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Identification of Rice Leaf Blight Disease by Using Image Processing Techniques

Çeltik Yanıklığı Hastalığının Görüntü İşleme Teknikleri Kullanılarak Tespit Edilmesi

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IDENTIFICATION OF RICE LEAF BLIGHT DISEASE BY USING İMAGE PROCESSING TECHNIQUESHAY

ABSTRACT:

In rice plant, accurate and timely detection of diseases helps to start agricultural practices on time and thus reduces economic losses significantly. For this purpose, image processing techniques were used to identify and classify the rice leaf blight disease (*Pyricularia oryzae Cav.*). In image processing, a clustering method was used for the segmentation of the diseased part, the non-diseased part and the background. Images of rice leaf blight disease were taken both from the ground and with the aid of a drone. Levenberg-Marquardt training algorithm was preferred in artificial neural networks model. While the RMS, R^2 and error values of the test data of MEITG proposed for identification were 0.000017, 0.9999 and 0.019%, respectively, they were found as 0.000007, 0.9999 and 0.002% for MERITD. The MCITG and MCRITD models presented for classification were found to have classification success rates of 92.2 percent and 100 percent, respectively. The results obtained for the identification and classification of rice leaf blight disease show the feasibility and effectiveness of the proposed model.

Keywords: *Artificial Neural Networks, Rice Leaf Blight Disease, Disease Detection.*

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ÇELTİK YANIKLIĞI HASTALIĞININ GÖRÜNTÜ İŞLEME TEKNİKLERİ KULLANILARAK TESPİT EDİLMESİ

ÖZ:

Çeltik bitkisinde, hastalıkların doğru olarak ve zamanında tespiti, zirai mücadele uygulamalarının zamanında başlatılmasına ve böylece ekonomik kayıpların önemli ölçüde azalmasına yardımcı olmaktadır. Bu amaçla, çeltik yanıklığı hastalığının (*Pyricularia oryzae Cav.*) tanımlanması ve sınıflandırılması için görüntü işleme teknikleri kullanılmıştır. Görüntü işlemede, hastalıklı kısım, hastalık olmayan kısım ve arka planın segmentasyonu için bir kümeleme yöntemi kullanılmıştır. Çeltik yanıklığı hastalığı görüntüleri, hem yerden hem de dron yardımıyla alınmıştır. Yapay sinir ağları modellerinde, Levenberg-Marquardt eğitim algoritması tercih edilmiştir. Tanımlama için önerilen ModelTYGA'nin test verilerine ait RMS, R^2 ve hata değerleri sırasıyla 0.000017, 0.9999 ve %0.019 bulunurken ModelTDUGA'nın ise 0.000007, 0.9999 ve %0.002 olarak bulunmuştur. Sınıflandırma için önerilen ModelSYGA ve ModelSDUGA modellerinin sınıflandırma başarıları sırasıyla %92.2 ve %100 olarak elde edilmiştir. Çeltik yanıklığı hastalığının tanımlanması ve sınıflandırılması için elde edilen sonuçlar, önerilen yöntemin uygulanabilirliğini ve etkinliğini göstermektedir.

Anahtar Kelimeler: *Yapay Sinir Ağları, Çeltik Yanıklığı Hastalığı, Hastalık Tespiti.*

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1. INTRODUCTION

Grains are the most widely used product group and they have an important place in human and animal nutrition. Rice plant, which is differentiated from other grains with its ability to germinate in water and to benefit from oxygen dissolved in water, is difficult to grow; however, its economic return is quite high (Öztürk and Akçay, 2010). Rice (*Oryza sativa L.*) is the second most consumed product in the world after wheat and is an essential nutrient for approximately 3.5 billion people. With the increase in population, the demand and consumption of rice also increase. Rice diseases cause large amount of loss in yield (Abed-Ashtiani et al., 2012). In order to meet the increasing food demand, rice production needs to be increased by more than 40% until 2030 (Khush, 2005; Roy-Barman and Chattoo, 2005). The nutrient content of rice includes protein, carbohydrate, fat and many vitamins (Juliano, 1985; Verma and Shukla, 2011; Alvaro et al., 2018).

Rice grows better between latitudes 35° South and 45° North, at an altitude of 1500 m above the sea, in low water permeability, deep, loamy, soil conditions which are rich in nutrients and which have a pH between 4.5 and 7.5 (Sürek, 2002; Xiongs et al., 2011). While the rice production area was 167.249.103 hectares in 2017, the amount of production was 769.657.791 tons. China, India, and Indonesia are in the top three in rice production, meeting 68% of world rice production. In our country, 900.000 tons of rice were produced in 109.505 hectares in the same year. 71% of this production occurred in the Marmara region, while the Western Black Sea region of the Black Sea region covered 26%. These two regions constitute 97% of the total rice production in Turkey. Rice yield has been 460 kg/da in the world and 822 kg/da in our country (Anonymous, 2019). Rice production in our country has changed over the years. Factors such as climatic conditions, breeding techniques, and insufficient cultural treatments cause fluctuations in yield.

There are many problematic diseases in rice farming. Three major diseases that can cause economic problems in our country are rice leaf blight disease (*Pyricularia oryzae*), crown rot (*Fusarium moniliforme*) and brown spot disease (*Helmithosporium oryzae*) (Sürek, 1995; Prajapati et al., 2017). Rice diseases have a devastating effect on rice production. In addition, they are also a big threat for food safety. The most important of these diseases is rice leaf blight disease. Its symptoms on the plant are seen on the leaves, ligule, sheath, nodes, panicle, peduncle, and grain husk. These symptoms are generally diamond-shaped, with two pointed ends, gray in the middle, with brown-reddish spots around; on the legule, they look like tightened with a thread, on the stalk they appear as an oil stain and petroleum green colored mold develops on these stains; no grains but white colored husks develop on the panicle (Bonman, 1992; Sürek, 2002; Devi and Neelamegam, 2018).

If the disease progresses, the plant may dry out completely, and sometimes no crops may be taken from the field. In addition to reducing the amount of product taken, the disease can also reduce the quality of the products. The disease can be carried with seeds, plant waste and soil (Sürek, 2002; Elmacı, 2012). Factors such as high relative humidity (over 80%), excessive nitrogen fertilization, late planting, high plant density, use of cold irrigation water and dehydration of the plant play an important role in the emergence of the disease (Feakin, 1971). By paying attention to these negativities, the disease is fought with cultural measures and chemical methods such as growing resistant varieties, alternate planting, removing diseased plant residues from the field after harvesting (Sürek, 2002). Rice leaf blight disease can cause loses of ranging from 30 to 100% in both the world and our country under suitable conditions (Göbelez, 1953; Feakin, 1971; Kihoro et al., 2013). For this reason, the diagnosis and identification of rice diseases play a very important role in ensuring high quality and high yields (Yang et al., 2017).

In many countries, agriculture is one of the major sources of income for people. The plants needed are grown by farmers depending on environmental conditions. However, farmers are faced with many problems such as natural disasters, water scarcity, and plant diseases (Pantazi et al., 2019). Most of the problems can be reduced by providing some technical features, detecting diseases on time and taking precautions can increase productivity and therefore the need to seek experts may not be necessary (El-kazzaz et al., 2015). Recently, the identification and classification of plant diseases has become one of the important research topics in agriculture (Yusof et al., 2018).

It is very important to recognize plant diseases in order to prevent the losses in the amount of agricultural product and yield (Kim et al., 2018). Studies conducted on the recognition of plant diseases mean that diseases are observable visible patterns in plants (Astonkar and Shandilya, 2018). The process of identifying plant diseases is more difficult with the traditional method. The traditional method requires more process time, more workload and experience and knowledge of experts in plant diseases. In order to eliminate these negativities, it is necessary to find out leaf diseases with new methods and techniques in evaluating agricultural products, increasing market value and meeting quality standards. Early and accurate identification and diagnosis of plant diseases is an important factor in plant production and enables reducing both qualitative and quantitative losses in

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crop yields. For this purpose, a large number of advanced techniques such as image processing and artificial neural networks are used for disease detection. Image processing techniques are one of the methods used for identifying plant diseases (Singh and Misra, 2017; Singh et al., 2018).

Image processing steps for disease recognition include image acquisition, image pre-processing, image fragmentation, feature extraction and finally classification (Kamal et al., 2018). These techniques can only be applied on the external appearance of infected plants (Patricio and Rieder, 2018). In most plants, leaves are generally an important source for detecting plant diseases. Symptoms of plant diseases vary for different plants. Plant diseases are different in terms of color, size and shape and each disease has its own unique characteristics. Some diseases are yellow, while some are brown (Barbedo et al., 2016). Some diseases have the same shapes, but different colors, while some have the same color but a different shape. After finding out the diseased and non-diseased normal parts, the features related to the disease can be found (Sladojevic et al., 2016).

Artificial neural networks (ANN) are used in many of the studies conducted in the field of engineering for model development. ANN is used especially in modelling non-linear and complicated structures and efficient results are obtained. While many of the models obtained with classical methods in similar structures give insufficient results, ANN models give more successful results. ANN has important potential in the classification and identification of agricultural products (Dubey et al., 2006; Visen et al., 2002).

The structure of ANN is made up of three layers; input, hidden and output, which consist of neurons and are connected to each other with weights (Figure 1). Weights are determined by a large number of existing learning algorithms. Backpropagation is a learning algorithm and it is one of the most widely used. Backpropagation algorithm is used to minimize the total error by changing the weights. The inputs coming from the previous layer are multiplied with the weights of the corresponding links. Each neuron processes the inputs weighted with a transfer function in order to produce its output. Transfer function may be linear or non-linear. The data are grouped into two as a training and test set. In this way, the weight values which minimize the difference between actual and estimated output values are found (Kalogirou, 2001).

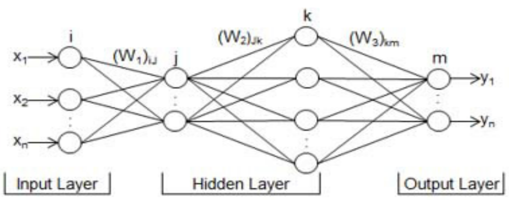


Figure 1. General structure of ANN.

Manual detection of plant diseases occurs as the observation of experts with the naked eye or testing in the laboratory and requires visual observation expertise, while laboratory testing is a time consuming and expensive method (Mohanty et al., 2016; Shrivastava et al., 2019). Disease detection process is difficult with this method, and sometimes there is also a possiblity of making mistakes while identifying the disease type (Mahlein, 2016). Rice plant production has been decreasing gradually in recent years due to the insufficiency of suitable methods to detect rice plant leaf diseases (Pinki et al., 2017). To overcome this, a suitable and rapid identification system for rice leaf diseases is required.

The present study recommends a method to identify rice leaf blight disease by using diseased images. For this purpose, the data set was prepared by taking the images of rice plant from cultivated areas. Background elimination for image processing was performed by preprocessing. The parts of diseased and non-diseased leaves were determined and ANN techniques were used for classification.

2. MATERIAL AND METHOD

In the study, images of rice leaf blight disease (*Pyricularia oryzae cav.*) were used as material. Of the 250 images used, 200 were taken from the ground and 50 were taken remotely with a drone.

The drone used in the study (DJI Mavic Pro) has a camera which can take photos in 2.3 inches and 12.3 megapixel resolution and record 4K video with C4K (4096 x 2160) and UHD (4K 3840 x 2160) resolution. The camera which was used for taking images from the ground (Lenovo Moto Z (XT1650-03)) has a resolution of 13.0 megapixels and was used as fixed on a specially designed apparatus (Figure 2).

Adobe Photoshop program and MATLAB program (Image Processing Toolbox) were used for image processing and MATLAB (Neural Network Toolbox) program was used for artificial neural network modelling.

Rice leaf blight disease was first identified by experts through ground observations. Images were taken after the disease was confirmed. The images were obtained with two different methods as from the ground and remotely with drone. The images taken were processed with image processing programs and the diseased parts were determined. In the study, these parts were evaluated as actual diseased areas (ADA) and diseased areas obtained with image processing (DAIP). Image taking started from the fourth week of May (the first appearance of the disease) and continued until the end of July. Images were taken on sunny, windless and rainless days. Ground images were taken with a camera placed on an apparatus designed to be vertical to the land surface. Images from the ground were taken from 80, 120 and 140 cm, depending on the growth period of the plant. Remote image taking with drone was carried out with a camera placed on the drone. The images were taken from 200 cm high with drone.

Figure 2. The drone used in the study.

In the methods of image taking from the ground and remote image taking with a drone, classifications were made based on the severity of the disease. The ground image acquisition method consists of 10 classes, while the drone remote image acquisition method consists of 4 classes. Disease severity was determined by taking weighted averages separately for both methods.

2.1. Image Processing

Image processing was carried out by taking the image, filtering the image, turning the image into a gray image, thresholding the image and determining the dimensions of the image (Gonzalez and Woods, 2008; Ağın and Taner, 2015). Filtering was carried out to remove the unwanted spots and stains on the image.

2.2. Obtaining Gray Images

The images of plants can be green in different shades depending on water, fertilizer and climatic conditions. Using colorful images in image processing may cause various problems in the differentiation of diseased and non-diseased areas (Husin et al., 2012). The images were converted into gray images in order to solve these problems and reach more accurate problems quickly.

2.3. Obtaining Black and White Images

Black and white images were obtained by converting the areas corresponding to gray tone (non-diseased) into black and the rest of the areas (diseased) into white with appropriate thresholding value on the gray image. The appropriate thresholding value was determined by reducing all of the green areas until they became black in steps of 0.01 from 1 to 0. With black and white image, non-diseased areas were obtained as black and the diseased areas were obtained as white.

2.4. Determining the Diseased Areas

With the image processing commands applied in the previous steps on original images, spatial losses occur, especially when removing disease-free areas from the image. Later, diseased areas obtained with image processing (DAIP) were measured in pixels.

All diseased areas in the image were cropped to the tolerance threshold of 25% in order to identify the actual diseased areas (ADA) with minimum loss. Later, the diseased areas were transferred to a white background in the same size as the original image and the actual diseased areas (ADA) in these images were identified (Figure 3).

The severity of the disease on the image was calculated by proportioning the diseased areas in the image, that is, the total number of pixels that make up that area, to the number of total pixels forming the image.

First Image	Gray Image	Black-White Image	Image of The Diseased Area Detected

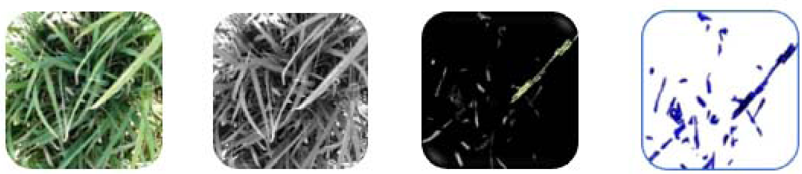


Figure 3. Image processing application example.

2.5. Artifical Neural Networks

In the study, models were developed for both image taking methods, image taking from the ground and remote image taking with drone with artificial neural networks (ANN) in order to estimate the diseased areas obtained with image processing (DAIP) and actual diseased areas (ADA). In addition, classes were created according to the severity of disease in the methods of image taking from the ground and remote image taking with drone. These classes were classified with ANN.

2.6. Estimation of the Diseased Areas with Artificial Neural Networks

In the present study, ANN techniques were used to estimate the actual diseased areas (ADA). In ANN method, the diseased areas obtained with image processing (DAIP) were included as input data, while actual diseased areas (ADA) were included as output data.

In the ANN model developed with image taking from the ground (MEITG), a total of 200 data - 160 for training, 10 for validation and 30 for test - were used.

In the ANN model developed with remote image taking with drone (MERITD), a total of 50 data - 37 for training, 3 for validation and 10 for test - were used.

In both methods, the input and output data used were normalized between 0 and 1 (Purushothaman and Srinivasa, 1994). For normalization;

$$y_{nor} = \frac{y - y_{\min}}{y_{\max} - y_{\min}} \tag{1}$$

formula was used. In order to obtain the actual values from normalized values, (y) values were calculated from the same formula.

In ANN models, Feed Forward Backprop, Multilayer Perceptron (MLP) network structure was used. Back propagation (BP) algorithm in this network improves the performance of the network by changing the weights and minimizes total error (Jacobs, 1988; Minai and Williams, 1990). Levenberg-Marquardt (LM) algorithm was used as training algorithm (Levenberg, 1944; Marquardt, 1963).

In the development of ANN models, tansig, logsig and linear (purelin) transfer functions were used in hidden and output layers (Vogl et al., 1988).

2.7. Classification with Artificial Neural Networks

There were 10 classes in the method of image taking from the ground, while there were 4 classes in the method of remote image taking with drone. Feed Forward Back Propagation network structure was used in the classification of output parameters (Jacobs, 1988; Minai and Williams, 1990). Levenberg-Marquardt (TrainLM) and Scaled Conjugate Gradiant (TrainSCG) training algorithms were used (Levenberg, 1944; Marquardt, 1963). Hyperbolic Sigmoid Tangent was used in the hidden layer, while Softmax Transfer function was used in the output layer (Bishop, 1995).

In the ANN model of image taking from the ground method (MCITG), 117 data were used for training, 32 data were used for validation and 51 data were used for testing. In the ANN model of remote image taking with drone method (MCRITD), 30 data were used for training, 5 data were used for validation and 15 data were used for testing.

The classification was grouped into two;"accurate" and "inaccurate". The neuron number of the output layer of ANN was chosen as the number of classes. While the network was trained with the training set, the over-learning status was prevented by checking with the validation set. The success of the network was checked with test set.

Models with single hidden layer were tested in this study. The optimum number of neurons was found by increasing the number of neurons in the hidden layer (Taner et al., 2010). The networks were compared by increasing the number of neurons 10 times, from 10 to 100. Ten more trials were made, ranging from five less neurons to five more neurons of the network that passed the test with minimum errors. Next, the network with the lowest error was chosen.

After the training of the network was successfully terminated, the network was tested with test data (Kalogirou, 2001). The success of ANN models was determined with the total error value of the network. Error Matrix was used to express the success of the network numerically (Bishop, 1995).

2.8. Determining the Performance of Estimation Models

In order to find out the performances of the results, RMSE and R2 values, which are based on mean error concept and which are widely used, were calculated with the following formulas (Bechtler et al., 2001).

$$\mathrm{RMSE} = \left(\frac{1}{m}\sum_{i=1}^{m}(x_{1i} - x_i)^2\right)^{1/2} \tag{2}$$

$$R^2 = 1 - \left[\left(\sum_{i=1}^{m}(x_{1i} - x_i)^2\right) / \left(\sum_{i=1}^{m}(x_{1i})^2\right)\right] \tag{3}$$

The relative error between the actual values and estimated values was calculated with the help of the following equation (Bağırkan, 1993).

$$\varepsilon = \frac{100}{m}\sum_{i=1}^{m}\left|\frac{(x_i - x_{1i})}{x_{1i}}\right| \quad (4)$$

2.9. Assessment of Classification Success

Classificaton success is generally determined with the total error value of the network. For success in classification networks, it must be shown whether the specific classification was done correctly. Error matrix was used to express the state of success numerically (Figure 4). Accuracy (A), sensitivity (S), precision (P) and F score calculations were used (Gribskov and Robinson, 1996) to evaluate the classification networks.

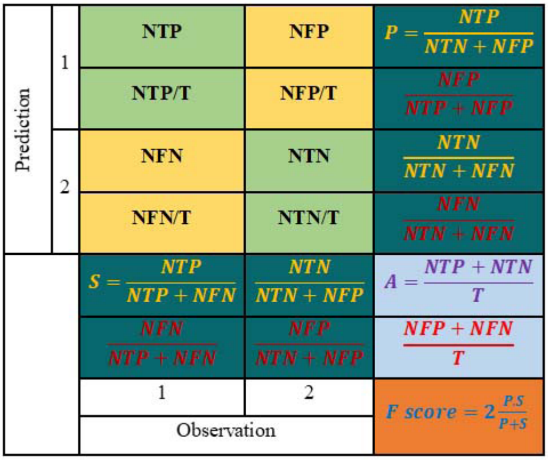


Figure 4. Error matrix.

3. RESULTS AND DISCUSSION

3.1. ANN model in image taking from the ground (MEITG)

In the ANN model, the structure of the network is (1-7-1), and it was designed as 1 input layer, 1 hidden layer and 1 output layer (Figure 5). Levenberg-Marquardt training algorithm was used for the training of the network. The best results were obtained by using tansig transfer function at the hidden layer and by using purelin transfer function at the output layer in the hidden structure of the network. The lowest training error value was obtained at 537 epoch number for the network.

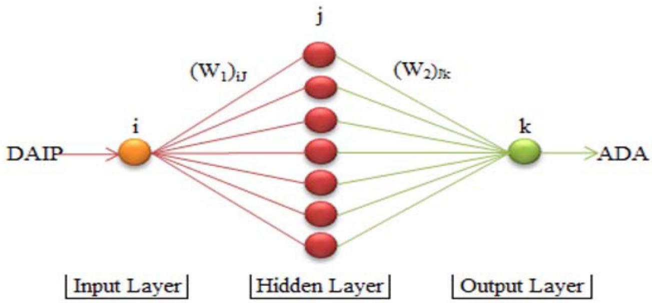


Figure 5. Network structure of MEITG.

Performance values of MEITG model were obtained at the hidden layer with 7 neurons with the lowest relative error. In the obtained ANN model, while R^2 value was found as 0.999999 and RMSE value was found as 0. 000007 for training, R^2 value was found as 0.999999 and RMSE value was found as 0.000017 for test (Table 1).

Table 1. MEITG performance values.

Number of Neurons	Training		Validation		Test	
	RMSE	R^2	RMSE	R^2	RMSE	R^2
7	0.000007	0.999999	0.000405	0.999998	0.000017	0.999999

ADA test data set and ANN estimated values were compared. It was found that the test data results obtained from MEITG model were compatible with the ADA data (Figure 6).

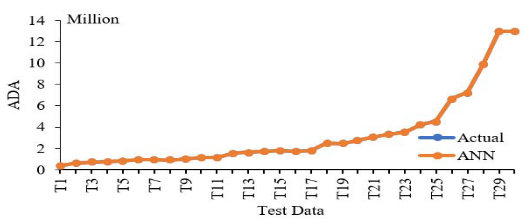
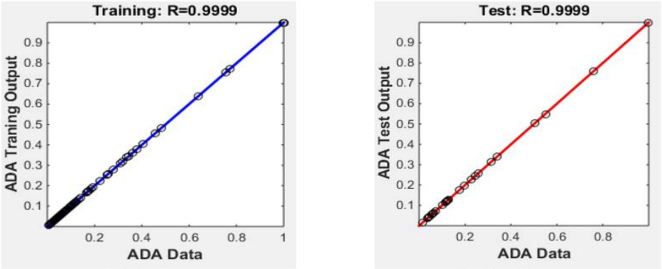


Figure 6. Actual and estimated test data of the diseased areas in image taking from ground.

Estimated values of ADA data were obtained with the developed MEITG model. The results obtained from ANN model and ADA results were compared with each other. The coefficient (R^2) of the relationship between these test data was found as 99.99% (Figure 7). An average relative error value of 0.019% was obtained between ADA data and test data obtained from ANN model.



a. Training data set
b. Test data set

Figure 7. Regression analysis for training and test sets in in image taking from ground.

3.2. ANN Model in Remote Image Taking with Drone Method (MERITD)

In ANN model, the structure of the network is (1-5-1) and it was designed as 1 input layer, 1 hidden layer and 1 output layer (Figure 8). Levenberg-Marquardt training algorithm was used for the training of the network. In the structure of the network, tansig was used in the hidden layer, while purelin transfer functions were used in the output layer. The lowest training error value was obtained at 943 epoch number for the network.

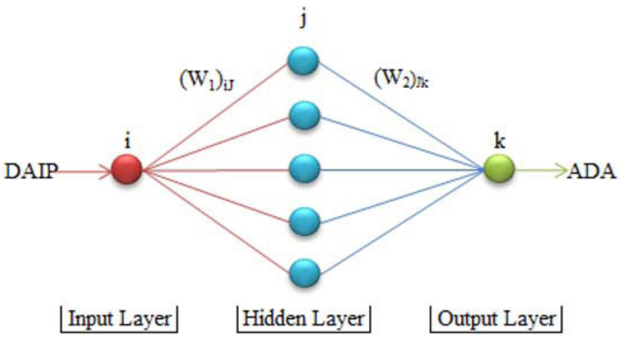


Figure 8. Network structure of MERITD.

Performance values of MERITD model were obtained at the hidden layer with 5 neurons with the lowest relative error. In the ANN model obtained, while R^2 value was found as 0.999999 and RMSE value was found as 0.0000005 for training, R^2 value was found as 0.999999 and RMSE value was found as 0.000007 for test (Table 2).

Table 2. MERITD performance values.

Number of Neurons	Training		Validation		Test	
	RMSE	R^2	RMSE	R^2	RMSE	R^2
5	0.0000005	0.999999	0.000004	0.999999	0.000007	0.999999

ADA test data set and ANN estimation values were compared. It was found that the test data results obtained from MERITD model were compatible with the ADA data (Figure 9).

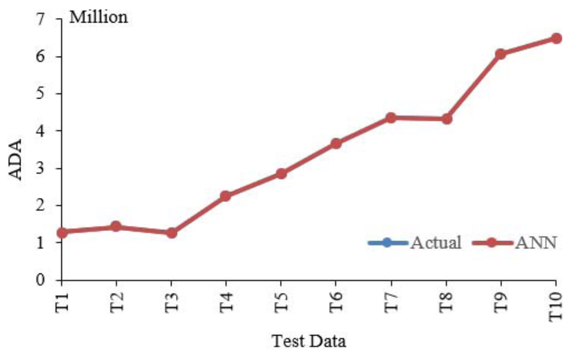


Figure 9. Actual and estimated test data of diseased areas in remote image taking with drone.

With the help of the developed MERITD model, estimated values of ADA data were obtained. The results obtained from ANN model and ADA results were compared with each other. The coefficient of the relationship between these test data (R^2) was found as 99.99% (Figure 10). 0.002% average relative data was found between ADA data and the test data obtained from ANN model.

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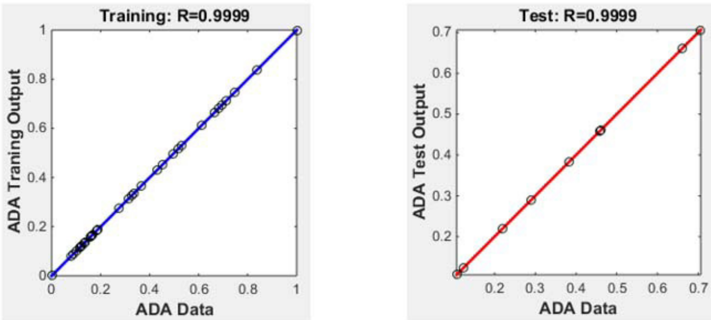

a. Training data set

b. Test data set

Figure 10. Regression analysis for training and test sets in remote image taking with drone.

3.3. Classification in Image Taking from the Ground Method (MCITG)

There were 2 independent variables and 10 dependent variables in this study. Feed Forward Backpropagation, Levenberg-Marquardt training algorithm, and as transfer function Hyperbolic Sigmoid Tangent function in the hidden layer and Softmax functions in the output layer were used in the classification with ANN. The networks were trained with training set, they were checked with the validation set and the training was terminated before the training was overlearned. The success of the network was checked with the test set. Termination cycle limit of the training algorithm was chosen as 1000 and validation was made in all trainings. 6 consecutive validation errors were set as the criterion to terminate training and the training was set to stop when the calculated training error became 0.

Networks were initially trained by increasing the number of neurons from 10 to 100 by 10. By re-training from the 5 lower and 5 higher of the best result found here, it was found that the network with 25 neurons gave the best result at 286 epoch number. In the training set, 111 of the 117 data were classified correctly, while 6 were classified incorrectly and an accuracy of 94.9% was obtained. In the test set, 47 of the 51 data were correct, 4 were classified incorrectly and an accuracy of 92.2% was obtained (Table 3). Disease severity in this model was found as 18.61%.

Table 3. Test set classification results of MCITG.

Prediction											
C1	6 11.8%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100.0% 0.0%
C2	0 0.0%	8 14.5%	1 0.9%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	88.9% 11.1%
C3	0 0.0%	0 0.0%	7 13.7%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100.0% 0.0%
C4	0 0.0%	0 0.0%	0 0.0%	4 11.1%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100.0% 0.0%
C5	0 0.0%	0 0.0%	0 0.0%	2 1.7%	6 11.1%	0 0.0%	1 0.9%	0 0.0%	0 0.0%	0 0.0%	66.7% 33.3%
C6	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	4 6.8%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100.0% 0.0%
C7	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	2 6.0%	0 0.0%	0 0.0%	0 0.0%	100.0% 0.0%
C8	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	3 4.3%	0 0.0%	0 0.0%	100.0% 0.0%
C9	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	3 6.8%	0 0.0%	100.0% 0.0%
C10	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	4 8.5%	100.0% 0.0%
MCITG	100% 0.0%	100% 0.0%	88% 12.5%	67% 33.3%	100% 0.0%	100% 0.0%	67% 33.3%	100% 0.0%	100% 0.0%	100% 0.0%	92.2% 7.8%
Classes	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	Test

3.4. Classification in Remote Image Taking with Drone (MCRITD)

There were 2 independent variables and 4 dependent variables in this study. Feed Forward Backpropagation, Levenberg-Marquardt training algorithm, and as transfer function Hyperbolic Sigmoid Tangent function in the hidden layer and Softmax functions in the output layer were used in the classification with ANN.

Networks were initially trained by increasing the number of neurons from 10 to 100 by 10. By re-training from the 5 lower and 5 higher of the best result found here, it was found that the network with 44 neurons gave the best result at 18 epoch number. In the training set, all of the 30 data were classified correctly, and an accuracy of 100% was obtained. In the test set, all of the 15 data were classified correctly, and an accuracy of 100% was obtained (Table 4). Disease severity in this model was obtained as 27.73%.

Table 4. Test set classification results of MCRITD.

Prediction					
C1	2 13.3%	0 0.0%	0 0.0%	0 0.0%	100.0% 0.0%
C2	0 0.0%	5 26.7%	0 0.0%	0 0.0%	100.0% 0.0%
C3	0 0.0%	0 0.0%	4 26.7%	0 0.0%	100.0% 0.0%
C4	0 0.0%	0 0.0%	0 0.0%	4 30.0%	100.0% 0.0%
MCRITD	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	100.0% 0.0%
Classes	C1	C2	C3	C4	Test

Classification was made with ANN and performance was evaluated (Table 5). Sensitivity and accuracy values were found to be very high in both training and test sets for MCITG. F Score was also found to be high enough. Since classification was obtained with 100% accuracy in MCRITD, performance values gave the highest value.

Table 5. Comparison of Model performances.

Set	Model	Accuracy	Sensitivity	Precision	F Score
Training	MCITG	0.9487	0.9397	0.9517	0.9457
Test		0.9216	0.9208	0.9556	0.9379
Training	MCRITD	1.0000	1.0000	1.0000	1.0000
Test		1.0000	1.0000	1.0000	1.0000

Accuracy alone is insufficient to show the success of the classification model. While evaluating the classification success of the models, both sensitivity and precision should be taken into consideration together. High sensitivity and precision are expected from a successful classification model. F score is an important parameter for evaluating sensitivity and precision together. When evaluated in general, it was found that both models were reliable enough to be used.

Many studies have been carried out using ANN to detect rice leaf blight disease. In these studies, the success of detecting the disease was 79.71% (Billah et al., 2007), 70% (Phadikar and Sil, 2008), 95.48% (Yang et al., 2017), 99% (Ramesh and Vydeki, 2019).

4. CONCLUSION

Image processing and ANN are valuable methods that can be used in theory and practice in the field of agriculture. In the present study, both methods were used together and an innovative approach was presented to develop the estimation and classification skills of ANN.

Of the ANN-based models proposed, MCITG could successfully classify 10 disease classes through image recognition, while MCRITD could effectively classify 4 disease classes. In areas with rice leaf blight disease, it was found that the proposed ANN models (MEITG and MERITD) could identify the diseased areas accurately and effectively. These models have a good training performance and recognition ability.

It would be appropriate to increase the number of high-quality images to increase the identification accuracy of rice diseases further. In addition, it may also be suggested to make use of other neural network architectures and deep learning algorithms.

Author Contribution Rates

Design of Study (Çalışmanın Tasarlanması): OS (%40), AT (%60)

Data Acquisition (Veri Toplanması): OS (%50), AT (%50)

Data Analysis (Veri Analizi): OS (%20), AT (%80)

Writing up (Makalenin Yazımı): OS (%40), AT (%60)

Submission and Revision (Makalenin Gönderimi ve Revizyonu): OS (%20), AT (%80)

REFERENCES

Abed-Ashtiani, F., Kadir, J.B., Selamat, A.B., Hanif, A.H.B., Nasehi, A., 2012. Effect of foliar and root application of silicon against rice blast fungus in mr219 rice variety. Plant Pathology Journal. 28: 164-171.

Ağın, O., Taner, A., 2015. Determination of weed intensity in wheat production using image processing techniques. Anadolu Journal of Agricultural Sciences, 30: 110-117.

Alvaro, D.M., Lanier, N.L., Greg, T., 2018. The implications of red rice on food security. Global Food Security, 18: 62-75.

Anonymous., 2019. Food and Agriculture Organization of the United Nations Classifications and Standards. http://www.fao.org/economic/ess/ess-standards.

Astonkar, S.R., Shandilya, V.K., 2018. Detection and analysis of plant diseases using image processing. International Research Journal of Engineering and Technology, 5 (4): 3191-3.

Bağırkan, Ş., 1993. Statistical analysis. Bilim Teknik Publishing House P: 301. İstanbul, Turkey [in Turkish].

Barbedo, J.G.A., Koenigkan, L.V., Santos, T.T., 2016. Identifying multiple plant diseases using digital image processing. Biosystems Engineering, 147: 104-116.

Bechtler, H., Browne, M.W., Bansal, P.K., Kecman, V., 2001. New approach to dynamic modelling of vapour-compression liquid chillers: artificial neural networks. Applied Thermal Engineerıng, 21: 941-53.

Bera, T., Das, A., Sil, J., Das, A.K., 2019. A survey on rice plant disease identification using image processing and data mining techniques. In emerging technologies in data mining and information security, Springer, Singapore. pp. 365-376.

Billah, M.M., Islam, M.P., Rahman, M.G., 2007. Identification of rice diseases using artificial neural network. Journal of the Bangladesh Society for Agricultural Science and Technology, 4: 189-194.

Bishop, C.M., 1995. Neural network for pattern recognition. Clarendon Press, Oxford, Birmingham, UK.

Bonman, J.M., 1992. Rice Blast. In: Compendium of rice diseases. Eds. r.k. webster and p.s. gunnel. American Phytopathological Society Press. St. Paul, Minnesota. USA. Pages 14-18.

Daskalov, P., Kirilova, E., Georgieva, T., 2018. Performance of an automatic inspection system for classification of Fusarium Moniliforme damaged corn seeds by image analysis. 22nd International Conference on Circuits, Systems, Communications and Computers, MATEC Web of Conferences, 210, 02014.

Devi, T. G., Neelamegam, P., 2018. Image processing based rice plant leavesdiseases in Thanjavur Tamilnadu. Cluster Computing. 22: 13415-13428.

Dubey, B.P., Bhagwat, S.G., Shouche, S.P., Sainis, J.K. 2006. Potential of artificial neural networks in varietal identification using morphometry of wheat grains. Biosystems Engineering, 95: 61-67.

El-kazzaz, M.K., Salem, E.A., Ghoneim, K.E., Elsharkawy, M.M., El-Kot, G.A.E.N., Kalboush, Z.A.E., 2015. Integrated control of rice kernel smut disease using plant extracts and salicylic acid. Archives of Phytopathology and Plant Protection. 48 (8): 664-675.

Elmacı, A., 2012. Studies on the prevalence, incidence and severity of rice blast disease (*pyricularia oryzae cavara*) in the south marmara region. Master's thesis. Ege University, Department of Plant Protection, 55, İzmir-Turkey.

Feakin, S.D., 1971. Pest control in rice. Pans Manual No:3, 270.

Göbelez, M., 1953. Roasting of black sea paddy (*pyricularia oryzae bri. cav.*). Tomurcuk 22: 12-13. [in Turkish].

Gonzalez, R.C., Woods, R.E., 2008. Digital image processing. Pearson International Edition, Pearson Prentice Hall, United States of America, ISBN: 0-13-168728-x 978-0-13-168728-8.

Gribskov, M., Robinson, N.L., 1996. Use of receiver operatting characteristic (ROC) analysis to evaluate sequence matching. Computers Chemistry, 20 (1): 23-33.

Husin, Z., Shakaff, A.Y.M., Aziz, A.H.A., Farook, R.S.M., Jaafar, M.N., Hashim, U., Harun, A., 2012. Embedded portable device for herb leaves recognition using image processing techniques and neural network algorithm. Computers and Electronics in Agriculture, 89: 18-29.

Islam, T., Sah, M., Baral, S., Choudhury, R.R., 2018. A faster technique on rice disease detection using image processing of affected area in agro-field. In: In: Proc. Second International Conference on Inventive Communication and Computational Technologies. p. 62-66.

Jacobs, R.A., 1988. Increased Rate of Convergence Through Learning Rate Adaptation. Neural Networks, 1 (4): 295-307.

Juliano, B.O., 1985. Rice chemistry and technology. 2 nd ed. St. Paul, MN, USA, AACC International, pp. 774.

Kalogirou, S.A., 2001. Artificial neural networks in there new able energy systems applications: A review. Renewable and Sustainable Energy Reviews, 5: 373-401.

Kamal, M.M., Masazhar, A.N.I., Rahman, F.A., 2018. Classification of leaf disease from image processing technique. Indonesian Journal of Electrical Engineering and Computer Science, 10 (1): 191-200.

Khush, G.S., 2005. What it will take to feed 5.0 billion rice consumers in 2030. Plant Molecular Biology, 59: 1-6.

Kihoro, J., Bosco, N.J., Murage, H., Ateka, E., Makihara, D., 2013. Investigating the impact of rice blast disease on the livelihood of the local farmers in greater Mwea region of Kenya. Springer plus. 2 (1): 308.

Kim, D.Y., Kadam, A., Shinde, S., Saratale, R.G., Patra, J., Ghodake, G., 2018. Recent developments in nanotechnology transforming the agricultural sector: a transition replete with opportunities. Journal of the Science Food and Agriculture, 98 (3): 849-864.

Levenberg, K., 1944. A method for the solution of certain nonlinear problems in least squares. Quarterly of Applied Mathematics, 2: 164-168.

Liu, L., Zhou, G., 2009. Extraction of the rice leaf disease image based on BP neural network. In: International Conference on Computational Intelligence and Software Engineering, IEEE, pp. 1-3.

Mahlein, A.K., 2016. Plant disease detection by imaging sensors-parallels and specific demands for precision agriculture and plant phenotyping. Plant Disease, 100 (2): 241-51.

Marquardt, D.W., 1963. An algorithm for least-squares estimation of nonlinear parameters. Journal of the Society for Industrial and Applied Mathematics. 11: 431-441.

Minai, A.A., Williams, R.D., 1990. Back-Propagation Heuristics: a Study of The Extended Delta-bar-delta Algorithm International Joint Conference on Neural Networks. 1: 595-600, San Diego, CA, USA.

Mohanty, S.P., Hughes, D.P., Salathé, M., 2016. Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7 (1419): 1-10.

Öztürk, D., Akçay, Y., 2010. A General Evaluation of Rice Production in Southern Marmara Region. Journal of Agricultural Faculty of Tokat Gaziosmanpasa University, 27 (2): 61-70.

Pantazi, X.E., Moshou, D., Tamouridou, A.A., 2019. Automated leaf disease detection in different crop species through image features analysis and one class classifiers. Computers and Electronics in Agriculture, 156: 96-104.

Patricio, D.I., Rieder, R., 2018. Computer vision and artificial intelligence in precision agriculture for grain crops: a systematic review. Computers and Electronics in Agriculture, 153: 69-81.

Phadikar, S., Sil, J., 2008. Rice disease identification using pattern recognition techniques. In: 11th International Conference on Computer and Information Technology, IEEE, pp. 420-423.

Pinki, F.T., Khatun, N., Islam, S.M.M., 2017. Content based paddy leaf disease recognition and remedy prediction using support vector machine. In: In: Proc. 20th International Conference of Computer and Information Technology (ICCIT), 22-24 December, p.1-5.

Prajapati, H.B., Shah, J.P., Dabhi, V.K., 2017. Detection and classification of rice plant diseases. Intelligent Decision Technologies, 11 (3): 357-373.

Purushothaman, S., Srinivasa, Y.G., 1994. A back-propagation algorithm applied to tool wear monitoring. International Journal of Machine Tools and Manufacture, 34 (5): 625-631.

Ramesh, S., Vydeki, D., 2019. Application of machine learning in detection of blast disease in South Indian rice crops. Journal of Phytology, 11: 31-37.

Roy-Barman, S., Chattoo, B.B., 2005. Rice blast fungus sequenced. Current Science, 89: 930-931.

Shrivastava, V.K., Pradhan, M.K., Minz, S., Thakur, M.P., 2019. Rice plant disease classıfication using transfer learning of deep convolution neural network. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLII-3/W6, 631-635.

Singh, A.K., Ganapathysubramanian, B., Sarkar, S., Singh, A., 2018. Deep learning for plant stress phenotyping: trends and future perspectives. Trends in Plant Science, 23 (10): 883-98.

Singh, V., Misra, A.K., 2017. Detection of plant leaf diseases using image segmentation and soft computing techniques. Information Processing in Agriculture, 4 (1): 41-49.

Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., Stefanovic, D., 2016. Deep neural networks based recognition of plant diseases by leaf image classification. Comput Intell Neurosci, 1-11.

Sürek, H., 1995. Disease of rice in Turkey. In the Proceeding of Rice Diseases in The Mediterranen Region and Breding for Resistance, 15-17 May 1995, Montpellier, France. Cahiers Options Mediterranennes. 15 (3): 45-47.

Sürek, H., 2002. Paddy farming. Hasad Press, İstanbul, Turkey. [in Turkish].

Taner, A., Gültekin, S.S., Çarman, K., 2010. Prediction of the parameters radial centrifugal pumps with artificial neural networks. Selcuk Journal of Agriculture and Food Sciences, 24 (1): 28-38. [in Turkish].

Verma, D. K., Shukla, K., 2011. Nutritional Value of Rice and Their Importance. Journal of Indian Farmers' Digest, 44 (1): 21-35.

Visen, N.S., Paliwal, J., Jayas, D.S., White, N.D.G., 2002. Specialist neural Networks for cerealgrain classification. Biosystems Engineering, 82: 151-159.

Vogl, T.P., Mangis, J.K., Rigler, A.K., Zink, W.T., Alkon, D.L., 1988. Accelerating the convergence of the backpropagation method. Biological Cybernetics, 59: 257-263.

Xiongs, Z.Y., Zhang, S.J., Ford-Lloyd, B.V., Jin, X., Wu, Y., Yan, H.X., Liu, P., Yang, X., Lu, B.R., 2011. Latitudinal distribution and differentiation of rice germplasm: ıts ımplications in breeding. Crop Science, 51 (3): 1050-1058.

Yamamoto, K., Togami, T., Yamaguchi, N., 2017. Super-resolution of plant disease images for the acceleration of image-based phenotyping and vigor diagnosis in agriculture. Sensors, 17 (11): 2557.

Yang, L., Shujuan, Y., Nianyin, Z., Yurong, L., Yong, Z., 2017. Identification of rice diseases using deep convolutional neural networks. Neurocomputing, 267: 378-384.

Yusof, M.M., Rosli, N.F., Othman, M., Mohamed, R., Abdullah, M.H.A., 2018. M-DCocoa: M-agriculture expert system for diagnosing cocoa plant diseases. In: Ghazali R., Deris M., Nawi N., Abawajy J. (eds) Recent Advances on Soft Computing and Data Mining. 363-371.