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Research Article

Classification of tea leaves diseases by developed CNN, feature fusion, and classifier based model

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ABSTRACT

Due to the increase in the world population day by day, the amount of food needed is also increasing day by day. Diseases that occur in plants reduce the amount and quality of the product obtained. In this study, a computer-aided model was developed to detect diseases in tea leaves. Because plant diseases can be difficult and misleading to detect with the naked eye by farmers or experts. It is very important to detect diseases in tea leaves using artificial intelligence methods. Three Convolutional Neural Network (CNN) architectures accepted in the literature were used as the basis for the classification of diseases in tea leaves. With these three CNN architectures, feature maps of the images in the data set were obtained. After combining the feature maps obtained in each architecture, they were classified in the Linear Discriminant classifier. In addition, the performance of the proposed model was compared with seven CNN architectures accepted in the literature. The performance of the models used in the study was evaluated using different performance measurement metrics. The obtained results showed that the proposed model can be used to classify diseases in tea leaves.

1. Introduction

Tea is one of the most consumed beverages in the world for years. In the process of growing tea, it is adversely affected by different diseases. Understanding tea leaf diseases manually are quite difficult and time-consuming. At the same time, in case of a disease in the plant, the amount and quality of the product obtained decreases. In this respect, the quality of the product obtained from plants depends on the protection of plants from diseases. Therefore, due to the importance of early detection of diseases that reduce productivity in tea production, computer-aided models are widely used in the detection of such diseases [1,2]. Thanks to computer-aided systems, the amount of product and the quality of the product will increase with the early detection of diseases in plant leaves.

The aim of this study is to detect diseases in tea leaves with various pre-trained deep-learning models and the proposed model. A public dataset of 8 classes consisting of various diseases was used to classify the diseases in the tea leaf. In the study, results were obtained from the CNN architectures Alexnet [3], Resnet101 [4], Googlenet [5], Shufflenet [6], Efficientnetb0 [7], Darknet53 [8], and MobilenetV2 [9]. The same training parameters were used in the training of the models. In addition, a model has been developed for the classification of diseases in tea leaves. When the results obtained in the developed model are compared with other CNN architectures used in the study, it has been observed that the proposed model is more successful.

Since tea is an important agricultural product both economically and in terms of consumption, and it is difficult to detect diseases in plant leaves with the naked eye, studies on tea leaves have been carried out in the literature.

Latha et al. used a CNN architecture to classify tea leaf diseases in their study. In the study, they used 80% (688 images) of the 8-class dataset consisting of 860 images for

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training and 20% (172 images) for testing. The model used in the study achieved an accuracy value of 94.45%. In the study, researchers observed that the accuracy of the proposed model increased when the epoch value increased. Therefore, they stated that it is important to find the most appropriate epoch value [1].

Gayathri et al. used a convolutional neural network model called LeNet to detect diseases in tea leaves. They used a 4-class dataset containing 80 images of tea leaf diseases. Sensitivity and Specificity were used to evaluate the performance of the model [2].

Hossain et al. developed an automated system based on the Support Vector Machine (SVM) classifier with fewer features that can detect, identify, and classify three-class tea leaf diseases consisting of Brown blight and Algal leaf diseases, which are the two most common and healthy tea leaf diseases. They applied image processing techniques to extract various features from the images, including 150 training and 50 tests. 10 features are taken to train the classifier. With their proposed method, the researchers were able to classify 300 ms faster and more than 90% more accurately than in previous studies using SVM [10].

Xiaoxiao et al. used a convolutional neural network-based model in their study to prevent diseases in tea leaves. First, they used image segmentation and data augmentation and fed the data to the network in this way. In order to achieve a higher recognition accuracy in the CNN architecture, the learning rate has often adjusted the number of iterations. While the accuracy of CNN-related disease recognition was 93.75% in the SVM classifier [11].

Chen et al. developed a CNN model called LeafNet with feature extraction filters of different sizes that automatically extract the features of diseases in tea leaves from the images. It is used to extract features with DSIFT (intensive scale invariant feature transformation) and create a BOVW-Bag of visual words model. Afterward, they classified seven different diseases using the multilayer perceptron, SVM, and their proposed LeafNet classifier. While the LeafNet algorithm achieved 90.16% classification accuracy in recognizing tea leaf disease, they achieved 70.77% accuracy in multilayer perceptron and 60.62% in SVM. In their study, they compared the performances of two feature extraction methods and three classifiers [12].

The remainder of the article is organized as follows; In the second part of the article, the materials and methods used in the study, the results of the application in the third part, and the conclusion in the last part are presented.

2. Background

In this section, the data set used in the study, CNN architectures, and the proposed model are examined. CNN architectures have been used frequently in image processing problems in recent years. In image classification problems, feature extraction is done manually in traditional methods. Therefore, expert knowledge is of great importance in traditional machine-learning methods. Since feature extraction is done by the model in CNN architectures, there is no need for expert knowledge. In the study, seven different CNN architectures accepted in the literature were used. In order to classify images into eight different classes, one of which is healthy, results were obtained from the pre-trained architectures of Alexnet, Resnet101, Googlenet, Efficientnetb0, Darknet53, Mobilenetv2, Shufflenet, which are popular architectures of CNN in image classification. The models receive the data in the input layer in the dimensions presented in Table 1.

Table 1. Input dimensions of models

Alexnet	227x227
Resnet101, Googlenet	224x224
Mobilenetv2, Efficientnetb0, Shufflenet	224x224
Darknet53	256x256

2.1. Dataset

The tea dataset used in this study was taken from the Kaggle platform [13]. The images used in the study have 8 different classes of seven common tea leaf diseases. Seven of the classes are red leaf spot (RLS), algal leaf spot (ALS), bird eye spot (BES), gray light (GL), white spot (WS), anthracnose (ANT), brown light (BL). Another class is healthy (H). The dataset used in the study consists of 885 JPG images in total [6]. The number of images for each class is presented in Table 2.

Table 2. Total number of images of the classes

RLS	ALS	BES	GL	WS	ANT	BL	H
143	113	100	100	142	100	113	74

80% of the images with 8 different classes in the data set were used in the training set and 20% in the test set. This dataset has been classified with pre-trained convolutional neural network architectures. Images showing a sample from each class taken from the dataset are given in Figure 1.

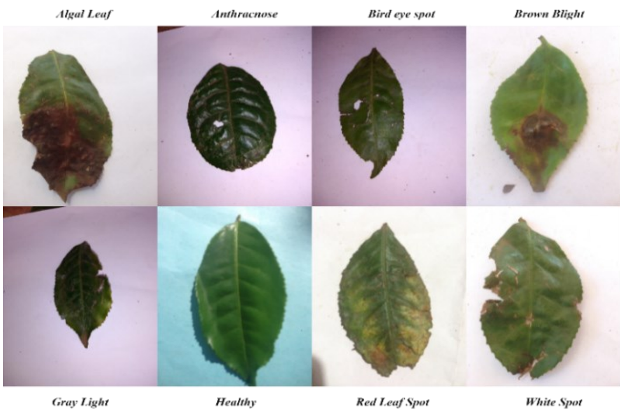

Figure 1. Sample images from the dataset

2.2. Suggested Model

The disease detection achieved high classification performance by using the pre-trained CNN-based models included in the study as a hybrid to classify the images with 8 different classes in the dataset consisting of 885 tea leaf images. Efficientnetb0, Resnet101, Shufflenet architectures were used as the base in the study. In the proposed hybrid model, feature maps of the images in the dataset were obtained by using the Efficientnetb0, Resnet101, Shufflenet architectures. The number of features obtained for each image from each architecture is 1000. Then, a new feature map with 3000 features was obtained for each image by combining the features obtained from the three CNN architectures. The size of the feature map obtained at the end of this process was 850x3000. The feature map obtained in the last step of the proposed model has been classified using Linear Discriminant [14] classifiers. The diagram of the proposed method is presented in Figure 2.

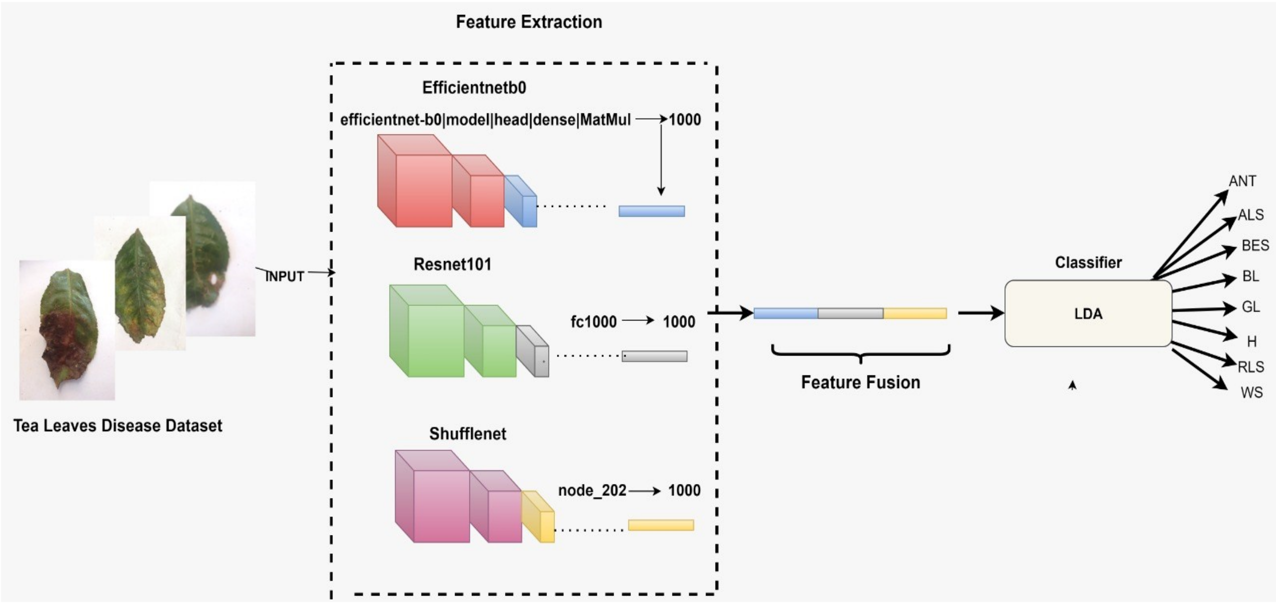

Figure 2. Suggested Model

3. Experimental Results

In this section, information about the seven different CNN architectures used in the study and the classification results of the proposed model are included. This study for the classification of diseases in tea leaves was carried out in Matlab R2021a environment on a computer with i7 processor and 16 GB RAM memory. In this study, 80% of the images in the data set were used in the training process of the models and 20% in the testing process.

Different performance measurement parameters were used to measure the performance of the models and to compare the performances of the models. Accuracy, Sensitivity, Specificity and F1-score are the main performance measurement parameters used [15].

The first architecture used in the classification process of tea leaf diseases is Alexnet. The complexity matrix obtained in the Alexnet architecture is shown in Table 3.

Table 3. Confusion matrix of Alexnet

Alexnet		ANT	ALS	BES	BL	GL	H	RLS	WS
True Class	ANT	12		8					
	ALS		19						4
	BES	1		18		1			
	BL				23				
	GL			3		17			
	H						15		
	RLS		1					28	
	WS				12				16
		Predicted Class							

As seen in Table 3, when looking at the confusion matrix in general, the Alexnet model predicted 148 of the 178 images used for the test correctly and predicted 30 images incorrectly. As seen in the complexity matrix, the most successful classes are BB and H classes with 100% accuracy. All of the images used for testing in this class were predicted correctly. The most failed class is the WS class. The accuracy rate in this class is 57.14%. In this category, the Alexnet model predicted 16 of the 28 images correctly, while predicting 12 incorrectly. Alexnet incorrectly guessed 12 images belonging to the WS class and placed them in the BB class. With the Alexnet model, an accuracy value of 83.15% was obtained.

Another architecture used in the classification of diseases in tea leaves is the Resnet101 architecture. The confusion matrix of the Resnet101 architecture is shown in Table 4.

Table 4. Confusion matrix of Resnet101

	Resnet101	ANT	ALS	BES	BL	GL	H	RLS	WS
True Class	ANT	17		2		1			
	ALS		22		1				
	BES	1		17		1		1	
	BL		3		15				5
	GL	6				14			
	H						15		
	RLS							29	
	WS		1		9				18
		Predicted Class							

According to Table 4, when looking at the confusion matrix in general, the Resnet101 model predicted 147 of the 178 images used for the test correctly and predicted 31 images incorrectly. As seen in the confusion matrix, the most successful classes are RLS and H classes with 100% accuracy. All of the images used for the test in this class were predicted correctly. The most failed class is the WS class. The accuracy rate in this class is 64.28%. Resnet101 model predicted 18 of 28 images correctly and 10 of them incorrectly predicted in this class. 1 image belonging to the WS class was placed in the ALS class, and 9 images were incorrectly predicted and placed in the BL class. With the Resnet101 model, an accuracy value of 82.58% was obtained. The confusion matrix of the Googlenet architecture is shown in Table 5.

Table 5. Confusion matrix of Googlenet

	GoogleNet	ANT	ALS	BES	BL	GL	H	RLS	WS
True Class	ANT	13		4		1		2	
	ALS		16		4			1	2
	BES			18		2			
	BL		1		19				3
	GL	2		2		16			
	H						15		
	RLS		2					27	
	WS		4		9				15
		Predicted Class							

As seen in Table 5, when looking at the confusion matrix in general, the Googlenet model predicted 139 of the 178 images used for the test correctly and estimated 39 images incorrectly. As seen in the confusion matrix, the most successful classes were obtained in the H class with 100% accuracy, and then in the RLS class with 93.10% accuracy. Of the 29 images used for testing in the RLF class, 27 were predicted correctly. The most failed class is the WS class. The accuracy rate in this class is 53.57%. In this category, the Googlenet model predicted 15 of the 28 images correctly and predicted 13 incorrectly. He incorrectly predicted and placed 4 images belonging to the WS class in the ALS class and 9 images in the BL class. As with other models, high accuracy could not be obtained in the WS class in the Googlenet model. With the Googlenet model, an accuracy value of 78.09% was obtained. The confusion matrix of the Darknet53 architecture is shown in Table 6.

Table 6. Confusion matrix of Darknet53

	DarkNet53	ANT	ALS	BES	BL	GL	H	RLS	WS
True Class	ANT	14		4		2			
	ALS		22		1				
	BES			18		2			
	BL				19			1	3
	GL	6				14			
	H						15		
	RLS							29	
	WS				12			1	15
		Predicted Class							

When the confusion matrix in Table 6 is examined, the

Darknet53 model correctly predicted and classified 146 of the 178 images used for the test, while it predicted 32 images incorrectly. As seen in the complexity matrix, the most successful classes are RLS and H classes with 100% accuracy. All of the images used for testing in these classes were predicted correctly. The most failed class is the WS class. The accuracy rate in this class is 53.57%. The Darknet53 model correctly predicted and classified 15 of the 28 images in this category, while it predicted 13 incorrectly. He incorrectly guessed and placed 1 image belonging to the WS class in the RLS class and 12 images in the BL class. With the Darknet53 model, an accuracy value of 82.02% was obtained. The confusion matrix of the Efficientnetb0 is shown in Table 7.

Table 7. Confusion matrix of Efficientnetb0

	Efficientnetb0	ANT	ALS	BES	BL	GL	H	RLS	WS
True Class	ANT	12		5				3	
	ALS		11		2	1		1	8
	BES	10		6		4			
	BL		3		10			1	9
	GL	7		1		12			
	H						15		
	RLS							28	1
	WS		1		2			1	24
		Predicted Class							

According to Table 7, when looking at the confusion matrix in general, the Efficientnetb0 model correctly predicted and classified 118 of the 178 images used for the test, while it predicted 60 images incorrectly. As can be seen in the confusion matrix, the most successful class is class H with 100% accuracy, and all of the images used for the test were placed in the correct class. Following this class, the second highest value is the RLS class with an accuracy of 96.55%. In this class, 28 of the 29 images used for the test were predicted correctly. 1 incorrectly predicted image was placed in the WS class. The most failed class is the BES class. The accuracy rate in this class is 30%. The Efficientnetb0 model correctly predicted and classified 6 of the 20 images in this category, while it predicted 14 incorrectly. He incorrectly guessed and placed 10 images belonging to the BES class in the ANT class and 4 images in the GL class. In addition, the number of images that the Efficientnetb0 model predicted incorrectly in ALS and BL classes is more than the number of images it predicted correctly. The obtained accuracy rate is 47.82% in the ALS class and 43.47% in the BL class. With the Efficientnetb0 model, an accuracy value of 66.29% was obtained. The confusion matrix of the MobilenetV2 architecture is shown in Table 8.

Table 8. Confusion matrix of MobilenetV2

	MobilenetV2	ANT	ALS	BES	BL	GL	H	RLS	WS
True Class	ANT	14		5		1			
	ALS	1	16		2				4
	BES	4		13		3			
	BL				20				3
	GL	4				16			
	H						15		
	RLS							29	
	WS				14				14
		Predicted Class							

As seen in Table 8, when looking at the confusion matrix in general, the MobilenetV2 model correctly predicted and classified 137 of the 178 images used for the test, while it predicted 41 images incorrectly. As seen in the confusion matrix, the most successful classes are RLS and H classes with 100% accuracy. All of the images used for testing in this class were predicted correctly. The most failed class is the WS class. The accuracy rate in this class is 50%. While the MobilenetV2 model predicted and classified 14 of the 28 images correctly in this category, it predicted 14 of them incorrectly. 14 images were incorrectly predicted and placed in the BL class when they should have been in the WS class. An accuracy value of 76.97% was obtained with the MobilenetV2 model. The confusion matrix of the ShuffleNet architecture is shown in Table 9.

Table 9. Confusion matrix of ShuffleNet

	ShufleNet	ANT	ALS	BES	BL	GL	H	RLS	WS
True Class	ANT	17		3					
	ALS		23						
	BES	2		15		2		1	
	BL				16				7
	GL	3		1		16			
	H						15		
	RLS							29	
	WS		4		5				19
		Predicted Class							

As seen in Table 9, when looking at the confusion matrix in general, the Shufflenet model correctly predicted and classified 150 of the 178 images used for the test, while it predicted 28 images incorrectly. As seen in the confusion matrix, the most successful classes are RLS, ALS, and H classes with 100% accuracy. All of the images used for testing in these classes were predicted correctly. The most failed class is the WS class. The accuracy rate in this class is 67.85%. With the ShuffleNet model, an accuracy value of 84.27% was obtained.

The classification of diseases in the tea leaf was carried out with the recently developed hybrid model. The confusion matrix obtained in the developed hybrid model is presented in Table 10.

Table 10. Confusion matrix of Proposed Model

Proposed Model		ANT	ALS	BES	BL	GL	H	RLS	WS
True Class	ANT	82		10		8			
	ALS		104		4				5
	BES	14		84		2			
	BL		2		100				11
	GL	4		3		93			
	H						73		1
	RLS		1					140	2
	WS		3		6			1	132
		Predicted Class							

Looking at the confusion matrix in Table 10 in general, it predicted and classified 808 of the 885 images used for the proposed model correctly, while it predicted 77 images incorrectly. As seen in the confusion matrix, the most successful class is H with 98.64% accuracy, and 97.90% RLS classes. The most unsuccessful class is ANT. The accuracy rate in this class is 82%. Performance evaluation metrics of the proposed model are presented in Table 11.

Table 11. Performance values of the proposed model

	Accuracy	Sensitivity	Specificity	F1
ANT	82%	82%	97.70%	82%
ALS	92.03%	94.54%	98.83%	93.27%
BES	84%	86.59%	97.96%	85.27%
BL	88.49%	90.90%	98.32%	89.68%
GL	93%	90.29%	99.10%	91.62%
H	98.64%	100%	99.87%	99.31%
RLS	97.90%	99.29%	99.59%	98.59%
WS	92.95%	87.41%	98.63%	90.10%

According to Table 11, it is seen that the highest accuracy value was obtained in the H class with 98.64%, and the lowest accuracy value was obtained in the ANT class with 82%. The accuracy values of the models are compared in Figure 3.

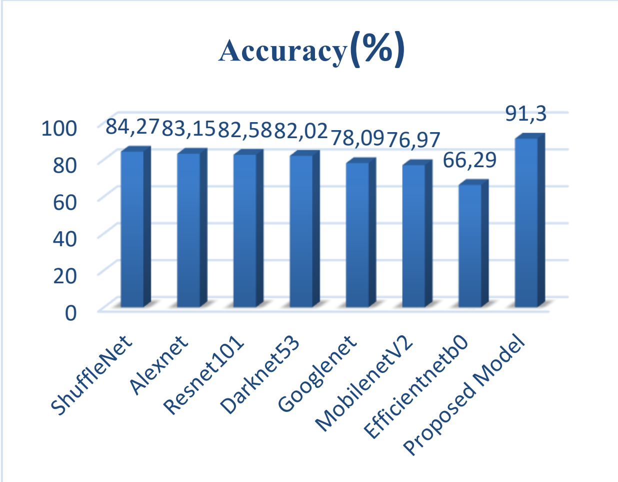

Figure 3. Accuracy rates of the models

When Figure 3 is examined, among the 7 different CNN architectures used in the study, the highest accuracy value was obtained in Shufflenet architecture with 84.27%, and the lowest accuracy value was obtained in Efficientnetb0 architecture with 66.29%. In the proposed hybrid model, the highest accuracy value was obtained at 91.3%.

4. Experimental Results

Technological developments play an important role as well as making positive contributions to the field of agriculture as in every field. Diseases in plants are difficult to detect by traditional methods. In addition, traditional methods are more likely to delay treatment. It is very important to detect and classify the disease by using artificial intelligence methods for the tea leaf, which is one of the plants that are important in terms of the agricultural economy. Therefore, in this application, pre-trained deep models were used to detect diseases in tea leaves and a hybrid-based model was proposed. An accuracy value of 91.3% was obtained in the proposed model. This ratio shows that the proposed model can be used in the classification of diseases in tea leaves.

Conflict of Interest

There is no conflict of interest.

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