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Convolutional Neural Networks Based Hybrid Deep Model for Grapevine Leaves Detection and Classification

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ABSTRACT

The problem of determining the type of grapevine leave (GL) has an important place in the agricultural field and especially in the field of viticulture. It is a foodstuff that is consumed as a table especially in every Middle Eastern country and its export to Europe has been increasing in recent years. GL are usually consumed as wraps. Considering the economic situation of such a widely used plant, the determination of the plant type is very important. Because early intervention is required for diseases that will occur in the plant. As it is known, early diagnosis will facilitate treatment. In this study, leaf types were classified using artificial intelligence techniques in order to help experts diagnose the type of vine leaf. In addition, a hybrid model was proposed for classification processes. In this proposed hybrid model, feature maps were first extracted from the Resnet50 and Inceptionv3 deep models and these features were combined. Then, the most valuable features in the feature map were selected with the Neighborhood Component Analysis (NCA) method. Then, the feature map containing the most valuable features was classified in the best-known supervised classification methods. The proposed hybrid model reached an accuracy value of 89.2%. Thus, it has been determined that the proposed hybrid model achieves a highly competitive accuracy value in the classification of vine leaf images and can be used for this purpose.

1. INTRODUCTION

It is known that total grape production worldwide is approximately 61.95 million tons, on approximately 7.3 million hectares. Its leaves are as important as the grapes in terms of nutrition and economy. Grapevine leaves (GL) are consumed in Middle Eastern countries by wrapping boiled rice and bulgur in food such as boiled rice and bulgur. It contains plenty of vitamins, minerals and dietary fiber in its GL structure [1, 2]. This very beneficial food can be served cold or hot. When GL is evaluated economically, it is known that some types can provide more profit than grapes. While vinegar, wine or juice can be made from grapes, using its leaves in meals is quite attractive for farmers [3, 4]. In addition to all these positive aspects, another important point is that not every grape leaf can be used in meals. The reason for this is that thick, hairy leaves or bitter types are not liked by consumers. People prefer to use the hairless, thin and sour types in meals. It is extremely important to determine the types of such a beneficial and economically profitable food. However, it is not an easy process to determine this. GL types are very similar to each other. Even farmers or experts who have devoted their years to this work may have difficulty distinguishing some types and may make mistakes. In addition, diseases can occur in GL types and it is necessary to determine the type before starting the treatment. Because the same treatment cannot be applied to every GL type. Or the same dosage of medicine cannot be given. Species determination is also extremely important for early diagnosis of the disease that will occur and early start of treatment. It should be known that early diagnosis is also extremely important for the plant to hold on to life [5, 6].

In recent years, image classification, segmentation, and processing have been studied extensively. Artificial intelligence techniques are used in many areas such as agriculture, medicine, defense industry, aviation, and logistics. In recent years, artificial intelligence-supported applications in the field of agriculture have made the work of farmers and experts much easier [7-10].

In this study, a hybrid deep model developed based on deep learning architectures, a sub-branch of artificial intelligence techniques, is proposed for the classification of GL.

1.1 Related works

The following are a few papers that use deep learning techniques in the literature to classify GL.

Koklu et al. [5] converted a dataset containing 500 GL images with 5 classes into a dataset containing 2500 images by multiplexing them. They stated that they tried to classify

2500 images using the Mobilenetv2 architecture in their study. They classified GL types with 97.6% accuracy. However, data augmentation methods were used in this study. Data augmentation methods can reveal the overlearning of deep architectures. In this way, models can show high accuracy rates.

In their study classifying tea buds, Paranavithana and Kalansuriya [11] developed a Convolutional Neural Network (CNN) based model for determining the suitability of tea buds. It is stated that the accuracy rate of the model they proposed is 70.15%. They stated that they used a two-class dataset consisting of 10000 images in this study.

Ahmed et al. [12] have increased the number of images in the 5-class GL dataset from 500 to 2800 by multiplexing them. In this dataset, 98.02% accuracy was achieved by using the Densenet201 deep architecture. It is seen that this study did not work with the raw dataset but image multiplexing was performed.

Pereira et al. [13] proposed an Alexnet-based model for classifying grape species. It is stated that the proposed model has an accuracy of 89.75% in classifying grape species.

Nagi and Tripathy [14] proposed a CNN-based method to classify diseases occurring on grapevine leaves. The dataset they used included 3423 images. They conducted their experiments on a dataset with a total of 4 classes, 3 diseased and 1 healthy. They stated that the success rate of the proposed model in detecting diseased grapevine leaves was 98.4%.

Alessandrini et al. [15] proposed a machine learning-based method for the detection of esca disease in grape leaves. It was stated that the proposed model achieved 99.48% accuracy on the data allocated for testing. The authors stated that a total of 2-class dataset was used in their study, diseased and non-disease.

1.2 Contribution and novelty

In this study, GL images were tried to be classified according to their types using artificial intelligence techniques from computer-aided recognition systems. The basis of the study is to demonstrate the success of CNN-based architectures in revealing the differences that the human eye has difficulty distinguishing when examining the GL image. First of all, Inceptionv3 and Resnet50 architectures were used to reveal the features of GL images. The feature maps obtained using these two architectures were combined. The basic logic of feature fusion is to bring together the valuable features obtained by different architectures. Thus, the features obtained from different pixels of the same image were brought together. Therefore, it was aimed to increase the success of deep architectures in the classification process. In the last step, the NCA optimization technique was used to the obtained feature map. Thanks to this stage, where the training time will be shortened, the model works faster since the number of features is decreased. Finally, the optimized feature map was tested and classified with the best-known machine learning techniques.

1.3 Organization of paper

General information regarding the significance of GL classification is provided in the paper's first section. The study's dataset, deep architectures, optimization strategy, suggested hybrid model, and machine learning approaches are all covered in the second section. The outcomes of the experiment are presented in the third section. In the fourth section, the experimental results obtained are evaluated. The study's findings are examined in the fifth and final section.

2. MATERIAL AND METHODS

In this section of the article, the data set used during the experiments, deep learning methods, machine learning techniques and finally the optimization technique NCA are presented.

2.1 Dataset

The publicly available 5-class GL dataset was utilized for the experiments. Each class contains 100 images. There are a total of 500 images in the dataset [5]. The species in the dataset are Ak, Ala İdris, Buz Gülü, Dimnit, and Nazlı. Some randomly selected sample images from each class in the GL dataset are given in Figure 1.

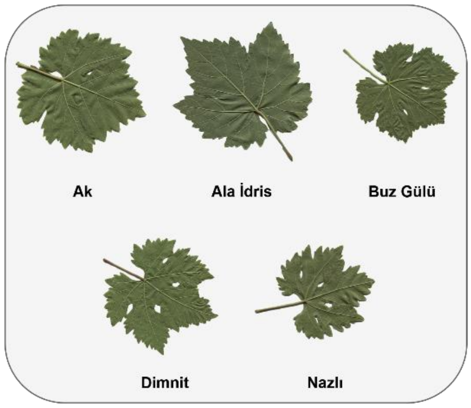

Figure 1. GL images examples from the dataset

2.2 CNN models, machine learning methods and NCA

Deep learning techniques have widely been used in disease and species detection in recent years. The reason behind the high accuracy classification success of deep learning is due to its ability to select effective features from images. Deep learning methods extract features without expert knowledge. This can be shown as the most important aspect that distinguishes it from others. It is known that the less expert knowledge is needed, the more time and cost will be saved. Many well-known CNN architectures are known. The most commonly used deep architectures were preferred during the experiments. These deep architectures are Resnet50 [16], Alexnet [17], Efficientnetb0 [18], Inceptionv3 [19], Mobilenetv2 [20], and Shufflenet [21] architectures.

Alexnet architecture consists of 25 layers. The input layer of this model accepts images of 227×227×3 size. Resnet architecture was proposed by He et al. [16], they tried to solve the convergence problem by rejoining the redundant blocks to the network. The Efficientb0 architecture was designed with a philosophy that basically scales the depth and width of the neural network equally. Efficientnetb0 accepts the image size of 224×224×3, just like the Resnet50 architecture. Inception architecture was developed by Google. This architecture, which accepts 299×299×3 images, consists of 48 layers. Mobilenetv2 architecture is also known as a lightweight model. It can be used effectively by devices with low computing power. Shufflenet architecture is a CNN architecture used in devices with limited processing power, such as Mobilenet architecture. It uses channel mixing and point group convolution operations to reduce computational cost without losing accuracy. This architecture, which has 50 layers, takes 224×224×3 images as input.

The machine learning classifiers used in the study are Support Vector Machine (SVM) [22], Decision Trees (DT) [23], k-Nearest Neighbors (KNN) [24], Naive Bayes (NB) [25], Neural Network (NN) [26], and Logistic Regression (LR) [27]. In addition, in this study, the NCA method was used to select the most valuable features while obtaining the feature map. Thanks to NCA [28, 29], the training time of the model was shortened and effective results could be obtained with fewer features. The NCA technique does not delete any features. This method is a technique for selecting effective ones from the large feature map.

2.3 Proposed model

In this study, a CNN-based hybrid model is proposed that enables species detection from GL images. In the study, firstly, the 6 best-known deep architectures were tested independently on the same dataset under equal conditions. The two deep architectures (Resnet50, Inceptionv3) that achieved the highest accuracy value were selected to form the basis of our proposed model. Each image in the dataset has 1000 features. The features obtained from each architecture selected as the base are combined. In this way, the proposed model is trained with different features of the same image. In this way, the proposed model will have the opportunity to receive better training.

The feature map that resulted from this stage was subjected to the NCA dimension reduction approach. Following the merging process, the feature map's size was 500x2000, whereas the NCA size reduction approach produced a feature map that was 500×450. Six distinct machine-learning classifiers were used to classify the resultant feature map. Figure 2 displays the suggested model's block diagram.

During the experiments, features were extracted from the last fully connected (FC) layer of each architecture since the most valuable features were located in the last FC of the deep architectures. When examining Figure 2, the Inceptionv3 architecture is utilized to obtain the feature map, and the "predictions" layer of this architecture is utilized. The "fc1000" layer of the Resnet50 architecture provided the feature map.

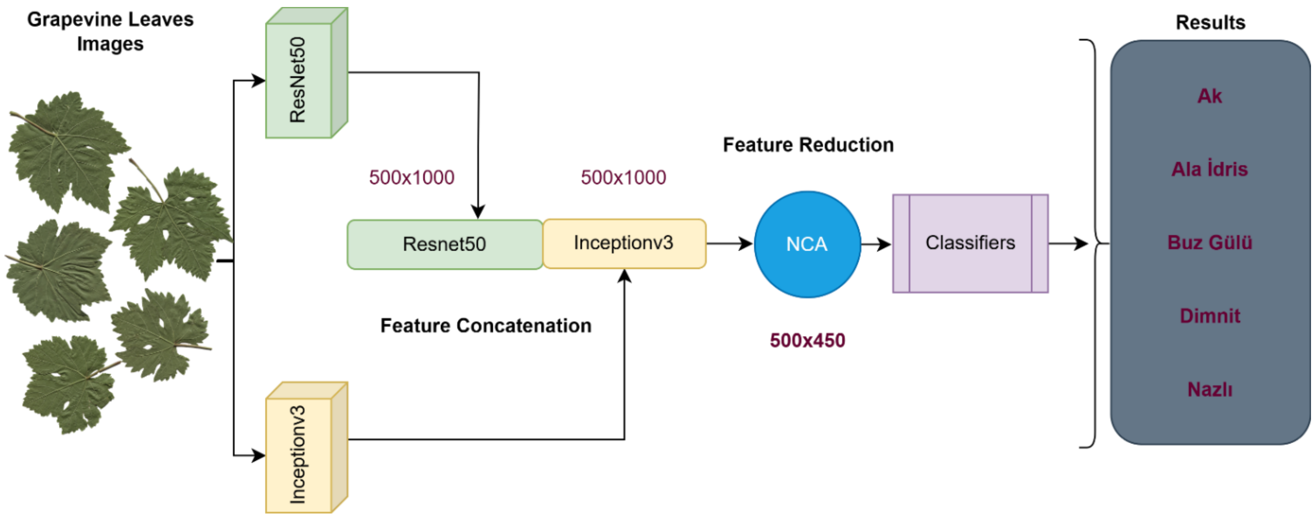

Figure 2. Block diagram of the suggested model

3. EXPERIMENTAL RESULTS

All experiments conducted in the study were carried out under equal conditions. Table 1 includes hyperparameter information of deep models. In addition, the experiments were conducted on a laptop with an i7 processor, 32 GB RAM, and 6 GB graphics card. When using machine learning classifiers, a cross-validation ratio of 5 was chosen. The following measures were used to compare the methods' performances: F-score (F1), Accuracy (Acc), Specific (Spc), Precision (Pre), Sensitivity (Sens), False Discovery Rate (FDR), False Negative Rate (FNR), and False Positive Rate (FPR) [29]. Ak, Ala İdris, Buz Gülü, Dimnit, and Nazlı classes in the confusion matrix are represented as 1, 2, 3, 4, and 5 respectively.

3.1 Results of pre-trained CNN models

Six deep architectures were evaluated on the GL dataset. During the experiments, the GL dataset was split into two as training and testing. The training set was determined to be 70% and the test set to be 30%. Table 1 lists the hyperparameters employed in these deep models.

Table 1. Hyperparameters of deep architectures

Environment	Max Epochs	Mini Batch Size	Learn Rate	Optimization
Matlab 2023	10	8	1e-4	SGDM

The accuracy values derived from the deep models are presented in Table 2.

Table 2. Accuracy of CNN models

Efficientnetb0	MobilenetV2	Resnet50
60%	80%	83.33%
Alexnet	**InceptionV3**	**Shufflenet**
79.33%	**83.33%**	78.67%

During the experiments, it was observed that Resnet50 and Inceptionv3 architectures achieved the highest accuracy value. Both of these architectures reached 83.33% accuracy value. These two architectures are followed by Mobilenetv2, Alexnet, Shufflenet, and Efficientnetb0 architectures with 80%, 79.33%, 78.67%, and 60% accuracy, respectively. With an accuracy score of 60%, the Efficientnetb0 architecture has the lowest accuracy value among the deep models used in this work. Table 3 shows the confusion matrices derived from deep models.

Table 3. Confusion matrices get from state-of-the-art architectures

Efficientnetb0

1	17	4		8	1
2	3	16	8	1	2
3	2	3	22	2	1
4	5	5	4	16	
5	1	2	4	4	19
	1	**2**	**3**	**4**	**5**

MobilenetV2

1	24		3	2	1
2		22	8		
3	1		28	1	
4	5	1	4	20	
5			3	1	26
	1	**2**	**3**	**4**	**5**

InceptionV3

1	22	1	3	3	1
2		19	10		1
3			29	1	
4	1	1	2	26	
5				1	29
	1	**2**	**3**	**4**	**5**

Resnet50

1	21	1	1	7	
2	1	21	6	1	1
3	1		29		
4			1	28	1
5				4	26
	1	**2**	**3**	**4**	**5**

Shufflenet

1	25	1		4	
2		21	8		1
3			27	3	
4	3	1	5	21	
5	1		3	2	24
	1	**2**	**3**	**4**	**5**

Alexnet

1	23	4		1	2
2	7	21	2		
3	2		28		
4	6	3	1	20	
5				3	27
	1	**2**	**3**	**4**	**5**

Of the 150-test data, 125 were properly identified by the InceptionV3 model, but 25 were incorrectly classified. Buz Gülü and Nazli classes were classified with the highest accuracy. The accuracy rate is 96.66%. Inceptionv3 architecture correctly classified 29 out of 30 test Buz Gülü images, only 1 of which was incorrectly classified. Inceptionv3 architecture correctly classified 19 of 30 test Ala İdris images and incorrectly classified 11. Of the 11 incorrectly classified images, 10 were classified as Buz Gülü. Finally, the Inceptionv3 architecture classified 26 of the 30 Dimnit test images correctly and 4 incorrectly.

In addition, the Resnet50 architecture, like the Inceptionv3 architecture, correctly classified 29 of the 30 Buz Gülü test images. It achieved the highest class-based accuracy value of 96.66%. Resnet50 architecture correctly classified 21 of 30 Ak and Ala İdris images. In other words, the accuracy rates of these two classes are equal. Resnet50 correctly classified 28 of the Dimnit class images and incorrectly classified 2 of them. Finally, the Resnet50 architecture correctly classified 26 of the 30 Nazlı images.

When the confusion matrix in Table 3 is checked, it can be seen that the architecture that gives the lowest accuracy value is Efficientnetb0. This architecture achieved the highest class-based accuracy in Buz Gülü, while the lowest class-based accuracy was achieved in Ala İdris and Dimnit classes.

It has been observed that deep architectures can produce different results on the same dataset under equal conditions. In addition, 10 epochs of training processes in all tests were sufficient to flatten the accuracy and loss curves.

3.2 NCA, deep architecture, and feature extraction

In the second stage of the study on the GL image dataset, features of each image were extracted. Then, these features were optimized with the NCA technique. No features were deleted, only the most valuable features were selected. NCA parameters were determined equally for each architecture. In the experiments conducted in the second stage of the study, the cross-validation value was selected as 5. The reduced feature map was tested with machine learning classifiers. In CNN architectures, each image has 1000 features. The size of the feature maps get using deep models is 500×1000 in each CNN model. The new feature map size that is produced when the NCA method is applied independently to the retrieved features is 500×142 in InceptionV3 and 500×76 in Resnet50. Table 4 lists the accuracy values obtained from deep models.

Table 5 lists the confusion matrices derived from two architectures.

Table 4. CNN Models + NCA + machine learning methods

CNN Models / Feature Numbers	Values for Accuracy Derived from the Algorithms (%)					
	DT	LR	NB	SVM	KNN	NN
InceptionV3(142)	43.40	75.80	69.40	**82**	73	76.8
Resnet50(76)	51.80	76.80	72.40	**83.20**	76.80	79.20

Table 5. Confusion matrices of deep models

InceptionV3

1	85	7	5	3	
2	6	77	13	2	2
3	6	8	80	5	1
4	7	2	5	81	5
5	4	3	3	3	87
	1	**2**	**3**	**4**	**5**

Resnet50

1	86	2	3	9	
2	2	85	8	2	3
3	12	8	74	5	1
4	7	1	9	79	4
5	3	2	1	2	92
	1	**2**	**3**	**4**	**5**

The highest accuracy value for the categorization of the features extracted using the Resnet50 model is 83.20%, according to the accuracy rates provided in Table 4 and the confusion matrices in Table 5.

Resnet50 architecture correctly classified 92 of 100 Nazli images and achieved a class-based accuracy value of 92%. After Nazli, this model achieved the highest class-based accuracy in the Ak, Ala İdris, Dimnit, and Buz Gülü classes, respectively.

Since the architectures given in Table 4 could not achieve higher accuracy values than the experiments in Table 3, which is the first experiment, a model based on the combined use of features extracted from both architectures was proposed within the scope of this study.

3.3 Proposed model

In the last stage of this study where GL images are classified, the model we proposed is available. The concatenated process was applied to 1000 features extracted for each image from Resnet50 and InceptionV3 architectures. The reason for extracting features with these two models is that they achieved more successful results than the other 4 different models tested in the study. After this process, the size of the feature map became 500×2000. After this process, NCA optimum features were selected. After the NCA process, the size of the feature map decreased to 450. In other words, the size of the feature map became 500×450 in the last stage. Default parameter values were used for the NCA method. Verbose's value was set at 1, and SGD was chosen as the solvent. The accuracy values derived from traditional machine learning methods in the suggested model are presented in Table 6.

Table 6. Accuracy values derived from the suggested model

	Accuracy Values Derived from the Algorithms (%)					
	DT	LR	NB	SVM	KNN	NN
Proposed model	50.80	78.80	72.60	**89.20**	77.60	88

Several supervised intelligent classification techniques are used to categorize the features that were taken from the suggested hybrid model. At 89.20% accuracy, SVM (Quadratic) produced the best results. In the GL dataset, the DT classifier achieved the worst accuracy value among six different classifiers. In the model proposed in Table 6, after the SVM classifier, the highest accuracy values were achieved by NN, LR, KNN, NB and DT, respectively. The DT classifier obtained much worse results than the other classifiers. The confusion matrices derived from the employed supervised learning techniques are shown in Table 7.

Table 7. Confusion matrices derived from the proposed model

	Proposed Method + SVM				
1	93		2	4	1
2	2	91	6		1
3	7	6	83	4	
4	4	2	5	86	3
5	1	1	2	3	93
	1	**2**	**3**	**4**	**5**

When the confusion matrix of the proposed model given in Table 7 is examined, it is seen that 93 of the 100 GL images belonging to the Ak and Nazlı types were classified correctly, while only 7 were classified incorrectly. The proposed model achieved a class-based accuracy value of 93% in these two types. The proposed model performed the worst classification on the Buz Gülü type. It correctly classified 83 of 100 GL images and reached 83% accuracy. The proposed hybrid model incorrectly predicted 17 out of 100 images belonging to the Buz Gülü class. It incorrectly placed 7 of the incorrectly predicted images in the Ak class, 6 in the Ala idris class, and 4 in the Dimnit class. It was observed that this Buz Gülü leaf type was similar to the other 4 leaf types except for the Nazlı leaf type. Additionally, when Table 8 was examined, it was seen that the highest class-based F1 value was in the Nazlı species with 93.94%. Performance metrics of the proposed model are listed in Table 8.

In this study, the accuracy metric has a very important place in classification problems. The data in the GL dataset is balanced. There are 100 images in each class. Since it would be a healthier approach to evaluate the problem in terms of different metrics, the performance metrics of the proposed model shown in Table 8 were also examined. It was observed that the lowest FPR value (1.74%) belongs to the Nazlı class, which has the highest accuracy value. It was observed that the class with the lowest FNR (5.10%) value belongs to the Nazlı species, which is the class with the highest accuracy.

Table 8. Performance values of the proposed model (%)

	Acc.	Spc.	Sens.	Pre.	FPR	F1	FNR	FDR
Ak	93	98.21	86.91	93	1.78	89.85	13.08	7
Ala İdris	91	97.75	91	91	2.25	91	9	9
Buz Gülü	83	95.77	84.69	83	4.22	83.83	15.30	17
Dimnit	86	96.52	88.65	86	3.47	87.31	11.34	14
Nazlı	93	98.25	94.89	93	1.74	93.94	5.10	7

Table 9. Values of the performance metrics obtained from the deep models

	Softmax (%)	DT (%)	LR (%)	NB (%)	SVM (%)	KNN (%)	NN (%)
Efficientnetb0	60	-	-	-	-	-	-
MobilenetV2	80	-	-	-	-	-	-
InceptionV3	83.33	43.40	75.80	69.40	82	73	76.80
Alexnet	79.33	-	-	-	-	-	-
Resnet50	83.33	51.80	76.80	72.40	83.20	76.80	79.20
Shufflenet	78.67	-	-	-	-	-	-
Proposed model	-	50.80	78.80	72.60	**89.20**	77.60	88

When Table 8 is checked, it can be seen that the data is consistent and can be used effectively in the classification of GL species. Table 9 shows the accuracy rates achieved by both the best-known CNN architectures and our proposed hybrid model on machine learning classifiers.

4. DISCUSSION

Recognizing plant species is a subject that requires a great deal of expertise. Correctly identifying these species is essential for the detection of diseases and the determination of the amount of fertilizer, nitrogen, and water to be used for plant development [30, 31]. Leaves play an important role in determining plant diseases, plant species and development [32]. Grape leaves have an important place in Mediterranean tables. It is known that grape leaves bring more income than grapes in some cases. As it is known, CNN architectures are quite popular in image classification and detection problems. The main reason for this popularity is the high accuracy it shows. The fact that it does not require expert knowledge is the most important reason for its widespread use. This study proposes a hybrid model that detects grape leaf species with a very competitive accuracy rate. If the grape leaf type cannot be determined early, the loss of money, time and labor spent on the development of the plant or the treatment of its disease can reach extremely serious dimensions [33, 34]. Some studies in the literature on the classification of GL types are given in Table 10. In order for this study to produce reliable results, the original dataset was used. Data augmentation methods were not used. Data augmentation was performed in all studies that produced higher accuracy than the model proposed in this study and listed in Table 10. Data augmentation is not preferred even though it is known that higher accuracy will be achieved, as it will generally cause the model to over-fitting. The main purpose of this study is to propose an artificial intelligence-based model to classify GL images that are not diseased but are very similar to each other and are extremely difficult to distinguish, rather than just diseased images.

This study has some limitations. The most important limitation is that the GL species in the dataset generally include grape species found on the Mediterranean coast. It does not include all GL species. Another limitation is the small number of images in the dataset. Another limitation is that the data are taken from a single center and different conditions are not taken into account.

Among the future studies, it is planned to develop deep models that classify GL species with higher accuracy. Additionally, testing the hybrid model by increasing the number of images and leaf images of grape species that are unknown or less known to experts will allow us to obtain more realistic results.

Table 10. Studies on classification of GL

Reference	Method	Data Augmentation	Number of Images	Number of Class	Acc (%)
Koklu et al. [5]	MobilenetV2	Yes	2500	5	97.6
Paranavithana and Kalansuriya [11]	CNN	No	10000	2	70.15
Ahmed et al. [12]	Densenet201	Yes	2800	5	98.02
Proposed model	(InceptionV3 + Resnet50) + NCA + SVM	**No**	500	5	**89.20**

5. CONCLUSION

Automatic realization of GL types with computer-aided systems is an important process. In this study, it was observed that the hybrid model developed for the detection of GL types reached a very competitive accuracy value of 89.20%. This accuracy value shows that a practical and reliable system that can help experts in the detection of GL types, where early diagnosis and intervention are critical, is possible. Since the study was conducted with original data and no data augmentation was made, the success achieved by the proposed model was seen to be extremely satisfactory, and it is thought that it can be used for the detection of GL types.

DATA AVAILABILITY

The used publicly available Grapevine Leaves Image Dataset can be reached at http://www.muratkoklu.com/datasets/Grapevine_Leaves_Image_Dataset.rar.

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