Detection of the Quality of Zivzik Pomegranate Grown in Siirt Using Deep Learning Methods

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Abstract— **This study aims to determine the quality of the Zivzik pomegranate, a fruit unique to the Siirt region whose quality can only be understood by experts engaged in this business with deep learning methods. Since there is no existing database of Zivzik pomegranate, we first visited the Şirvan district of Siirt, where Zivzik pomegranate grows, many times to create a database, and over a thousand pomegranate photographs were taken and labeled. After the Zivzik pomegranate quality dataset was created, the aim was to determine the quality of Zivzik pomegranate using deep learning methods. AlexNet, VGG-16, VGG-19, ResNet, Inception, XCeption, EfficientNet, and MobileNet deep learning models were applied, and the results were evaluated. As a result of the study, the best accuracy value was obtained from the EfficientNetV2 B0 model at 81.83%. In addition to contributing to the scientific literature, our study is expected to contribute positively to the recognition of the Zivzik pomegranate, the regional economy, and the awareness of consumers and producers about agriculture 4.0 applications.**

Keywords—: deep learning, nar kalitesinin tespiti, transfer öğrenme, Zivzik narı

I. INTRODUCTION

Today, we face the problem of decreasing our limited natural resources [1]. Due to population growth and climate change, problems in quality food production and preserving the natural balance are becoming increasingly important [2]. For all these reasons, technology in agriculture has given birth to a new field called "digital agriculture" and is developing rapidly [3]. Fast selection, quality, and yield increase are possible much faster with digital agricultural technologies.

Turkey has been conducting studies on digital agriculture for a long time. The HASSAS project within TUBITAK is one of them [4]. Today, we are in a period we call Agriculture 4.0, and with this concept, smart systems and devices are used intensively in agriculture [1]. One of the innovations of Agriculture 4.0 is using artificial intelligence technologies to determine product quality [5, 6].

Today, with the agriculture 4.0 process, the interaction of agricultural products with artificial intelligence is increasing. Zivzik pomegranate is a juicy and delicious variety grown in the Zivzik region of the Şirvan district of Siirt. According to TUIK data, Zivzik pomegranate production created a crucial economic value in Siirt in 2021 with 10,187 tons [7]. Zivzik pomegranate, which has an essential economic value in the region, is a fruit consumed throughout the winter months thanks to its long-term durability in Siirt.

The weight of Zivzik pomegranate fruit varies between 161.45 and 302.35 grams, the length between 67.27 and 86.92 mm, and the width between 60.79 and 78.67 mm [8]. In existing studies using colorimetry, the brightness, redness, blue-yellow color values, and color intensity of pomegranate were found in the range of 22.83 - 23.67, 4.50-6.08, 1.25-1.42, and 3.62-5.05, respectively [8].

Artificial neural networks are cellular structures capable of receiving, storing, and utilizing information and are used to solve many problems [9]. In recent years, the success of deep learning methods on image data has increased interest in this field [10]. In agriculture, deep learning applications are frequently utilized to increase yield and quality and improve product processes [1]. Plant disease detection, crop detection, crop classification, and crop quality assessment are examples of deep learning applications in agriculture.

Many studies in the literature have used artificial neural networks to solve quality control problems [11]. Many studies have been conducted on quality and disease detection on pomegranate fruit. In their study, Kumar et al. worked on two different datasets, the spatial domain feature dataset and the wavelet feature dataset, to develop an effective method to determine pomegranate quality. ANN and SVM models were trained with these datasets. As a result of the study, ANN showed the highest success rate of 92.65%, while SVM achieved a maximum success rate of 80%. In addition, more successful results were obtained on the wavelet feature dataset [12].

Okere et al. evaluated methods for determining pomegranate quality in their study. Machine Vision systems, Spectroscopy-based methods, Nuclear Magnetic Resonance and Magnetic Resonance imaging methods, Hyperspectral and Multispectral imaging methods, and Electronic Nose are among the main quality determination methods. In this study, pomegranate quality characteristics were classified as external quality characteristics such as color and texture, internal quality characteristics such as chemical properties and bioactive compounds, and quality characteristics of pomegranate products. It was reported that the color of pomegranate peel provides essential information about ripeness and freshness [13].

Madhavan et al. used image processing and machine learning techniques to detect disease in pomegranate leaves. The algorithm used in the study was 98.39% successful in classifying healthy leaves, and a 98.07% success rate was obtained in classifying disease in leaf images. The study also performed contrast adjustment, identification of diseased parts with the K-means algorithm, and classification with multi-class SVM [14].

Pawara et al. researched early detection of pomegranate diseases using machine learning and IoT. In the study, detection and diagnosis were performed using a hidden Markov Model and sensor networks. A dataset of pomegranate leaf images was used in the study. The study is based on pomegranate plant diseases, factors affecting disease development, and the use of the system. The developed system evaluates parameters such as temperature and humidity through the IoT system established with the GSM module [15].

Gopi Kiran et al. conducted a study based on feature extraction and machine learning to classify pomegranates according to their quality automatically. The study uses spatial domain features, frequency domain features, and the Histogram of Oriented Gradients (HOG) method to extract features from images. Various machine learning classifiers are trained by extracting these features. As a result of the study, HOG features performed better than the spatial domain and frequency domain features. An Artificial Neural Network (ANN) model was trained with a dataset containing HOG features, and 93.51% accuracy was achieved [16].

Kantale et al. wrote a paper on machine learning classification of pomegranate diseases and image segmentation techniques. The study provides a general framework for digital image processing, disease detection, and machine learning and summarizes the studies on machine learning for pomegranate disease detection [17].

Kumar et al. studied pomegranate quality analysis using machine learning and feature extraction for classification. The study mentioned that pomegranate is rich in nutrients and minerals and has high antioxidant and flavonoid content. The positive effects of pomegranate in preventing cell damage, boosting immunity, facilitating digestion, fighting type-2 diabetes, keeping vital parameters under control, and preventing cancers were emphasized. It is stated that the quality classification of pomegranates is based on external appearance, such as color, texture, size, and shape. The necessity of machine learning in quality assessment and the limitations of doing it by humans are discussed. This study proposes a method for pomegranate quality analysis using Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP) feature extraction methods. In the model designed in this study, K-Nearest Neighbor (KNN) and Naive Bayes (NB) algorithms are applied with both feature extraction methods. The results revealed that the LBP + NB model performed more efficiently and accurately [18].

Our study used deep neural networks to classify Zivzik pomegranates grown in Siirt province [19-23]. The Python language, image processing, Keras libraries, and Pytorch library were utilized in the pre-processing of the photographs and deep learning phase. The next section of the paper discusses the materials and methods, followed by the experimental results. The last section provides an overall evaluation.

II. MATERIALS AND METHODS

A. Convolutional Neural Networks

Convolutional neural networks are widely used in many fields and include some layers not found in classical neural networks [24]. Deep learning algorithms solve problems using growing data sizes [25, 26]. Deep learning enables computers to understand the world and learn from experience [27]. The basic architecture of deep learning is a convolutional neural network (CNN), which consists of several layers. In ESA, the information given as input is processed layer by layer, and the result is obtained. The error is calculated for the result and updated with the back-propagation algorithm [28]. Convolutional neural networks consist of convolution, activation, pooling, and fully connected layers.

1) Convolution layer: This is the layer where filters are applied to the image data. The result is an activation map showing the filter coefficients.

2) Activation layer: It is a layer that takes the network away from linearity and accelerates learning. Real-world problems have a non-linear structure, and the data is also this way. It aims to increase success by using structures such as a non-linear activation layer based on the nature of the data.

3) Pooling layer: This layer allows reducing the input size for the next convolution layer. It reduces the computational burden and avoids memorization, creating a better abstraction.

4) Fully connected layer: This is a layer where each input is connected to all outputs from the previous layer. It has benefits such as optimizing the outcome and achieving ultimate success.

B. Convolutional Deep Neural Network Architectures

AlexNet, VGG-16, VGG-19, ResNet, Inception, XCeption, and EfficientNet are deep neural network architectures that have successfully classified image data in the literature. AlexNet is a milestone neural network architecture in the field of deep learning. In 2012, it outperformed traditional methods at the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), laying the foundations for more complex neural network models. The architecture consists of 25 layers, organized by alternating convolutional and pooling layers. These layers enable hierarchical learning of image data and consequently significantly improve object recognition accuracy. [29].

VGG-16 is distinguished from other neural network models by a double or triple-convolution layer structure. In total, there are 41 layers in this model. In the architecture of VGG-16, the convolution layers are placed consecutively, and a pooling layer follows each convolution layer. This regularity allows the network to learn deeper and more complex features. There are 16 deep layers, including 13 convolution layers and three fully connected layers. This 41-layer network structure allows the network to learn deeper and more extensive features to achieve higher accuracy in object recognition tasks. [30].

VGG-19 is a neural network model that stands out in deep learning. This model performs impressively by reducing the number of parameters using some strategic filters. It consists of 24 layers in total. In the architecture of VGG-19, convolution, and pooling layers take turns. Furthermore, carefully using some filters reduces the number of parameters without affecting its performance while reducing the overall complexity of the model. This design provides high object recognition and classification accuracy while creating a lighter model. [31].

ResNet is a neural network model that has brought essential innovations in deep learning. This architecture avoids problems that complicate deep network training by adding direct transitions between layers. It consists of 50 layers in total. ResNet is characterized by a "residual block" structure, where the input before each layer is added to the output at the end of the layer. This structure allows the layers to learn more efficiently and improves the network's performance even though it is deeper [32].

Inception is a neural network model called GoogLeNet, which uses unique modules and filters between layers. It consists of 22 layers in total. The distinctive feature of Inception is that it processes information in parallel, using different sizes and types of convolution filters in each layer simultaneously. These Inception modules learn features at different scales separately, allowing the model to represent them more comprehensively and effectively. This modular structure controls the number of parameters while improving the network's overall performance. Therefore, the Inception model is an essential example of an architecture used effectively in complex visual recognition tasks [33].

XCeption is a deepened derivative of the Inception model. This model uses the basic ideas of Inception to create more complex and deeper network structures.XCeption extends Inception's idea of multilayer and parallel processing to provide a more complex structure. This extension includes deeper and extended Inception modules to learn different features of the input data more effectively. This way, it offers more learning capacity to achieve higher accuracy in more complex visual recognition tasks [33].

EfficientNet is a neural network model that uses the MBConv convolution with a compound scaling technique. MBConv is a convolution block designed to run efficiently on mobile devices. It provides better classification with fewer parameters, significantly improving resource utilization efficiency. The distinctive feature of EfficientNet is that it uses a composite scaling strategy that combines networks of different scales. This strategy performs better by scaling the network's width, depth, and resolution balanced. The different versions of EfficientNet include various architectures with layers ranging from 240 to 816. These versions are optimized for different application scenarios and hardware constraints. This allows them to be used effectively and efficiently in various cases [34].

This study aims to determine the quality of the Zivzik pomegranate, a fruit unique to the Siirt region whose quality can only be understood by experts engaged in this business with deep learning methods. Since there is no existing database of Zivzik pomegranate, we first visited Şirvan district of Siirt province, where Zivzik pomegranate grows, many times and took over a thousand individual pomegranate photographs to create a database. After the Zivzik pomegranate quality dataset was created, models that detect the quality of Zivzik pomegranate were applied using deep learning methods. The results obtained with Alex Net, VGG-16, VGG-19, ResNet, Inception, XCeption, EfficientNet, and MobileNet deep learning models were evaluated according to success criteria. The highest achievement was 81% accuracy with the pre-trained EfficientNet architecture.

In addition to contributing to the scientific literature, our study is expected to contribute positively to the recognition of the Zivzik pomegranate, the regional economy, and the awareness of consumers and producers about agriculture 4.0 applications. The dataset to be created in this study has the characteristics of being a basic database for many future studies. The aims and objectives of our study consist of the following items:

- To create a unique Zivzik pomegranate dataset that can be used in current and future studies.
- Contributing to scientific studies.
- To contribute positively to the regional economy.
- Raising producers' awareness of agriculture 4.0 applications.

C. Creating the Dataset

In our study, 1254 photographs of Zivzik pomegranate were taken to create a database. To take the photographs the product photographs were taken in the garden environment by going to Dişlinar village of Şirvan district, 67 km from the city center of Siirt province, many times. In addition, the photographs of the harvested and shipped to the market were photographed by arranging the pomegranates on a white background with one fruit in each frame. Using the labeled photographs, pomegranate quality was determined from the photographs using various deep learning algorithms. Figure 3.1 shows some sample images of Zivzik pomegranate taken from our dataset. This binary classification problem study aims to identify good and bad-quality pomegranates.

a) b)

Fig. 1. Some Zivzik pomegranate images from the generated dataset: a) Low quality and b) Good quality.

D. Preprocessing of the Data Set

After our pomegranate images were acquired and labeled, they were pre-processed before model training. First, blurred images during the labeling phase or images with out-of-standard capture style were removed from the dataset. Then, the images were classified into two different classes according to the quality of the fruit. While making this classification, the main criteria were whether the fruit has reached sufficient ripeness, whether there is sunburn on the fruit, whether the development of the crown is sufficient, the prominence of the grains on the outer surface, and the surface's smoothness. After removing the unclear photos that did not meet the standard, 1254 photos remained in the data set. After labeling these images, 726 images labeled as low quality and 528 images labeled as good quality were obtained. Data augmentation methods were applied to the dataset to minimize the imbalance in classification. In this section, after the images were reduced by 80%, horizontal flip, rotate, random brightness contrast, random gamma, and random crop operations were applied at random rates. In this way, the equivalence of the dataset classes was ensured. As a result of the process, 627 images from both classes were included in the training dataset. The data set was divided into 80% training and 20% test data.

E. *Training of Deep Learning Models*

Python language, pandas, numpy, matplotlib, Open CV, seaborn, sklearn, tensorflow-keras, and Pytorch libraries were used in the study. A Linux operating system server with 1 NVIDIA T4 GPU, 15 GB graphics processor, 12.7 GB RAM, and 78.2 GB disk capacity was used as hardware. Model training was performed after our data set was uploaded to the server.

After our dataset, necessary software and hardware were prepared, our models were trained, and their performance was evaluated using Alex Net, VGG-16, VGG-19, ResNet, Inception, XCeption, EfficientNet, and MobileNet convolutional neural network architectures [29-34]. After dividing the dataset into test and training datasets, the model trained with the training set was used with the data in the test set for performance calculations. Precision, recall, F1-score, support, and accuracy values were calculated in the success evaluation. Again, a complexity matrix was created for each model, and the graphs of loss, accuracy, and f1-score change with epoch were obtained. While training the model, the aim is to minimize the loss function and achieve maximum success. The method steps used in this study are shown in Figure 2.

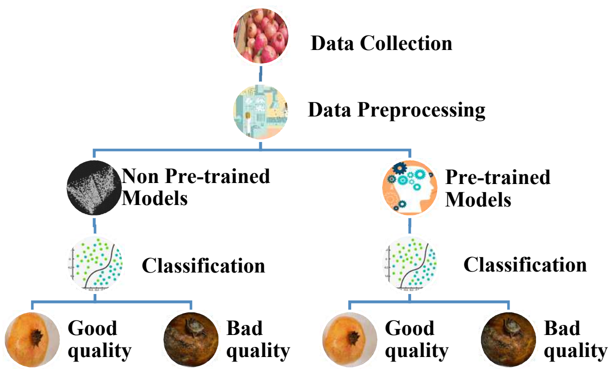

Fig. 2. Steps of the methods

As shown in Figure 3.2, our convolutional neural network architectures were trained with non-pre-trained models in the first stage, while pre-trained models were preferred in the second stage. In the second stage, we took advantage of transfer learning with architectures already trained with large data sets.

III. EXPERIMENTAL RESULTS

This study classified pomegranate quality using deep learning architectures, using pre-trained and non-pre-trained weights. In this context, pomegranate quality detection was performed with AlexNet, VGG-16, VGG-19, ResNet, Inception, XCeption, MobileNet, and EfficientNet methods that have proven their success in the literature. All training was performed using Tensorflow with a learning rate of 0.001, and results of up to 15 epochs were evaluated.

The EfficientNetV2 B0 model obtained the best classification accuracy. Then, MobileNetV3 and Xception models achieved high success. Figure 3 presents the loss, accuracy, and f1 score values obtained at each epoch for these models. Figure 4 shows the confusion matrix test results of these models.

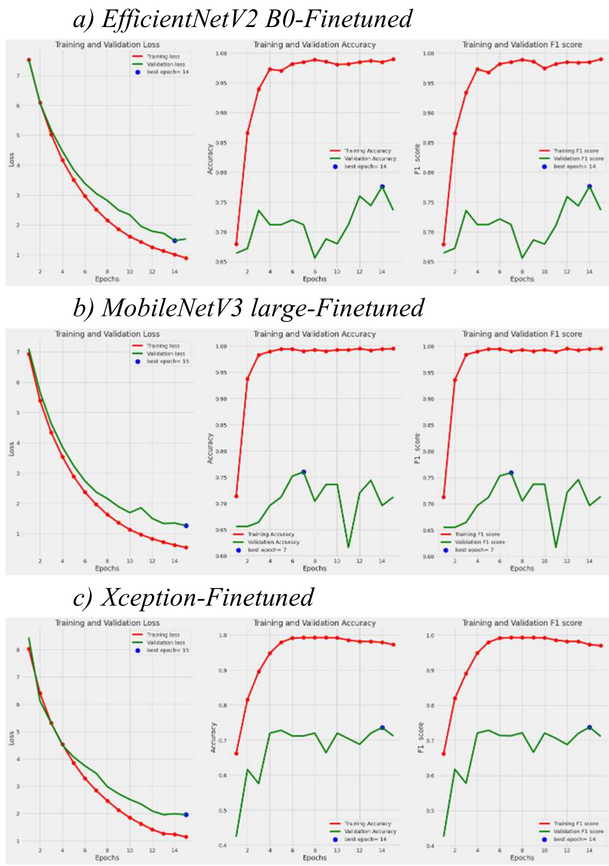

Fig. 3. Training plots of the three models with the highest accuracy.

a)

59	14
9	44

b)

54	19
8	45

c)

50	23
9	44

Fig. 4. a) EfficientNetV2 B0-Finetuned b) MobileNetV3-Finetuned c) Xception-Finetuned confusion matrix

As a result of the training, the accuracy values given in Table 1 were obtained. When the table is analyzed, it is seen that the best score is obtained from the EfficientNetV2 B0 model with 81.83%. It is also evident that training with pre-trained weights yields much higher success. The Inception V3 model achieved a classification accuracy of 73.18% without using trained weights. When the previously trained weights obtained on huge data are used as initial values, more successful results are obtained, as seen here. Table 2 shows the results of the precision, recall, f1-score, and accuracy test data for the models using the pre-trained weights.

TABLE I. CLASSIFICATION RESULTS FOR DEEP LEARNING MODELS

Pre-trained Models		Non-Pre-trained Models	
Model	**Accuracy**	**Model**	**Accuracy**
EfficientNetV2 B0	0.8183	InceptionV3	0.7318
MobileNetV3 large	0.7871	ResNet50	0.6418
Xception	0.7474	EfficientNetV2 B0	0.5702
InceptionV3	0.7423	VGG19	0.5447
Alexnet	0.7200	Alexnet	0.4585
VGG19	0.7080	MobileNetV3 large	0.4251
ResNet50	0.7073	Xception	0.4251
VGG16	0.6976	VGG16	0.4251

TABLE II. PERFORMANCE RESULTS OF DEEP LEARNING MODELS USING TRANSFER LEARNING

Model	Precision	Recall	f1-score	Accuracy
EfficientNetV2 B0	0.8676	0.8082	0.8369	0.8183
MobileNetV3 large	0.8710	0.7397	0.8000	0.7871
Xception	0.8475	0.6849	0.7576	0.7474
InceptionV3	0.7531	0.8356	0.7922	0.7400
Alexnet	0.76	0.75	0.76	0.7200
VGG19	0.8000	0.6575	0.7218	0.7080
ResNet50	0.7531	0.8356	0.7922	0.7073
VGG16	0.7333	0.7534	0.7432	0.6976

IV. CONCLUSION

In this study, a dataset consisting of Zivzik pomegranate images grown in the center and districts of Siirt province was created, cleaned, and classified. The resulting dataset was then directly applied to 8 different convolutional learning models. After the results were obtained, the aim was to increase the classification performance using pre-trained weights.

Within the study, the EfficientNetV2 B0 model obtained the best classification accuracy in detecting pomegranate quality, with 81.83%. After EfficientNetV2 B0, MobileNetV3 and Xception models obtained the most successful results. According to the performance results, more successful results are obtained by training with pre-trained weights.

In future studies, to increase performance, training can be performed with different models, and re-training can be performed by changing the model parameters and algorithms used. Again, different data augmentation methods can be applied to the images to increase performance. Finally, it is expected that adding new images to the dataset, enlarging it, and checking the data labels will positively affect the performance.

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