	90.61	90.12	91.22	90.00	90.67
Mean ± SD	86.23 ± 2.66	89.98 ± 5.03	82.51 ± 10.03	89.96 ± 6.42	85.43 ± 3.87

[a] Acc: Accuracy, Pre: Precision, Sen: Sensitivity, Spe: Specificity, SD: Standard Deviation.

Table 4. Classification results for the improved CapsNet.[a]

Fold	Acc (%)	Pre (%)	Sen (%)	Spe (%)	F1 score (%)
Fold 1	93.67	92.72	94.78	92.56	93.74
Fold 2	96.44	97.18	95.67	97.22	96.42
Fold 3	95.11	93.84	96.56	93.67	95.18
Fold 4	90.33	84.57	98.67	82.00	91.08
Fold 5	96.78	94.98	98.78	94.78	96.84
Mean ± SD	94.47 ± 2.34	92.66 ± 4.30	96.89 ± 1.60	92.04 ± 5.25	94.65 ± 2.09

[a] Acc: Accuracy, Pre: Precision, Sen: Sensitivity, Spe: Specificity, SD: Standard deviation.

Table 5. Hyper-parameters of CapsNet architectures.

	Routing	Optimizer	lr	Loss weight	Batch size	Epoch	Processing time [per epoch (s))]	Processing time of one image (ms)
Original CapsNet	3	Adam	0.0001	0.392	32	30	85	9
Proposed Network	3	Adam	0.0001	0.392	32	30	45	4

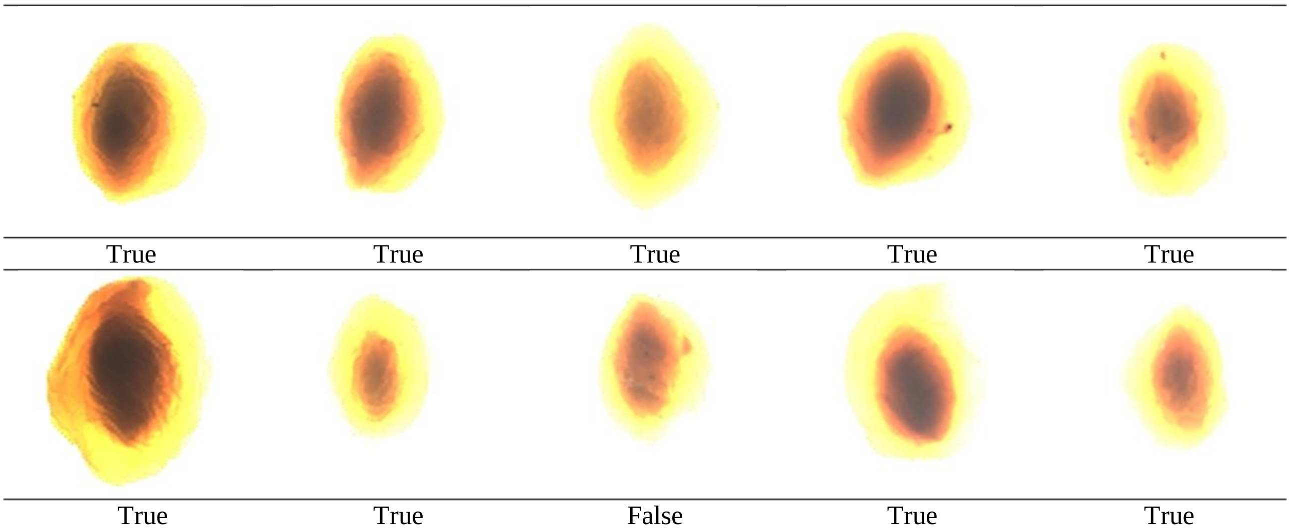

Figure 13. SDA images for classification results.

CONCLUSIONS

Separation of SDA from its stone is a significant process in commercial and economic terms. Since the extraction of apricot stone is a sensitive process and the processing time is remarkably short, all kinds of ergonomic operations can be valuable alternatives. In this study, a deep learning model was developed for the determination of apricot positioning in apricot stone extraction. In the developed model, a new CapsNet architecture is proposed. The improved architecture produced more successful results than the original architecture in terms of both processing time and evaluation parameters. Six hundred original images for apricot classification were increased to 9,000 by data augmentation. In future studies, it is planned to increase the number of original pictures. The results showed that the developed image processing model will have a significant contribution to the apricot stone extraction procedure and will also provide economic relief to apricot growers and processors. In addition, this method is also likely to make significant contributions to the elimination of the adversities arising from the use of manual labor in the extraction of the apricot stone, such as hygiene.

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استفاده از یادگیری عمیق (Deep Learning) برای تعیین محل قرار گرفتن زردآلو در دستگاه بیرون آوردن هسته زردآلو

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چکیده

با وجود توسعه در فناوری، بیرون آوردن هسته از زردآلو خشک سولفوره (SDA) (Prunus armeniaca) هنوز به صورت دستی انجام می‌شود و در نتیجه نیاز به کار و زمان قابل توجهی دارد و از نظر بهداشتی نیز مشکلات جدی ایجاد می‌کند. بر اساس استانداردهای بین المللی غذا (CXS 130-1981) و استاندارد ۴۸۵ ترکیه، هسته های SDA باید از سمت دمگل (peduncle)زردآلو خارج شوند. بنابراین، موقعیت محل قرار گرفتن صحیح دمگل زردآلو و سمت styleباید مشخص شود. در این مطالعه، برای نخستین بار، یک معماری(architecture) یادگیری عمیق(Deep Learning) برای تعیین موقعیت هسته های SDA به عنوان جزئی از ماشین کشاورزی توسعه یافته برای خارج کردن هسته های SDA بر پا شد. در این مطالعه از معماری شبکه کپسولی (Capsule Network architecture) جدید استفاده شد. با شبکه کپسول اصلی، تصاویر SDA با دقت ۸۶.۲۳٪ طبقه بندی شدند، در حالی که با شبکه کپسول بهبود یافته ، این دقت به ۹۴.۴۷٪ افزایش یافت. همچنین، زمان پردازش معماری شبکه توسعه یافته حدود دو برابر سریعتر از نسخه اصلی بود. این نتیجه به وضوح نشان می دهد که موقعیت هسته SDA به راحتی تعیین می شود. از این رو، این ماشین کشاورزی طراحی شده می تواند هسته های SDA را به صورت بهداشتی و سریع و بدون نیاز به نیروی انسانی استخراج کند.