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ARAŞTIRMA MAKALESİ **RESEARCH ARTICLE**

Classification of Pistachio Varieties Using Transfer Learning and a Custom MobileNet Architecture

Transfer Öğrenme Yaklaşımı ve Özel Tasarlanmış MobileNet Mimarisi Kullanılarak Antep Fıstığı Çeşitlerinin Sınıflandırılması

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Abstract

Pistachio nuts are widely recognized as one of the most valuable agricultural commodities, playing a significant role in both domestic and international markets. Turkey cultivates eight main domestic pistachio varieties in addition to five foreign varieties, each targeting different consumer preferences, market demands, and price segments. Despite this diversity, the current classification process in the pistachio industry largely depends on manual inspection and basic experiential knowledge. This traditional approach is time-consuming and highly susceptible to misclassification due to the strong visual similarities among different pistachio varieties. Such limitations negatively affect sorting accuracy, packaging efficiency, and overall product value. To overcome these challenges and support the transition toward smart agricultural practices, this study proposes an efficient deep learning-based classification system for pistachio varieties. A customized MobileNet architecture is developed to classify seven pistachio varieties with high accuracy while maintaining low computational complexity. The proposed model is specifically designed to address the shortcomings of conventional pre-trained models when applied to fine-grained agricultural image classification tasks. Experimental results demonstrate that the custom MobileNet model outperforms well-known pre-trained architectures, including VGG16, Inception-V3, and the original MobileNet, in terms of both accuracy and efficiency. The proposed model achieves a test accuracy of 98.09%, representing an improvement of 1.66% over the standard pre-trained MobileNet model. Moreover, the number of model parameters is reduced by approximately 79%, resulting in a compact model size of 12.82 MB. This significant reduction lowers computational and storage requirements, shortens training time, and facilitates real-time deployment. Consequently, the proposed approach is highly suitable for implementation on low-computing-power smart farming and automated packaging systems, offering a practical and scalable solution for the pistachio industry.

Keywords: Agricultural commodities, Innovative technologies, Automated sorting, Smart farming, Food industry automation, Deep learning in agriculture

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Öz

Antep fıstığı, hem ulusal hem de uluslararası pazarlarda önemli bir rol oynayan, en değerli tarımsal ürünlerden biri olarak geniş çapta kabul edilmektedir. Türkiye, sekiz ana yerli Antep fıstığı çeşidine ek olarak beş yabancı çeşidi de yetiştirmekte olup, bu çeşitlerin her biri farklı tüketici tercihlerini, pazar taleplerini ve fiyat segmentlerini hedeflemektedir. Bu çeşitliliğe rağmen, Antep fıstığı endüstrisinde mevcut sınıflandırma süreci büyük ölçüde manuel incelemeye ve temel deneyimsel bilgiye dayanmaktadır. Bu geleneksel yaklaşım, farklı Antep fıstığı çeşitleri arasındaki güçlü görsel benzerlikler nedeniyle zaman alıcı olmakta ve yanlış sınıflandırmaya son derece açık hale gelmektedir. Bu tür sınırlılıklar, ayıklama doğruluğunu, paketleme verimliliğini ve genel ürün değerini olumsuz yönde etkilemektedir. Bu zorlukların üstesinden gelmek ve akıllı tarım uygulamalarına geçişi desteklemek amacıyla, bu çalışmada Antep fıstığı çeşitlerinin sınıflandırılmasına yönelik verimli bir derin öğrenme tabanlı sınıflandırma sistemi önerilmektedir. Düşük hesaplama karmaşıklığını korurken yedi farklı Antep fıstığı çeşidini yüksek doğrulukla sınıflandırmak üzere özelleştirilmiş bir MobileNet mimarisi geliştirilmiştir. Önerilen model, ince taneli tarımsal görüntü sınıflandırma görevlerinde geleneksel önceden eğitilmiş modellerin yetersizliklerini gidermek amacıyla özel olarak tasarlanmıştır. Deneysel sonuçlar, geliştirilen özel MobileNet modelinin doğruluk ve verimlilik açısından VGG16, Inception-V3 ve orijinal MobileNet dâhil olmak üzere yaygın olarak kullanılan önceden eğitilmiş mimarilerden daha üstün performans sergilediğini göstermektedir. Önerilen model, test aşamasında %98,09 doğruluk oranına ulaşarak standart önceden eğitilmiş MobileNet modeline kıyasla %1,66'lık bir iyileşme sağlamıştır. Ayrıca, model parametre sayısı yaklaşık %79 oranında azaltılarak 12,82 MB boyutunda kompakt bir yapı elde edilmiştir. Bu önemli küçülme, hesaplama ve depolama gereksinimlerini azaltmış, eğitim süresini kısaltmış ve gerçek zamanlı uygulamaları mümkün kılmıştır. Sonuç olarak, önerilen yaklaşım düşük hesaplama gücüne sahip akıllı tarım ve otomatik paketleme sistemlerinde uygulanabilir, pratik ve ölçeklenebilir bir çözüm sunmaktadır.

Anahtar Kelimeler: Tarımsal emtialar, Yenilikçi teknolojiler, Otomatik sınıflandırma, Akıllı tarım, Gıda endüstrisinde otomasyon, Tarımda derin öğrenme

1. Introduction

Pistachio (*Pistacia vera* L.) is among the most popular tree nuts, ranking second to hazelnuts in fat content. It is rich in essential minerals such as phosphorus, potassium, calcium, magnesium, and iron, as well as vitamins E, C, B1, and B2 (Aktaş et al., 2022). The top global producers Iran, the USA, Turkey, and Syria contribute about 90% of total pistachio production. In Turkey, eight domestic and five foreign pistachio varieties are cultivated, each with unique characteristics influencing consumer preferences and market pricing (Ak and Acar, 2001). For instance, Kırmızı is favored in confectionery due to its dark green color and strong aroma, while Siirt, with its round shape and easy-to-crack shell, is popular as a snack (Ozkan et al., 2021). Iran has historically depended on pistachio production as a key non-oil export, producing over 50% of global output and supplying more than 70% of world exports until 2010 (Yaghoubi and Niknami, 2022). Pistachio classification plays a crucial role in the agricultural and food processing industries, ensuring product quality and sorting efficiency Pistachio classification primarily involves distinguishing between open and closed nuts and identifying different varieties. The traditional method, which relies on manual sorting, is prone to errors due to nuts' similar appearances. Accurately classifying pistachios is essential, particularly in ensuring proper packaging for commercial sales, as closed pistachio nuts have lower consumer acceptance and market value (Lisda et al., 2023). Advancements in technology, particularly machine vision systems, have shown promise in improving agricultural product evaluation. Despite the growing application of machine learning in agriculture, research on pistachio classification remains limited, with most studies only covering a few varieties. Transitioning from manual grading to AI-driven methods using machine learning and deep learning models can enhance accuracy, efficiency, and reliability in pistachio classification and processing (Dini et al., 2020). When the literature is investigated for pistachio classification, we come up with many studies on machine learning and deep learning methods. These studies are listed below (*Table 1*). Several studies have explored traditional ML techniques for pistachio classification, for instance, Omid (2011) employed fuzzy logic with 210 images to classify open and closed pistachio nuts, achieving an accuracy of 95.56%. Similarly, Beyaz (2024) used Decision Tree and Random Forest models on 385 images of Antep pistachios, classifying them into four categories (open, closed, semi-open, and few open mouths) with 100% accuracy for both models. Idress et al. (2024) tested Logistic Regression, Support Vector Machine (SVM), and Random Forest on 1000 images of Antep pistachios, achieving 93.6%, 94.8%, and 95.6% accuracy, respectively. Ataş and Doğan (2015) compared J48 Decision Tree, Naïve Bayes, and Multi-Layer Perceptron (MLP) on 200 images of different pistachio types (open-closed), reporting accuracies of 95.5%, 94.5%, and 94.5%, respectively. Ozkan et al. (2021) utilized an improved k-NN classifier on 2,148 images of Kırmızı and Siirt pistachios (open or closed), attaining an accuracy of 94.18%. Deep learning techniques have demonstrated superior performance in pistachio classification for instance, Singh et al. (2022) evaluated AlexNet, VGG16, and VGG19 on 2,148 images of Kırmızı and Siirt varieties, achieving 94.42%, 98.84%, and 98.14% accuracy, respectively. Farazi et al. (2017) developed a CNN model to sort open-shell, defected pistachios, and trash from 1000 images, obtaining 99% accuracy. Lisda et al. (2023) applied Inception-V3 and ResNet50 on 2.148 images of Kırmızı and Siirt varieties, achieving 96% and 86% accuracy, respectively. Rahimzadeh and Attar (2022) utilized ResNet50, ResNet152, and VGG16 on 3,927 images of various pistachio types (open-mouth or closed-mouth), with accuracies of 85.28%, 85.19%, and 83.32%. Soleimanipour et al. (2022) used EfficientNet-B3 on 600 images of Fandoghi, Kaleh-Ghouchi, Ahmad-Aghaei, and Akbari pistachios, reaching 98.00% accuracy. Hosseinpour-Zarnaq et al. (2022) employed CNN for open and closed pistachio classification on 1600 images, obtaining 98.75% accuracy. Idress et al. (2023) tested VGG16, Inception-V3, and a proposed CNN on 2,247 images of Siirt, Tekin, and Uzun pistachios, achieving 94.5%, 96.13%, and 97.02%, respectively.

Among the other studies on pistachio classification in literature, several approaches have been proposed, focusing on different varieties and classification methodologies. The effectiveness of these approaches varies based on dataset size, model architecture, and preprocessing techniques. Traditional machine learning models, such as Decision Trees and Random Forest, show reliable performance in simpler classification tasks. However, deep learning models, particularly CNN-based architectures, provide higher accuracy and are more effective in handling complex variations in pistachio images. However, these models come with challenges, including large parameter sizes, extended training durations, and computational complexity. This is particularly critical when deploying them on mobile and embedded devices, where reducing model complexity while preserving accuracy

is essential due to limitations in storage and computational resources. This study aims to design an efficient model for pistachio image classification to overcome the limitations of pre-trained models. We propose a lightweight network with fewer parameters, tailored for deployment of low-computing-power farm equipment.

Table 1. Using traditional machine learning and deep learning models to classify open-closed pistachio nuts and various pistachio varieties

Author/Authors	Model architecture	Images	Varieties	Accuracy
(Omid, 2011)	fuzzy logic	210	Classify open and closed pistachio nuts	95.56%
(Beyaz, 2024)	Decision Tree and Random Forest	385	Antep pistachio (Open, closed, semi-open, and few open mouth)	100%, and 100%
(Idress et al., 2024)	Logistic Regression, Support Vector Machine, and Random Forest	1000	Antep pistachio (Open and closed)	93.6%, 94.8%, and 95.6%
(Singh et al., 2022b).	AlexNet, VGG16 and VGG19	2.148	Kırmızı and Siirt	94.42%, 98.84%, and 98.14%.
(Farazi et al., 2017)	CNN	1000	Sort open-shell, defected pistachios, and trashes	99%
(Lisda et al., 2023)	Inception-V3 and ResNet50	2.148	Kırmızı and Siirt	96% and 86%
(Rahimzadeh and Attar, 2022)	ResNet50, ResNet152, and VGG16	3.927	Different pistachio types (open-mouth or closed-mouth)	85.28%, 85.19%, and 83.32%
(Soleimanipour et al., 2022)	EfcientNet-B3	600	Fandoghi, Kaleh-Ghouchi, Ahmad-Aghaei, and Akbari.	98.00%
(Ozkan et al., 2021)	Improved k-NN	2.148	Kırmızı and Siirt (open or closed)	94.18 %
(Ataş and doğan, 2015)	J48 Decision Tree, Naïve Bayes, and Multi-Layer Perceptron (MLP)	200	Different pistachio types (open – closed)	95.5%, 94.5% and 94.5%
(Hosseinpour-Zarnaq et al., 2022)	CNN	1600	Pistachio nut Open and closed	98.75%
(Idress et al., 2023)	VGG16, Inception-V3, and a proposed CNN	2.247	Siirt, Tekin, and Uzun	94.5%, 96.13%, and 97.02%

This approach contributes to advancing practical agricultural applications while also inspiring new research directions for the identification of pistachio varieties

2. Materials and Methods

2.1. Image acquisition

This study was conducted in the Agricultural Machinery and Technologies Engineering Laboratory at Ondokuz Mayis University, Samsun. A total of 5,243 pistachio samples, representing seven varieties Akuri, Halebi, Uzun, Antep, Kırmızı, Siirt, and Tekin were sourced from the Pistachio Research Institute in Gaziantep.

Image acquisition was performed using a high-resolution Guppy Pro F-032 camera equipped with a CCD progressive scan Sony ICX424 sensor (4.9 mm × 3.7 mm) with a resolution of 656 × 492 pixels and 12-bit analog-to-digital conversion. The camera was mounted on a stable tripod at a fixed distance of 30 cm above the sample platform. The imaging system was placed inside a partially enclosed box to minimize external light interference. Uniform illumination (two 8-watt fluorescent lamps) was provided by an internal lighting system to ensure consistent image quality. All samples were placed on a black background to enhance contrast between the pistachio samples and the background. The experimental setup, shown in (*Figure 1*), included a camera connected to a computer with an image capture card. (*Figure 2*) displays the different pistachio varieties examined in this study.

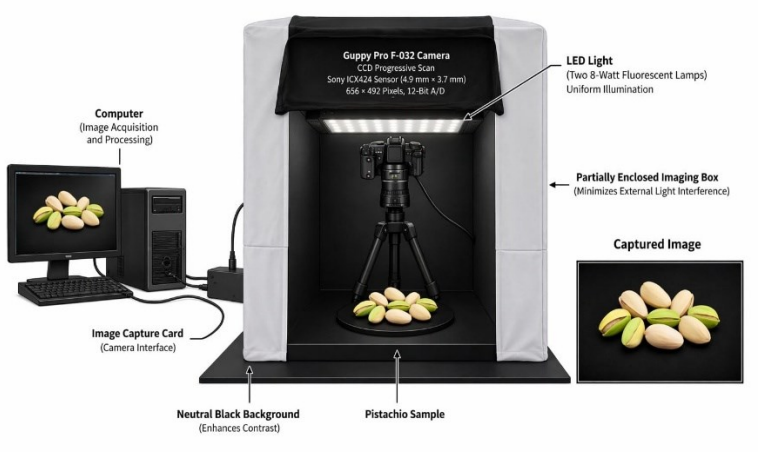


Figure 1. Image capturing system

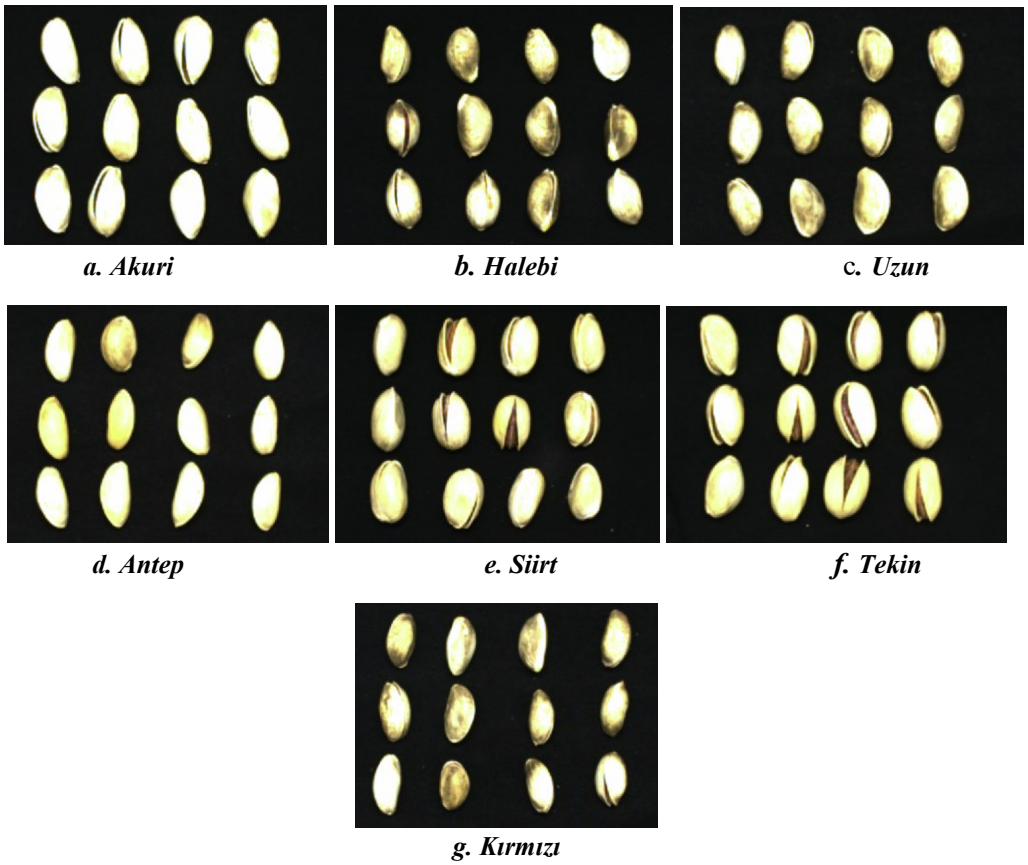


Figure 2. Pistachio varieties

2.2. Image pre-processing

This phase encompasses multiple operations conducted on the dataset. These operations consist of image scaling, conversion of images into arrays, and partitioning of the dataset. These steps are aimed at aiding subsequent classification procedures.

2.2.1 Image Resize

Image resizing involves modifying an image's dimensions to align with the model's input requirements. In this study, images were standardized to ensure consistency and optimize processing efficiency for the model.

2.2.2 Convert Image to Arrays

Each image will be stored as an array, with each integer representing a black-and-white value ranging from 0 to 255.

2.2.3 Dataset Allocation

In this phase, a random selection approach is employed to divide the dataset into three separate subsets: training, validation, and testing data. This process ensures a balanced and unbiased distribution, enhancing the model's generalization capability. Specifically, 70% of the dataset is allocated for training, allowing the model to learn essential patterns, while 15% is reserved for validation to fine-tune parameters and prevent overfitting. The remaining 15% is used for testing to evaluate the model's performance on unseen data. The dataset consists of seven pistachio varieties, namely Akuri, Halebi, Uzun, Antep, Kırmızı, Siirt, and Tekin. Each class contains 525 images for training, 112 images for validation, and 112 images for testing. In total, the dataset includes 3,675 training images, 784 validation images, and 784 testing images. This balanced allocation across all classes ensures that the model is trained and evaluated fairly without bias toward any specific pistachio type. Furthermore, the dataset is organized within a structured library folder, facilitating efficient data retrieval and management.

2.3 Pre-trained CNN Models

The literature covers a wide array of CNN architecture, each with its unique characteristics. Choosing the right architecture involves considering factors like classification accuracy, model size, and computational speed. In this study, the selection of CNN models was a result of conducting multiple experiments aimed at evaluating their performance based on these criteria.

2.3.1 VGG16 Model

VGG16, developed by the Visual Geometry Group (VGG), is an advanced convolutional neural network (CNN) architecture that builds upon AlexNet, offering improved image classification accuracy. A key feature of VGG16 is its consistent use of 3x3 filters across all convolutional layers, with filter quantities of 64, 128, and 256. While it surpasses AlexNet in performance, its higher parameter count requires greater memory capacity. The model consists of 16 layers, including 13 convolutional layers, three fully connected layers, pooling layers, ReLU activation, dropout layers, and a softmax layer for classification. It processes images with dimensions of 224 x 224 x 3 pixels, with the final layer generating class probabilities. (*Figure 3*) illustrates its architecture (Simonyan and Zisserman, 2015).

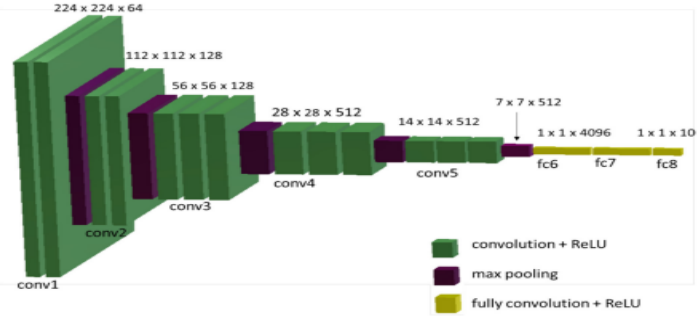


Figure 3. VGG16 architecture (Simonyan and Zisserman 2015)

2.3.2 Inception-V3 Model

The Inception-V3 model features a unique architecture that integrates convolution layers of three different sizes, with the smallest known as the unification layer. These convolutional layers divide input data into smaller segments, allowing for efficient feature extraction while enhancing computational efficiency and reducing overfitting. A concatenation layer connects different modules, ensuring smooth data flow within the model. The fully connected layer, which links all neurons, uses the SoftMax activation function for effective classification (Nour, Cömert et al., 2020). This structured design optimizes performance by improving feature processing and classification accuracy. A visual representation of the model's architecture is shown in (*Figure 4*).

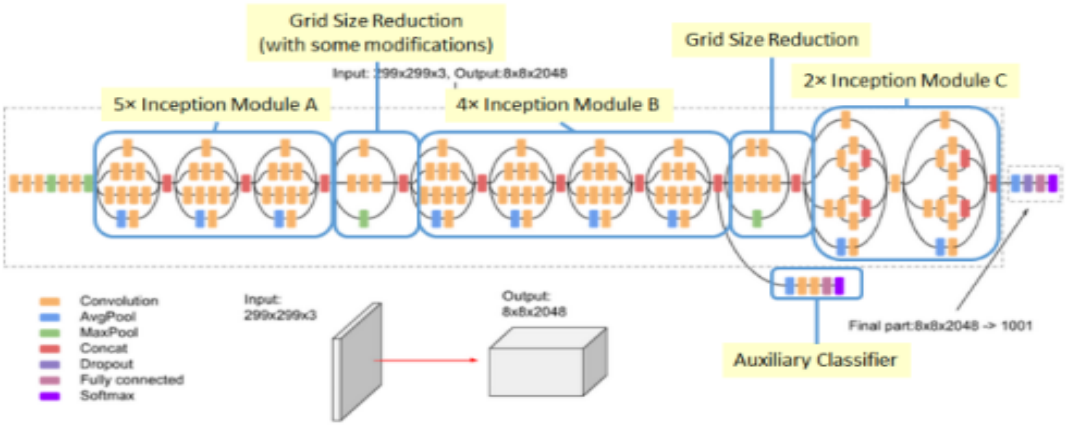
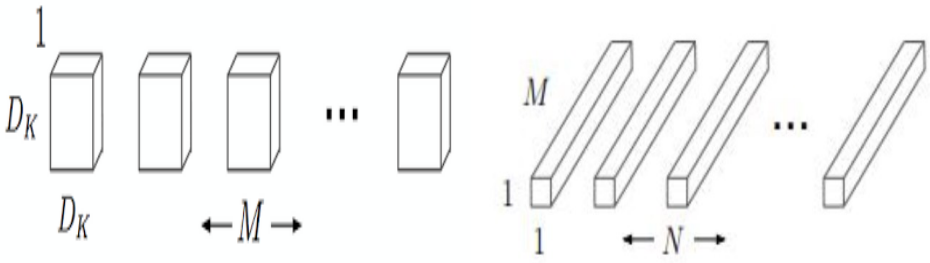


Figure 4. Architecture of Inception-V3

2.3.3 MobileNet Model

The MobileNet model was created for vision tasks on mobile and embedded devices. It employs depth-wise separable convolutional layers, where the separable layers are 1x1 convolutions known as point convolutions. In contrast to standard convolution which combines inputs into an output in a single step, the depth-wise separable convolutional layer consists of two parts: a deep convolution layer and a point convolution layer (*Figure 5*). Both parts use batch normalization and ReLU non-linearities. The only difference is that the final fully connected layer is an exception; before it, a 3x3 convolution layer is used, followed by batch normalization and ReLU activation (Gerdan, Koç and Vatandaş, 2023).



(A) **(b)**

Figure 5. Depth wise convolution (a), pointwise convolution (b)

2.3.4 The Costume Mobile Net Model

To enhance the performance of the Mobile Net-based model for classifying seven pistachio varieties, we have implemented several improvements that significantly boost the accuracy while reducing the total parameters. The major improvements are outlined below

2.3.4.4 Replaced Flatten with Global Average Pooling

Global Average Pooling is a technique that replaces fully connected layers in traditional CNNs. It aims to create one feature map per classification category in the final layer. Instead of using fully connected layers on top of the feature maps, it computes the average of each feature map and feeds the resulting vector directly into the SoftMax layer. By replacing the Flatten layer, which generates a large feature vector and increases parameter count, with a GlobalAveragePooling2D layer, the model's parameters were significantly reduced while preserving essential features.

2.3.4.5 Reduced Dense Layer Size

A dense layer, also referred to as a fully connected layer, is a key element in deep learning architecture. It plays an essential role in the network's ability to learn and model intricate patterns from data by connecting every neuron in one layer to every neuron in the next layer. This dense connectivity allows the network to capture complex relationships and interactions within the data (Kassem, El Hajjar, Abdallah, and Omrani, 2025). In this study the dense layer was reduced from 256 neurons to 128 neurons, to maintain sufficient complexity for classification while reducing overfitting and computational load.

2.3.4.6 Added Dropout for Regularization

Dropout is a regularization method used to reduce overfitting in neural networks by limiting the reliance on specific neurons in the training data. It works by randomly deactivating units (both hidden and visible) during training, forcing the network to learn more robust and generalized features. This technique is also an effective way to perform model averaging within networks. In deep learning projects, overfitting and underfitting are common challenges. Regularization techniques, such as dropout or hyperparameter adjustments, help address these issues by controlling model complexity. These approaches ensure the model learns to generalize effectively, avoiding overfitting (memorizing noise) or underfitting (failing to capture patterns). The dropout regularization technique was employed in deep learning on the second layer of a neuron network.

2.3.4.7 Incorporated Data Augmentation

To enhance the diversity of the training data and improve generalization, data augmentation techniques such as, rotation, width and height shifts, shear and zoom transformations, and horizontal flips were implemented. These augmentations were applied dynamically during training using the ImageDataGenerator. With the original training dataset containing 525 images, the application of these augmentations effectively increased the variety of training data by generating unique transformations of the existing images. This process resulted in a significantly more diverse dataset, improving the model's ability to generalize to unseen data.

2.4 Software

The project's code was written using the Python programming language and conducted using GPU run-time type of Google Colab notebook. The computer system utilized for the project operated on a Windows 10 Operating System and was equipped with an Intel (R) Core (TM) i7-6600U CPU, 8 GB RAM, and a 64-bit operating system featuring an x64-based processor. TensorFlow was selected as the framework due to its availability of pre-trained models and its incorporation of Keras, a high-level neural network API, starting from version 2.0 and above (Gulli, Kapoor, and Pal, 2019).

2.5 Training- Validation -Testing Data and Model Evaluation

In this study, the dataset was split into three distinct segments: 70% for training, 15% for validation, and another 15% for testing purposes. The training dataset consisted of 3675 images, while both the validation and testing datasets contained 784 images each. Several performance metrics were utilized to evaluate the Custom Mobile Net model, including precision, recall, and the F1-score. Precision measures the model's ability to accurately classify positive outcomes. Recall, on the other hand, assesses the model's capacity to correctly identify actual positive samples. The F1-score, a derived metric from precision and recall, offers a balanced overview of the model's performance (Hossin and Sulaiman, 2015). The key improvements for the custom Mobile net architecture that led to improved accuracy are shown in (*Table 2*).

Table 2. Custom Mobile Net training parameter

Layer (type)	Output Shape	Parameters
mobilenet_1.00_224 (Functional)	(7, 7, 1024)	3.228.864
global_average_pooling2d (GlobalAveragePooling2D)	(1024)	0
dense_2 (Dense)	(128)	131.200
dropout (Dropout)	(128)	0
dense_3 (Dense)	(7)	903
Total parameters	3.360.967 (12.82 MB)	
Trainable params:	1.994.759 (7.61 MB)	
Non-trainable params:	1.366.208 (5.21 MB)	

3. Results

In this study, we employed four distinct models: a pre-trained VGG16, Inception-V3, MobileNet, and a custom Mobile Net model to classify seven different pistachio varieties, namely Akuri, Halebi, Uzun, Antep, Kırmızı, Siirt, and Tekin. 70% of the total dataset was allocated for training, 15% for validating the accuracy, and the remaining 15% for the test set.

Table 4 shows the results of comparing the custom Mobile Net model to other pre-trained models to confirm the results. As we see in (*Table 3*), high accuracy rates were achieved using the custom Mobile Net model and the pre-trained models. This underscores their efficiency in accurately categorizing the different pistachio varieties.

Table 3. Accuracy of the custom Mobile Net model and the pre-trained models

Models	Validation		Testing	
Architectures	Loss	Accuracy	Loss	Accuracy
Inception-V3	0.037%	96.30%	0.058%	94.13%
VGG16	0.06%	93.2%	0.07%	92.35%
Mobile Net	0.023%	97.7%	0.035%	96.43%
Custom Mobile Net model	0.1026%	98.21%	0.0191%	98.09%

Table 4. Precision, recall, and F1-score for the Custom Mobile Net model

Varieties	Precision	Recall	F1-score
Akuri	0.9823	0.9911	0.9867
Halebi	1.0000	1.0000	1.0000
Uzun	0.9901	0.8929	0.9390
Siirt	1.0000	1.0000	1.0000
Kırmızı	0.9016	0.9821	0.9402
Tekin	1.0000	1.000	1.0000
Antep	1.0000	1.0000	1.0000
Macro avg	0.9820	0.9809	0.9808
Weighted avg	0.9820	0.9809	0.9808

The performance of the custom MobileNet model was assessed in comparison with pre-trained models, including VGG16, Inception-V3, and MobileNet, as shown in *Table 3*. Among these models, VGG16 exhibited the highest validation and testing loss, while the custom MobileNet model achieved the lowest, demonstrating its superior efficiency in minimizing classification errors. (*Table 4*) presents the evaluation of the custom MobileNet model's performance on the test dataset using precision, recall, and F1-score metrics, calculated for each class. The results indicate that the model excelled in classifying different pistachio varieties, achieving an

impressive average precision of 98.20%, signifying a low rate of false positive predictions. Additionally, the model demonstrated a strong recall value of 98.09%, highlighting its ability to correctly identify positive instances with minimal false negatives. The F1-score, which balances precision and recall, also yielded a high average of 98.08%, further confirming the model's robust classification capabilities. These findings suggest that the custom MobileNet model effectively distinguishes between different pistachio classes with a high level of accuracy and balanced performance across evaluation metrics. The confusion matrices illustrating the test accuracies of the custom MobileNet model and the pre-trained models are provided in (*Figures 6, 7, 8, and 9*).

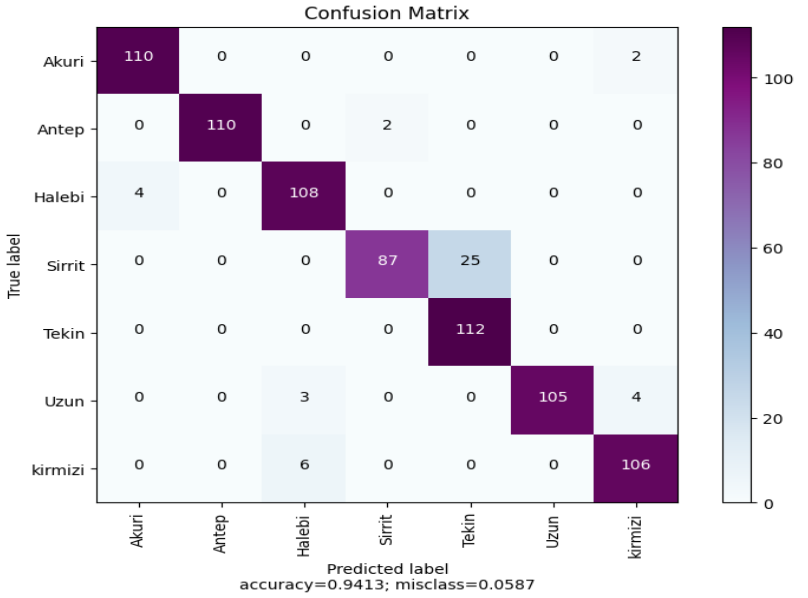


Figure 6. The confusion matrix of test accuracy for the Inception-V3 model

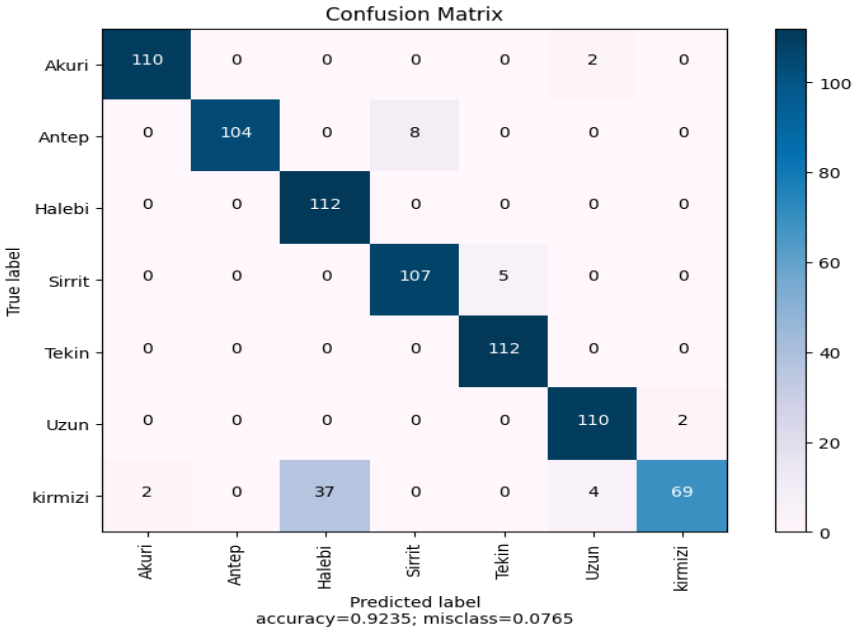


Figure 7. The confusion matrix of test accuracy for the VGG16 model

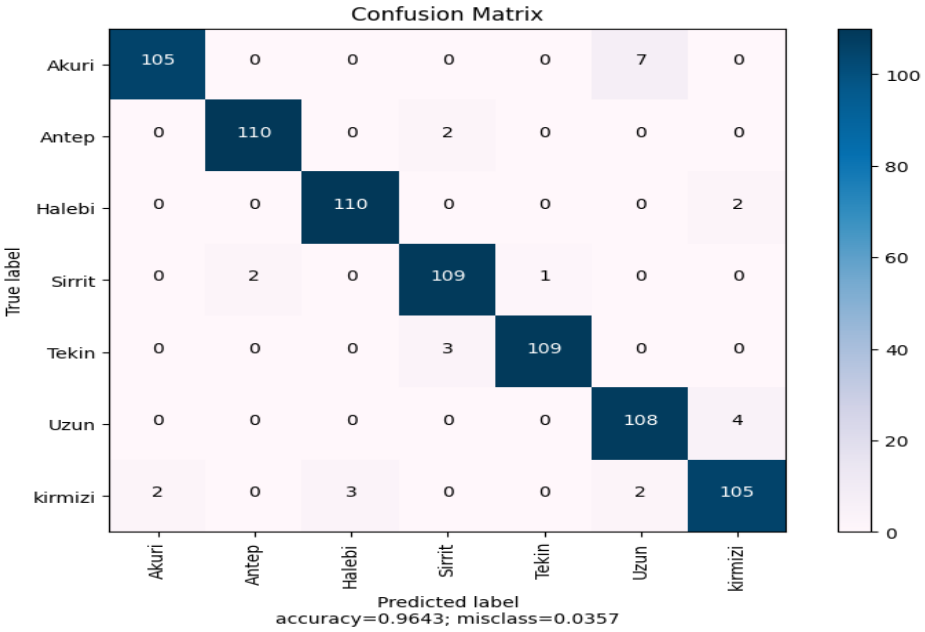


Figure 8. The confusion matrix of test accuracy for the MobileNet model

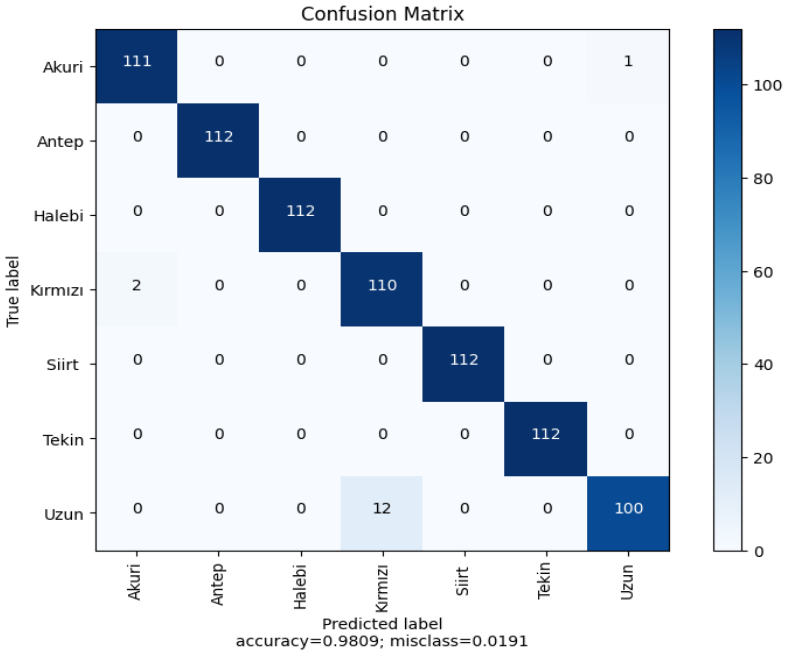


Figure 9. The confusion matrix of test accuracy for the custom Mobile Net model

4. Discussion

Numerous studies have employed machine learning and deep learning algorithms to improve the precision of identifying various types of pistachio nuts. (*Table 5*) showcases research specifically concentrating on two key areas: distinguishing between open and closed pistachio nuts and categorizing different pistachio varieties. The table provides details such as dataset image counts, classified varieties, utilized models, and their accuracy rates.

Most previous research has focused on classifying only two pistachio varieties, specifically Kırmızı and Siirt, and has largely concentrated on distinguishing between open and closed pistachio nuts, typically using traditional machine-learning methods. Among these studies, Singh et al. (2022) achieved the highest accuracy, with an impressive rate of 98.84%. This result is comparable to the 98.09% accuracy achieved by our custom

MobileNet model, especially considering that their study used only two pistachio varieties, while our model classified seven different varieties. From the results that we have achieved in this study, we noticed that our custom mobile Net model achieved higher test accuracies than pre-trained models, such as Mobile Net, IncepionV3, and VGG 16 because we have implemented several improvements techniques such as Replacing Flatten with Global Average Pooling, Reducing Dense Layer Size, Adding Dropout for Regularization, and Incorporating Data Augmentation technique which led to a significant increase in model accuracy, achieving a remarkable 98.09% classification accuracy on the test dataset. The total parameters were also reduced to (12.82 MB), making the model more efficient and faster to train and easy for deployment on low-computing-power smart farm equipment. We have noticed that The Custom Mobile Net model achieved an accuracy of 98.09%, demonstrating a 1.66% improvement over the pre-trained Mobile Net model, which achieved 96.43% accuracy. This enhancement can be attributed to several architectural modifications, including the use of GlobalAveragePooling2D, fine-tuning of the last 20 layers, reduced dense layer complexity, and data augmentation strategies. The Custom Mobile Net model significantly reduced the total number of parameters, leading to a 79% decrease in model size (from 61.32 MB to 12.82 MB). This reduction was achieved primarily by replacing the Flatten layer with GlobalAveragePooling2D, optimizing the dense layers, and applying regularization techniques such as dropout. The reduction in model size translates to lower computational requirements, making the Custom Mobile Net model more efficient for real-world deployment.

Table 5. Comparison of accuracy rates of classifying open-closed pistachio nuts and different types of pistachio varieties using traditional machine learning and deep learning models.

Author/Authors	Model architecture	Images	Varieties	Accuracy
Singh et al. (2022).	AlexNet, VGG16 and VGG19	2.148	Kırmızı and Siirt	94.42%, 98.84%, and 98.14%.
Lisad et al. (2023)	Inception-V3 and ResNet50	2.148	Kırmızı and Siirt	96% and 86%
Rahimzadeh and Attar (2022)	ResNet50, ResNet152, and VGG16	3.927	Different pistachio types (open-mouth or closed-mouth)	85.28%, 85.19%, and 83.32%
Soleimanipour et al. (2022)	EfcientNet-B3	600	Fandoghi, Kaleh-Ghouchi, Ahmad-Aghaei, and Akbari.	98.00%
Ozkan et al. (2021)	Improved k-NN	2.148	Kırmızı and Siirt (open or closed)	94.18 %
Ataş and Doğan (2015)	J48 Decision Tree, Naïve Bayes, and Multi-Layer Perceptron (MLP)	200	Different pistachio types (open – closed)	95.5%, 94.5% and 94.5%
Our study	VGG16, Inception-V3, MobileNet, and a Custom Mobile Net model	5.243	Akuri, Halebi, Uzun, Antep, Kırmızı, Tekin, and Siirt.	92.35%, 94.13%, 96.43, and 98.09%

5. Conclusion

Classifying different pistachio varieties presents a significant challenge due to their highly similar visual characteristics. Advanced technological solutions are essential in the pistachio industry to address this issue and improve the efficiency of the packaging process. This study introduces a specialized model designed to classify seven pistachio varieties with greater accuracy and efficiency, overcoming the limitations of pre-trained models. The proposed custom MobileNet model performs better than widely used image classification models such as VGG16, Inception-V3, and Mobile Net. Notably, the model improves test accuracy by 1.66% over the original pre-trained MobileNet while reducing the number of parameters by 79%, leading to lower computational and storage demands. These enhancements are attributed to integrating key techniques, including replacing Flatten layers with Global Average Pooling, reducing the size of dense layers, incorporating dropout for regularization, and applying data augmentation strategies. Although the custom Mobile Net model shows high accuracy in classifying different pistachio varieties and has fewer parameters than models such as the original Mobile Net

model, which makes it more suitable for classification needs in practical applications, there are still some limitations, which are as follows: (1) The dataset used in this study not fully represent all variations in pistachio appearances, such as differences due to growth conditions, lighting, or harvesting methods. (2) The model has not yet been tested in real-world industrial settings for real-time classification, where variations in imaging conditions and processing speed could affect performance. To address the above limitations of the custom Mobile Net model, future work can be optimized in the following directions:

(1) Future studies should collect and train on a more diverse dataset, including images from different growing conditions, lighting variations, and real-world industrial settings.

(2) Implementing and testing the model in an industrial environment will help validate its effectiveness in practical applications, considering speed, accuracy, and operational constraints.

Ethical Statement

There is no need to obtain permission from the ethics committee for this study.

Conflicts of Interest

We declare that there is no conflict of interest between us as the article authors.

Authorship Contribution Statement

Concept: Idress, K. A. D.; Design: Eissa, M. O. S.; Data Collection or Processing: Idress, K. A. D.; Statistical Analyses: Gadalla, O. A. A.; Literature Search: Baitu, G. P.; Writing, Review and Editing: Öztekin, Y. B.

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