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A CNN-SVM study based on selected deep features for grapevine leaves classification

Murat Koklu [a,*], M. Fahri Unlersen [b], Ilker Ali Ozkan [a], M. Fatih Aslan [c], Kadir Sabanci [c]

[a] Department of Computer Engineering, Selcuk University, Turkey, Konya, Turkey
[b] Department of Electrical and Electronics Engineering, Necmettin Erbakan University, Konya, Turkey
[c] Department of Electrical-Electronic Engineering, Karamanoglu Mehmetbey University, Karaman, Turkey

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ABSTRACT

The main product of grapevines is grapes that are consumed fresh or processed. In addition, grapevine leaves are harvested once a year as a by-product. The species of grapevine leaves are important in terms of price and taste. In this study, deep learning-based classification is conducted by using images of grapevine leaves. For this purpose, images of 500 vine leaves belonging to 5 species were taken with a special self-illuminating system. Later, this number was increased to 2500 with data augmentation methods. The classification was conducted with a state-of-art CNN model fine-tuned MobileNetv2. As the second approach, features were extracted from pre-trained MobileNetv2′s Logits layer and classification was made using various SVM kernels. As the third approach, 1000 features extracted from MobileNetv2′s Logits layer were selected by the Chi-Squares method and reduced to 250. Then, classification was made with various SVM kernels using the selected features. The most successful method was obtained by extracting features from the Logits layer and reducing the feature with the Chi-Squares method. The most successful SVM kernel was Cubic. The classification success of the system has been determined as 97.60%. It was observed that feature selection increased the classification success although the number of features used in classification decreased.

1. Introduction

Grapevine leaves are a type of leaf that is often used in the traditional food culture of Turkish cuisine by processing it brine, canned and frozen [1]. In some grape species, grapevine leaves are more expensive than fruit. Vine varieties have leaves that show very different characteristics in terms of criteria such as shape, thickness, featheriness, sliciness. For this reason, the leaves of each variety are not used for cooking. Thick, feathered, and over-sliced leaves are not preferred by consumers. It is preferred that the vine variety to be used for cooking is thin, featherless, thin-veined, as sliced as possible and leaves a sour taste on the palate. [2,3]. Therefore, the separation of edible species from other vine species and the determination of vine species from leaf and fruit images is an important requirement in this area. However, for non-specialists, it is quite difficult to determine the type from grapevine leaves.

Fig. 1 shows five types of grapevine leaves commonly consumed in the Central Anatolia region of Turkey. The shape and structure of grapevine leaves also differ between edible vine species of different quality [4,5]. As can be seen from the figure, although differences in shape and structure appear in different edible species, genetic variations within the species, as well as environmental factors such as light and water, can affect the shape of grapevine leaves [6]. In addition, the leaf shapes of grapevines may vary in the growth process [7]. Some species have high similarities between each other, and it can take a long time to distinguish them. For these reasons, it is very difficult to classify all the edible vine types for an expert and is not practical. Because of all these factors, different methods and techniques are needed to distinguish between edible Grapevine leaves varieties that have economic value.

Currently, the increase in artificial intelligence applications in the field of agriculture brings forth solutions to problems in this field and creates an alternative to the methods used until today [8]. In recent years, plant diagnostic systems have been successfully used to solve problems such as yield, disease, species estimation [9–11]. There is still a need to work on the identification of visual data obtained from the plants in the field of agriculture [12]. Fruit, flowers, and leaves are classified by using visual data. Flowers and fruits cannot be used in plant

* Corresponding author.
E-mail addresses: mkoklu@selcuk.edu.tr (M. Koklu), mfunlersen@erbakan.edu.tr (M.F. Unlersen), ilkerozkan@selcuk.edu.tr (I.A. Ozkan), mfatihaslan@kmu.edu.tr (M.F. Aslan), kadirsabanci@kmu.edu.tr (K. Sabanci).

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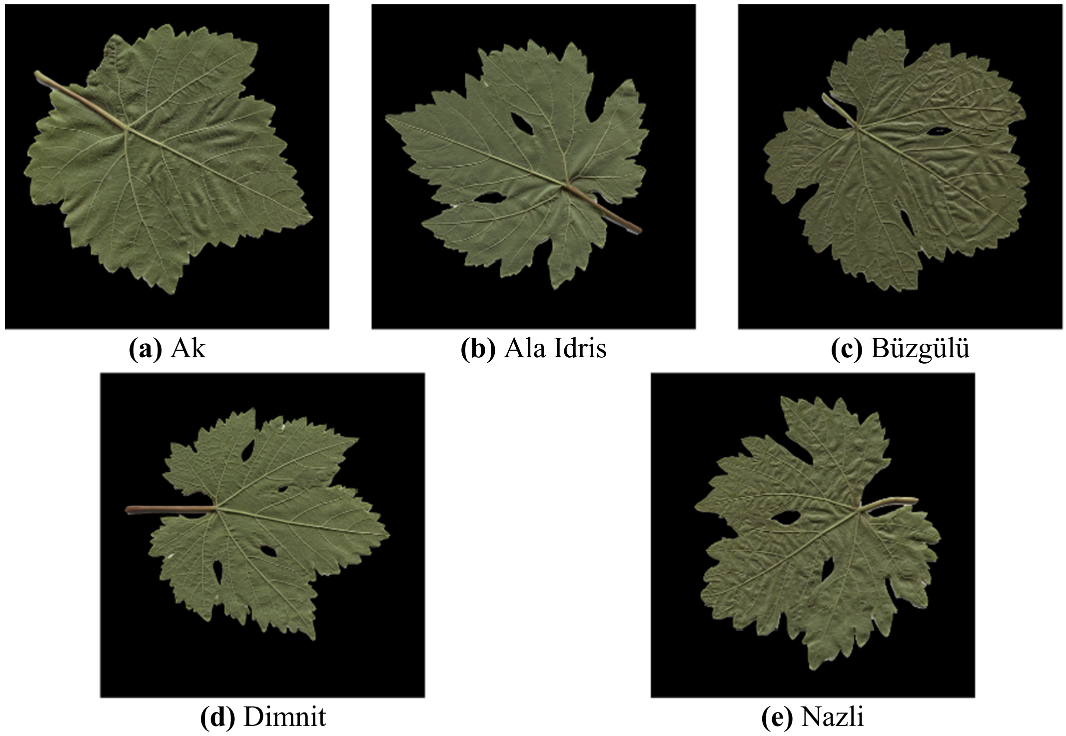

Fig. 1. Types of grapevine leaves used in cooking in the Central Anatolia region of Turkey.

identification problems for long-term, as they appear over a limited period of time. However, the use of leaves are more suitable for plant identification due to the fact that they contain plant-specific characteristics, are numerous and are available most of the year [13–15].

In recent years, many researchers have developed leaf image analysis and machine learning techniques for plant classification [16–19]. Formal characteristics of leaves are used to describe and classify plants. [20]. In these studies, morphological features of leaf images are extracted by image processing and the feature extraction process is performed [17,18,21–23]. When the literature is examined, it is observed that the extraction of a small number of features limits identification performance. In order to achieve high accuracy, studies are needed on methods that provide deeper information on the leaves of plants.

Deep learning approaches have become a newer technique in the field of computer vision and can extract more detailed information compared to machine learning techniques [24–29]. Deep learning approaches have come to the fore in recent years with their ability to automatically extract attributes. Deep learning is usually evaluated as a black-box approach. In this approach, images are given as input, and deep learning automatically determines features. Then, classification is performed with these features [30]. In recent years, various methods of plant leaf classification based on deep learning have been proposed [31–39].

Edible grapevine leaves contain many formal characteristics, and it is required to classify grapevine leaves with the most economic value through these characteristics. The separation of consumable grapevine leaves according to its quality also has an important place in marketing. The aim of this study is to develop a diagnostic system for grapevine leaves, which require expert knowledge and are quite difficult to distinguish visually. In this field, there are generally studies on determining the diseases of grapevine leaves, but on the other hand, manual measurement techniques have been used in the classification of grapevine leaves until now. In this study, three systems that automatically classify the grapevine leaves according to its type are proposed to address the mentioned problems. There are studies on the classification of different plants based on leaves. The studies are few in number and it is difficult to classify the leaf species because their characteristics are highly similar. Also, when the studies in the literature using leaf images are examined, it is seen that they are generally on disease and different plant species classification. Considering the studies on grape leaves, although there are studies on the classification of diseases, there is still no study to distinguish different grape leaf species belonging to the same region.

In this respect, this study differs from other studies in the literature. In the first system, species classification was made with a current CNN model. In the second system, the features were extracted from the CNN model and classified with SVM algorithms. In the third system, the determined portion of the features extracted from the CNN model with the feature selection is classified by SVM algorithms. The performance of the three models is compared.

The contributions of our study can be briefly summarized as follows:

- Classification of five classes of grapevine leaves by fine-tuned MobileNetv2 CNN Model
- Classification of features extracted from pre-trained MobileNetv2 models using SVMs with different kernel functions, i.e. CNN-SVM structure,
- Implementing a feature selection algorithm for high classification percentages.

This work successfully combines several concepts, approaches, techniques, and components, such as Image Acquisition, Image augmentation, Image classification, Feature Extraction, Deep Learning, Transfer learning, SVM, Grapevine leaves, Leaf identification. This is a typical combination novelty, which can be highlighted to show the contributions and/or advantages of the proposed method.

1.1. Related studies

In literature, there are various studies about disease estimation and species classification of plants by using leaf images and employing

Table 1
Comparative summary of the studies found in the literature based on leaf images.

Studies	Method	The Number of classes	The Number of images	Classification Accuracy (%)	Year	Ref.
Tea Bud(s) Classification	CNN	2	10,000	70.15%	2021	[44]
Classification of Leaves	CNN	50	50,000	93.40%	2021	[45]
Grape Leaf Disease Identification	CNN	2	1000	91.37%	2020	[46]
Apple and Grape Leaf Diseases Classification	VGG-16	8	17,638	97.87%	2020	[49]
Grape leaf diseases identification	CNN	4	1619	98.57%	2020	[42]
Grape Leaf Disease Identification	CNN	2	4023	97.22%	2020	[47]
Thai Herb Leaves Classification	ANN	8	400	90.50%	2020	[50]
Classification of Five Varieties of Tree	Hybrid ANN	5	516	94.04%	2020	[51]
Classification of Rice Leaf	Fuzzy Logic	4	80	90.00%	2020	[52]
Diseases Detection of Grape	Faster R-CNN	2	260	95.57%	2019	[48]
Plant species classification	RBF, MLP	100	1800	93.00 %	2018	[53]
Classification of rice plant diseases	SVM	3	120	73.33%	2017	[54]
Plant identification with leaves	k-NN	32	640	83.50%	2015	[55]
Grape leaf disease detection	SVM	2	137	88.89%	2016	[56]

different artificial intelligence methods so far. These classification studies have generally been used in the identification of leaf diseases. A comparative summary of the studies found in the literature based on leaf images is given in Table 1.

Barré et al. proposed a deep learning model, called LeafNet, where distinguishing features can be learned from leaf images. They stated that LeafNet revealed a better performance than traditional methods in different data [40]. Saini et al. has proposed a deep learning technique with the help of the deep CNN instead of traditional classification methods in the classification of plant leaves. They have shown that feature extraction is performed both automatically and in a short time with this method, and they have also achieved high accuracy [34]. Lee et al. has concluded that leaf shape is not enough by itself to recognize plant spices among closely related species. It has been implied that extracted features using CNN show better results compared to hand-crafted features [33]. Tan et al suggested the usage of a pre-trained CNN model for the feature extraction of 43 different plants' leaves. They have classified the extracted features from the suggested model using SVM, ANN, k-NN and NB machine learning algorithms. Compared to classical morphometric measurements which gave 66.55% accuracy, this method provided 94.88% accuracy [24]. There are also different papers about illness detection and recognition on grapevine leaves using deep learning methods [41–43].

There is no deep learning study to distinguish grapevine leaves species. Paranavithana and Kalansuriya employed CNN to predict the suitability of tea buds for the plucking in their study. They photographed the suitable and unsuitable tea buds. It is reported that the CNN model has a classification accuracy of 70.15%. For the same dataset, the SVM and Inception V3 methods have 65.86% and 68.70% respectively [44]. Naik and Shah took a total of 50,000 images of the leaves of 50 plant species growing in Southern Gujarat. Pre-trained models of CNN (Inception V4, Xception, ResNet, InceptionResNetV2, DenseNet,

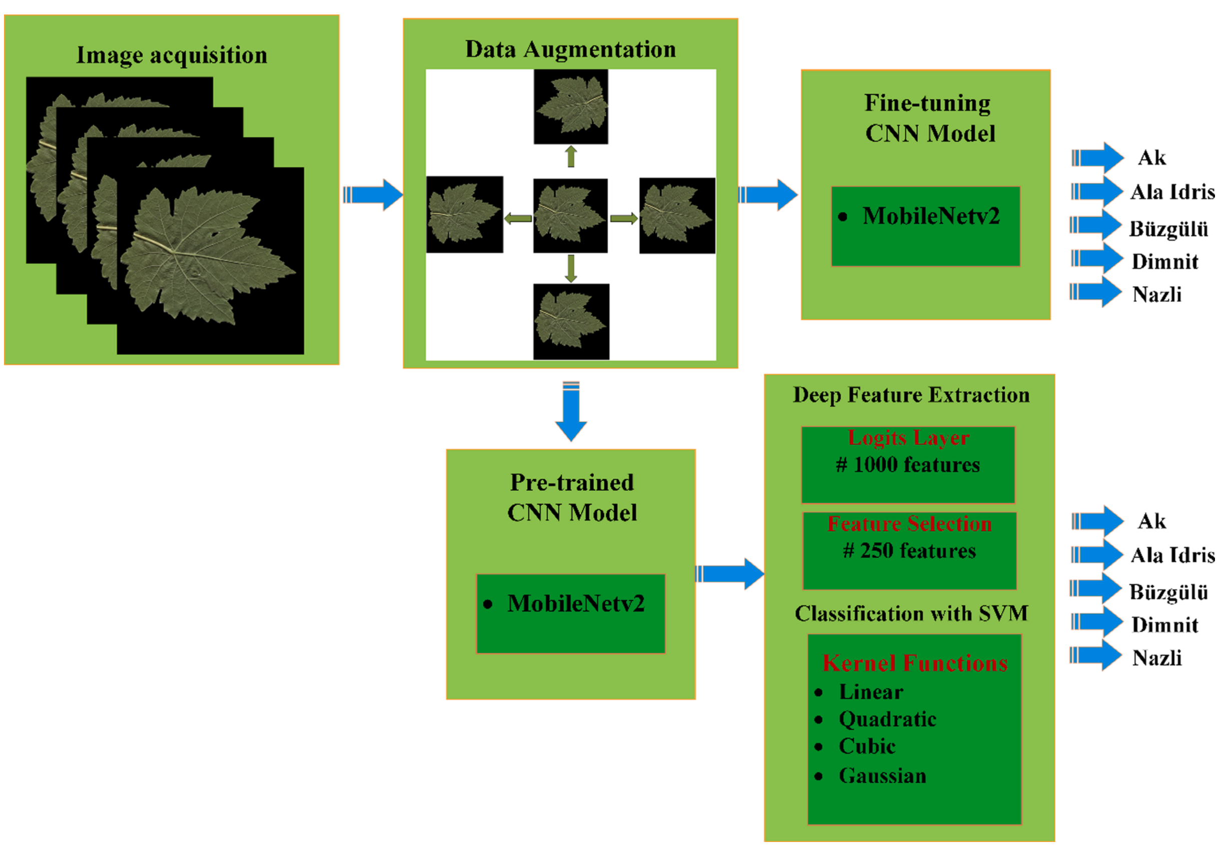

Fig. 2. Flow diagram of the proposed methods.

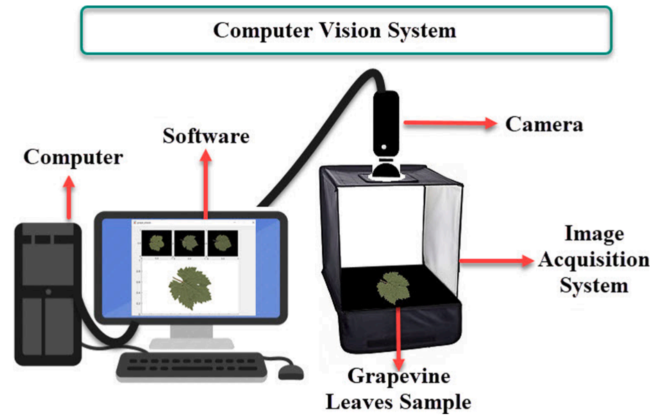

Fig. 3. Computer vision system used to obtain grapevine leaves images.

MobileNet) are employed for feature extractor. These features are classified by using the logistic regression machine learning method. In experiments, Xception has the best performance with an accuracy of 93.4% [45]. Hasan et al. proposed in their study a grape leaf diseases identification method based on CNN. The python Keras library is used in this article. The performance of the method is presented as 91.37% in terms of accuracy [46]. Ji et al. proposed a CNN architecture to distinguish the grape leaf diseases (black rot, esca and isariopsis leaf spot), and healthy leaf. Multiple CNNs combinations are presented in this article. The PlantVillage dataset is used for comparison of well known CNN models. The proposed structure archives 98.57% accuracy in tests [42]. Liu et al. proposed a CNN based leaf diseases diagnosis method. Totally 107.366 leaf image is created by augmenting 4023 newly taken images and 3646 images collected from public datasets. It is reported that the proposed DICNN has 97.22% accuracy which is bigger than GoogLeNet and ResNet-34 with the ratio of 2.97% and 2.55% respectively [47]. Ghoury et al. proposed a disease detection method for grape and grape leaf. SSD_MobileNet v1 and Faster R-CNN Inception v2 models have been employed for this purpose. The classification accuracy of the Faster R-CNN Inception v2 model is between 78% and 99%. It is reported that the image resolution, background change and noise increase the misclassifications [48].

Unlike the above studies, our study creates a grapevine leaf dataset and this leaf type has not been studied before. In terms of methodology, the proposed CNN-SVM structure and feature selection steps differ from previous studies.

2. Methodology

In this section, the methods used in the classification of grapevine leaves were presented in detail. The stages of the proposed methods and the order of these stages are presented in Fig. 2. First, an image acquisition system was prepared to take images of grapevine leaves and a dataset was created. The image acquisition system and its key properties

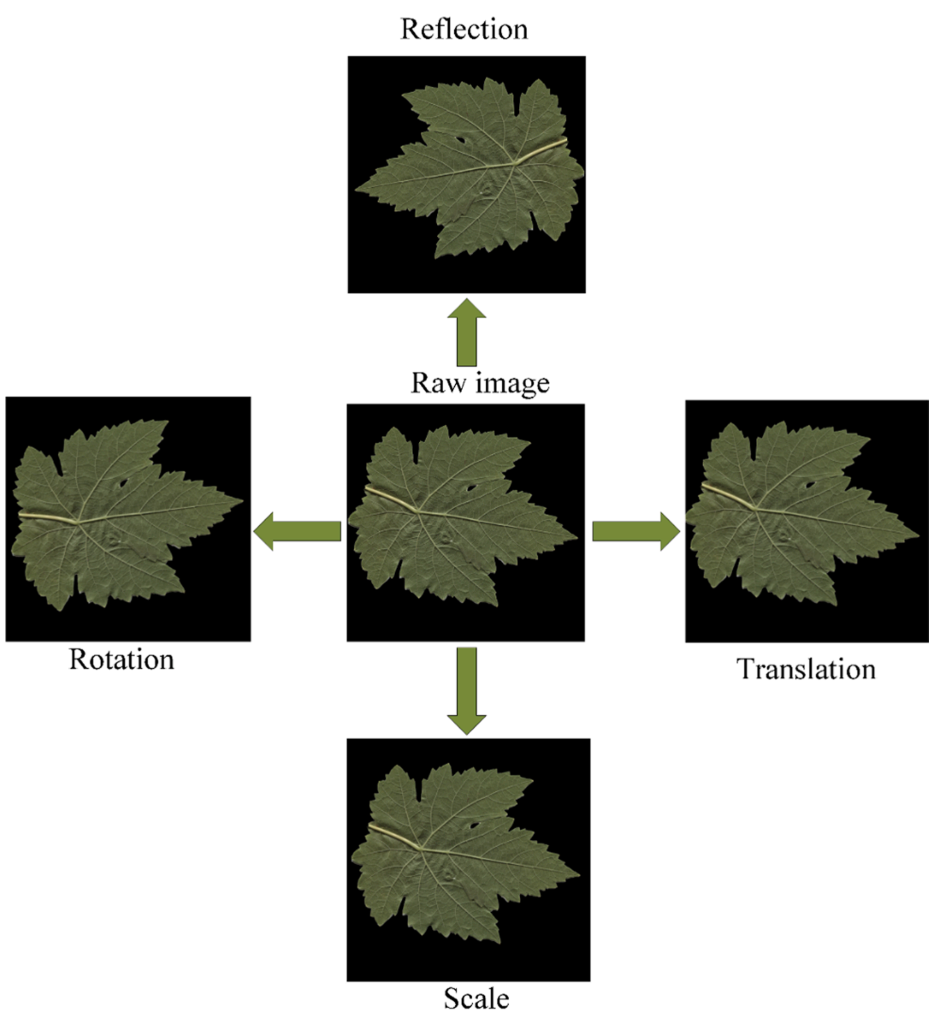

Fig. 4. The individual effects of data augmentation techniques.

Table 2
The data augmentation methods and limits

Techniques	Lower Limit	Upper Limit
Reflection	–	–
Rotation(Degree)	−45°	45°
Scale (Percentage)	80%	120%
Translation (pixel)	−15 px	+15 px

are described in the next subsection. Various image augmentation methods such as rotation, scaling, translation, etc. have been applied to increase the number of records in the dataset by using images obtained by the acquisition system. Three methods are suggested for the classification process. The proposed methods are explained under its own subtitle. In addition, all the issues mentioned here are explained in detail in the following subsections.

2.1. Image acquisition

A computer vision system has been designed so that it is not affected by outdoor light to obtain images of grapevine leaves. In order to prevent the formation of shadows and reduce noise in the images to be taken from the camera, the developed system is equipped with adequate interior lighting so that it does not receive light from the outside. Fig. 3 shows the computer vision system used in this study. The proposed system consists of a camera lens mount and an image capture camera (Prosilica GT2000C) and a special illumination box to prevent shadow formation in the background. The Prosilica GT2000C camera used for the study is a 2.2 megapixels, 2048 × 1088 resolution RGB camera obtaining full resolution at a maximum frame rate of 53.7fps, which has CMOS type sensor and an efficient operating temperature range of −20 °C to + 65 °C. The camera was placed at the top of the box which is about 20 cm above the samples. To provide a homogeneous lighting environment, the box was illuminated by led lights from the top. The box is completely closed during image capture to have uniform lighting and to eliminate shadow formation due to ambient lighting. The background colour has been selected as black for easy processing of grapevine leaves. With this system, 100 images belonging to each of the five different grapevine leaves varieties were obtained just before the grape harvest have different sizes: Ak, Ala Idris, Büzgülü, Dimnit and Nazli.

2.2. Data augmentation

Increasing the number of data used in the training neural networks has an important effect on their success rate in deep learning [25]. Due to various reasons, it is not always possible to collect enough data especially avoiding repetition. The number of images in the database can be increased with parameters such as size, angle, translation, etc. in a very orderly manner, avoiding duplication of each other. All the actions conducted on raw images in order to increase the record number in the dataset are called data augmentation. The data augmentation also makes the database ensures data diversity. In the dataset created by the images collected by imaging methods, especially if the number of records in the dataset is big enough, it is possible to be two images that have the same angle and same size. However, in the artificially created images by the methods presented in Table 1, it is quite easy to avoid producing two images at the same angle and size as each other. To reveal the effects of mentioned data augmentation actions, they were separately conducted on a sample image and presented in Fig. 4. Angle, scaling factor, translation values used for data augmentation are randomly determined within the limits presented in Table 2.

In the dataset, the images are collected from five species of grapevine leaves called Ak, Ala Idris, Büzgülü, Dimnit, and Nazli. This dataset is available for researchers through the website http://www.muratkoklu.com/datasets/Grapevine_Leaves_Image_Dataset.rar. There are 100 images for each species of grapevine leaves. Four data augmentation techniques are conducted on each species separately and created 400 new samples for each species. Thus, by adding the original grapevine leaves images, there have been 500 images for each species. Therefore, there are a total of 2500 images of different grapevine leaves species in the dataset. In addition, all images are sized to be 512x512 pixels. At the end of the data augmentation operations such as scaling, translation and rotation, if any absence of background occurs, the image is filled with the background pattern.

2.3. Classification of the grapevine leaves via Fine-Tuning MobileNetv2 model

In this study, instead of creating a new deep learning architecture, MobileNetv2 [57,58] which is one of the popular pre-trained CNN models was used for the classification of grapevine leaves according to their species. There are many CNN models designed in different structures. These models have different advantages and disadvantages when

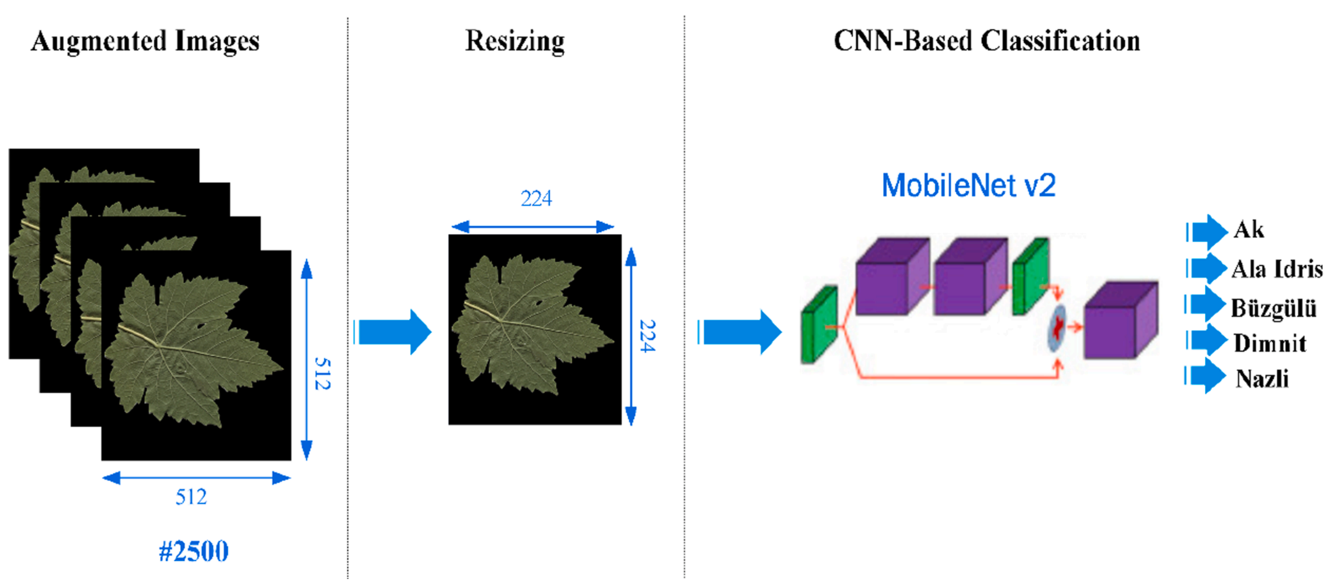

Fig. 5. Classification of grapevine leaves images with MobileNetv2.

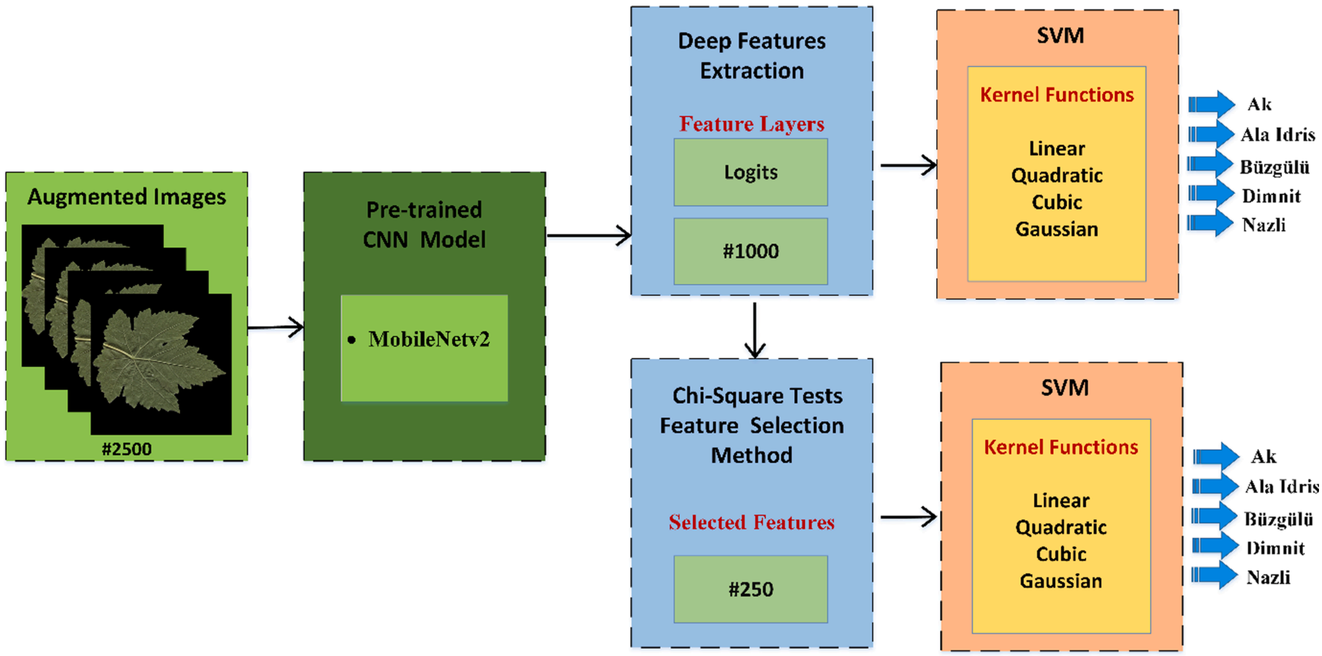

Fig 6. The process steps of deep feature extraction, classification with SVM and classification with SVM with feature selection.

compared to each other. The MobileNetv2 used in this study has advantages such as fast performance, few parameters and can be used in mobile applications [59].

After the data augmentation process, the MobileNetv2 model, one of the state-of-the-art CNN models, is employed in three different applications. First of all, as the first method, the Softmax layer, which is the output layer of the MobileNetv2, has been arranged to create 5 classes as output. The input of this model is a color image with a size of 224x224 pixel resolution. Therefore, all images were initially resized to 224x244 pixels, and then classification is performed using fine-tuning Mobilenetv2 as shown in Fig. 5. While 80% of the 2500 images in the database were used for training of CNN model, 20% were used for testing. Images used for training and testing include augmented images. In the training and test results, many metric values were calculated and the results were compared and discussed by using the calculated metric values.

2.4. Deep feature Extraction, feature selection and classification

As the second method, the classification is conducted with the SVM machine-learning algorithm using 1000 deep features extracted from the Logits layer of MobileNetv2. In other words, instead of feature extraction methods in traditional machine learning-based studies, MobileNetv2 is used here. The features extracted with CNN are fed as input to the SVM algorithm. In this classification, Linear, Quadratic, Cubic, and Gaussian SVM kernel functions have been employed and the results have been obtained. As the third method, 250 of 1000 features extracted from MobileNetv2 are selected by using Chi-Square Test feature selection method to improve classification results. Classification has been conducted by using the SVM machine learning algorithm with 250 selected features. Classification has been made using Linear, Quadratic, Cubic and Gaussian SVM kernel functions and the results have been compared. The general application flowchart of the second and third method is shown in Fig. 6.

2.4.1. Chi-Square test for feature selection

The Chi-square is a useful statistical method to create a rank about the effectivity of a cell in an information table. It is also known as the Pearson Chi-square test, or the Chi-square test. In the chi-square, the rank is associated with the difference of expected value and actual value of a cell. The cell Chi-square value is calculated by the following equation [60,61].

$$\chi_{i,j} = \frac{(O_{i,j} - E_{i,j})^2}{E_{i,j}} \tag{1}$$

Where:
$O_{i,j}$: The actual value of the associated cell
$E_{i,j}$: The expected value of the associated cell
$\chi_{i,j}$: The cell Chi-square value

In order to calculate the χ^2 value of a cell, the expected value has to be calculated first. To calculate the expected value of a cell, the marginals of the cell need to be calculated. A cell has two marginals, one of them is M_C, which is sum of the column where the cell is in, and the other one is M_R, which is sum of the row where the cell is in. The Chi-Square expecteds can be calculated by using the following equation [60].

$$E_{i,j} = \frac{M_R \times M_C}{N} \tag{2}$$

where N is sum of all the cells in the table. After calculating all the χ^2 values, to find the p-value of associated row, or column, or table, the sum of their χ^2 values $\sum\chi 2$ is calculated. Then this sum is used in probability density function $f(x,k)$. In this function, there are two inputs. One of them is $\sum\chi 2$, and the other one is degrees of freedom k. The k is calculated by the following formula [60].

$$k = (Numberofrows - 1) \times (Numberofcolumns - 1) \tag{3}$$

The probability density is calculated by the following equation [62].

$$f(x,k) = \begin{cases} \dfrac{x^{\frac{k}{2}-1}e^{-\frac{x}{2}}}{2^{\frac{k}{2}}\Gamma\left(\frac{k}{2}\right)} & x > 0 \\ 0, & x \leq 0 \end{cases} \tag{4}$$

The p-value is calculated by the following integration [62].

$$p - value = \int_{\sum\chi 2}^{\infty} f(x,k)dx \tag{5}$$

In many applications, this value is always obtained via Chi-square

Table 3
MobileNetv2 training parameters

Parameter name	Value
Execution Environment	GPU
Max Epochs	5
Learn Rate Drop Factor	0.1
Initial Learn Rate	0.001
Mini Batch Size	32
Optimization Algorithm	Stochastic Gradient Descent with Momentum (SGDM)

tables instead of calculating because the integration of this equation is not an easy way. The p-value is inverse proportional the meaningful of the data in the table. The lower p-value means high relation between class and cells. In feature selection, the table for which the chi-square value is to be calculated is constructed by grouping feature records versus the classes.

The p-value is calculated for each features. Using this value, features are sorted according to their relationship with the class. Then the most related 250 feature is selected to use in SVM classifier.

3. Results and discussion

In this section, the success of the three methods created using the state-of-the-art MobileNetv2 proposed for grapevine leaves classification is presented. MobileNetv2 is a pre-trained CNN model that uses images with 224x224x3 resolution and creates 1000 classes. A computer with an Intel core i7-7700HG processor, NVIDIA GeForce GTX 1050 4 GB display card and 16 GB of RAM is employed in the deep learning experiments in this study. In this study, three different methods based on state-of-art CNN model MobileNetv2 are presented.

In the first method, fine-tuning is performed on Mobilenetv2, the output layer is modified according to five classes. Then, 2500 grapevine leaves images in the database are divided into two groups as training data and test data with the ratio of 80% and 20% respectively. While the model is trained using the training dataset, the performance of the network is obtained using test dataset. In the proposed second and third methods, pre-trained MobileNetv2 is used to extract features. There are 1000 features in the Logits layer of the MobileNetv2 model. These features are extracted separately for the training and the test dataset. The features extracted in the second method proposed in this study are classified with Linear, Quadratic, Cubic and Gaussian kernels of SVM machine learning method. In the last method proposed in this study, 250

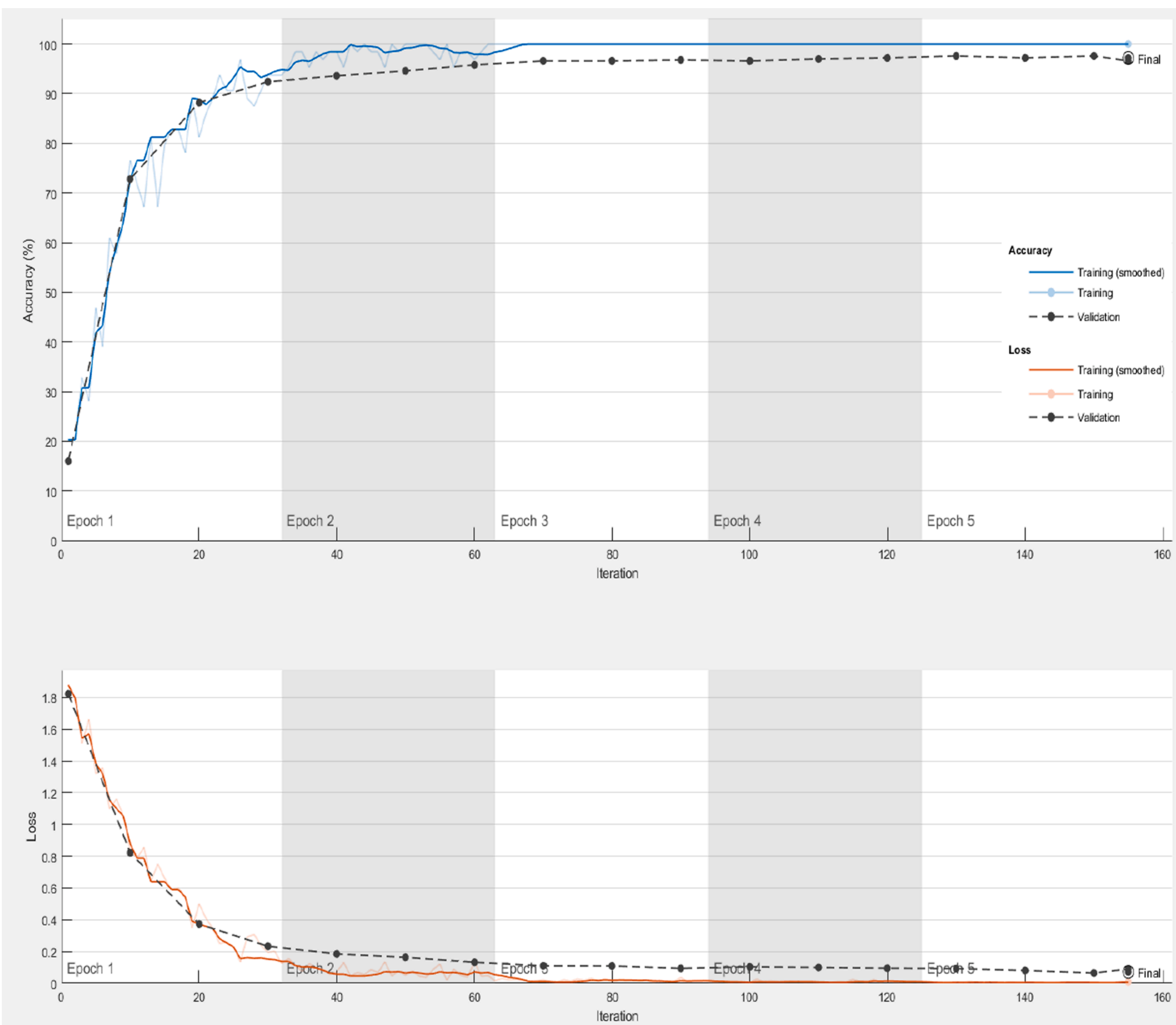

Fig. 7. Training and loss graphics of first method.

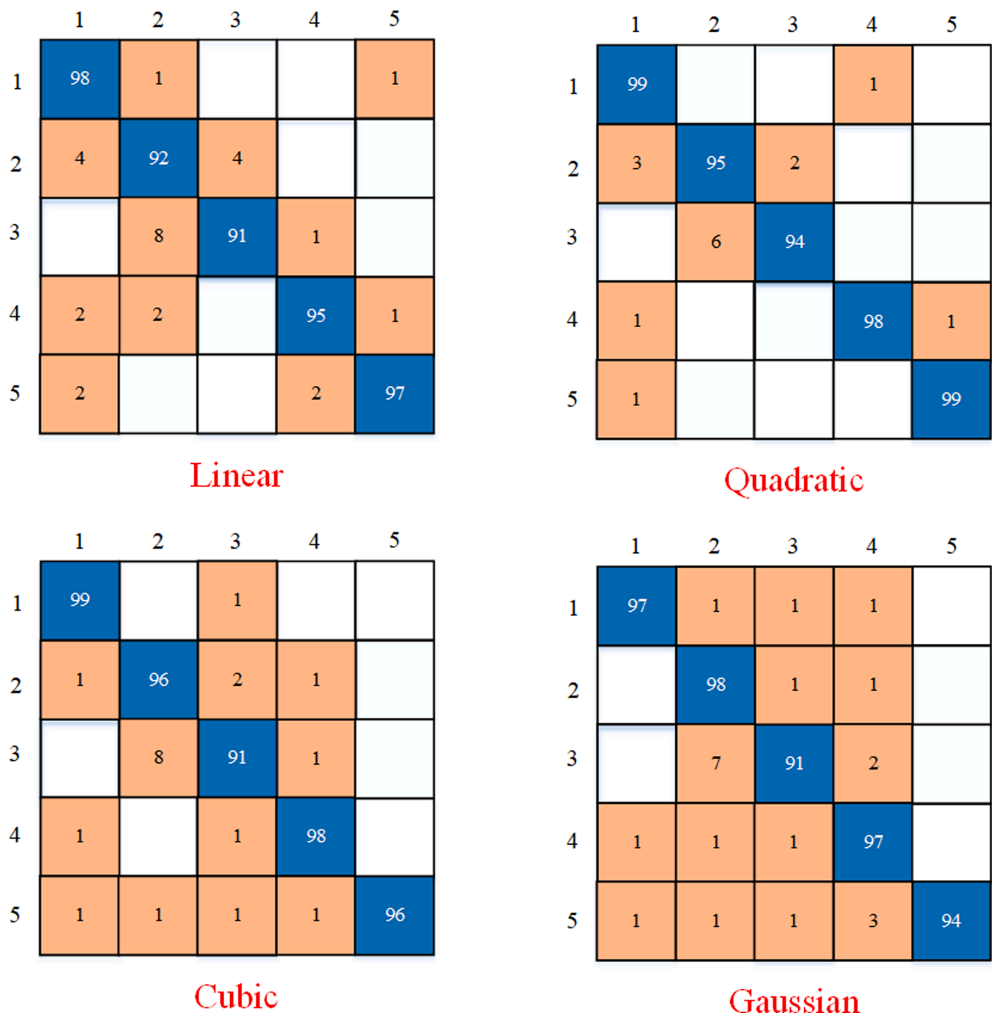

Fig. 8. Confusion matrices of SVM (250 features).

features are selected by Chi-square method from the 1000 features extracted from MobileNetv2′s Logits layer. Classification has been conducted using the selected features by Linear, Quadratic, Cubic and Gaussian kernels of SVM machine learning method.

Since the first proposed method was created in fine-tuning structure, training was carried out. The parameters adjusted for the training of the first method are given in Table 3. In the implementation of the other two methods, features extracted from the Logits layer of the pre-trained (via ImageNet) network are used. These features are not classified via softmax directly in the last two methods, but instead are evaluated using the SVM and feature selection steps.

Result values are obtained after training and testing for all methods proposed in the study. In the first method, the modified and trained MobileNetv2 achieves 97.20% accuracy. Fig. 7 is the training graph with MobileNetv2 for the first method. At the same time, this chart shows the test curve and the loss. The calculated Loss value in Fig. 7 shows the error in classification as a percentile. The Loss formula is as in Eq. (7).

In the last two experimental studies, the SVM method is employed for classification. In the second method where 1000 features of MobileNetv2 with pre-trained weights are classified with SVM, this method classifies the grapevine leaves with the accuracy of 96.40%. In the third approach where feature selection is made, the most successful classification accuracy is 97.60%. Fig. 8 shows the confusion matrices for the different SVM kernel functions of the last method.

In confusion matrices, the columns represent the actual class and the rows represent the predicted class. Also, the five species of grapevine leaves used in this study, Ak, Ala Idris, Büzgülü, Dimnit and Nazli are labeled as 1,2,3,4 and 5, respectively. It is observed that, feature

Table 4
Performance metrics of MobileNetv2 based methods

Model	Kernel	Acc. (%)	Spec.	Prec.	Sens.	F1-Score	MCC
MobileNetv2	–	97.20	0.9930	0.9721	0.9720	0.9720	0.9651
SVM with 1000 features	Linear	93.60	0.9840	0.9369	0.9360	0.9362	0.9204
	Quadratic	96.40	0.9910	0.9646	0.9640	0.9641	0.9553
	Cubic	96.00	0.9900	0.9606	0.9600	0.9600	0.9502
	Gaussian	95.40	0.9885	0.9556	0.9540	0.9541	0.9431
SVM with 250 selected features	Linear	94.60	0.9865	0.9467	0.9460	0.9461	0.9328
	Quadratic	97.00	0.9925	0.9703	0.9700	0.9700	0.9626
	Cubic	**97.60**	**0.9940**	**0.9762**	**0.9760**	**0.9760**	**0.9701**
	Gaussian	96.80	0.9920	0.9686	0.9680	0.9680	0.9602

selection process conducted by using Chi-Square method makes classification performance better in terms of accuracy.

The results of the above three methods are presented in detail in Table 3. As seen in Table 3, the most successful classification is obtained with the SVM with feature selection method with 97.60% accuracy. In addition, Accuracy, Precision, Sensitivity, Specificity, F1-score and MCC are calculated according to the results of classifications and presented in the Table 4. The formulas of the calculated metrics are given between Eqs. (6)–(12) [25].

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} x100 \quad (6)$$

$$Loss = (100 - Accuracy)/100 \quad (7)$$

$$Precision = \frac{TP}{TP + FP} \quad (8)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (9)$$

$$Specificity = \frac{TN}{TN + FP} \quad (10)$$

$$F1 - score = \frac{2TP}{2TP + FP + FN} \quad (11)$$

$$MCC = \frac{(TP^*TN) - (FN^*FP)}{\sqrt{(TP + FN)^*(TN + FP)^*(TP + FP)^*(TN + FN)}} \quad (12)$$

TP: True Positive *N*: True Negative *FP*: False Positive *FN*: False Negative

4. Conclusion

Grapevine leaves are classified using three different methods using MobileNetv2, one of the popular CNN models. Background color has been chosen as black for the leaves to be easily distinguished from the background in the images. A total of 500 images are obtained by taking 100 images for each type. The number of the grapevine image has been increased up to 2500 using different data augmentation techniques. Thus, sufficient data amount is reached for deep network training. Three different methods have been proposed for the classification of the grapevine leaves images. In the first method, a fine-tuned MobileNetv2 is used for classification. In the second method, features are extracted from the Logits layer of the pre-trained MobileNetv2 model. These features are classified using different SVM core functions. As the third method, features extracted from the Logits layer of the MobileNetv2 model are selected with the Chi-Square method and classified with SVM. The obtained classification accuracies are compared with each other. The results show the success of grapevine leaves classification by CNN-based, feature-selected, SVM classifier. In addition, the feature selection improves the classification performance with lower number of features. This study will shed light on future studies that CNN models can be applied to the determination of grapevine leave type. In future studies, applications will be made with different CNN models for comparison purposes.

CRediT authorship contribution statement

Murat Koklu: Investigation, Methodology, Writing – review & editing. **M. Fahri Unlersen:** Methodology, Writing – review & editing. **Ilker Ali Ozkan:** Investigation, Supervision. **M. Fatih Aslan:** Writing – review & editing. **Kadir Sabanci:** Methodology, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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