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# Classification of rice varieties with deep learning methods

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ABSTRACT

Rice, which is among the most widely produced grain products worldwide, has many genetic varieties. These varieties are separated from each other due to some of their features. These are usually features such as texture, shape, and color. With these features that distinguish rice varieties, it is possible to classify and evaluate the quality of seeds. In this study, Arborio, Basmati, Ipsala, Jasmine and Karacadag, which are five different varieties of rice often grown in Turkey, were used. A total of 75,000 grain images, 15,000 from each of these varieties, are included in the dataset. A second dataset with 106 features including 12 morphological, 4 shape and 90 color features obtained from these images was used. Models were created by using Artificial Neural Network (ANN) and Deep Neural Network (DNN) algorithms for the feature dataset and by using the Convolutional Neural Network (CNN) algorithm for the image dataset, and classification processes were performed. Statistical results of sensitivity, specificity, prediction, F1 score, accuracy, false positive rate and false negative rate were calculated using the confusion matrix values of the models and the results of each model were given in tables. Classification successes from the models were achieved as 99.87% for ANN, 99.95% for DNN and 100% for CNN. With the results, it is seen that the models used in the study in the classification of rice varieties can be applied successfully in this field.

## 1. Introduction

Image processing and computer vision applications in agriculture are of interest due to their non-destructive evaluation and low cost compared to manual methods (Mahajan et al. 2015). Computer vision applications based on image processing offer advantages compared to traditional methods based on manual work (Barbedo 2016). Evaluating or classifying grains by manual methods can be time-consuming and costly, as the human factor is at the forefront. In manual methods, the evaluation process may differ, as it is limited to the experience of the evaluation experts. In addition, rapid decision-making by manual methods can be difficult when an assessment is made on a large scale (Patrício & Rieder 2018).

Rice from grain products is among the products produced in many countries and consumed all over the world. Rice is priced on various parameters in the market. Texture, shape, color and fracture rate are some of these parameters (Aukkapinyo et al. 2019). After acquiring digital images of the products, various machine learning algorithms are used to determine these parameters and perform classification operations. Machine learning algorithms ensure that large amounts of data are analyzed quickly and reliably. It is important to use such methods in rice production to improve the quality of the final product and to meet food safety criteria in an automated, economical, efficient and non-destructive way (Al-Jarrah et al. 2015; Zareiforoush et al. 2015; Grinberg et al. 2020).

In recent years, many digital image features have been used to evaluate rice classification and quality. These include geometric parameters (length, perimeter, etc.), fracture rate, whiteness and determination of rice grain cracks can be given examples. Various features of grain products can be extracted by using systems based on image processing. Furthermore, these features are seen to be classified using algorithms such as ANN (Ebrahimi et al. 2014; Shrestha et al. 2016; Sabanci et al. 2017; Kaya & Saritas 2019), SVM (Cortes & Vapnik 1995), LR (LaValley 2008), DNN (Dahl et al. 2013; Liu et al. 2017) and CNN (Lin et al. 2018; Ahmed et al. 2020) from machine learning algorithms. These studies are compiled and summarized in Table 1.

In a study in the literature, a two-class dataset containing 1700 rice data was carried out and 98.5% classification success was achieved using the SVM algorithm (Sun et al. 2014). In another study, 200 pieces of data were examined from sixteen classes and 87.16% accuracy was obtained using the SVM algorithm (Liu et al. 2016b). In the study, which used three classes and 7399 pieces of data, a 95.5% success rate was

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**Table 1**
Similar studies found in the literature.

| No | Crop | Accuracy | Data Pieces | Class | Classifier | References |
|---|---|---|---|---|---|---|
| 1 | Soybean | 90.00% | 1670 | 4 | BPNN | (Kezhu et al. 2014) |
| 2 | Rice | 98.50% | 1700 | 2 | SVM | (Sun et al. 2014) |
| 3 | Wheat | 87.50% | 640 | 2 | ANN | (Ebrahimi et al. 2014) |
| 4 | Wheat | 95.00% | 180 | 2 | SVM | (Han et al. 2015) |
| 5 | Wheat | 86.81% | 7000 | 2 | SVM | (Liu et al. 2016a) |
| 6 | Soybean | 99.83% | 1200 | 4 | SVM | (Pires et al. 2016) |
| 7 | Rice | 87.18% | 843 | 16 | SVM | (Liu et al. 2016b) |
| 8 | Wheat | 72.80% | 150 | 16 | ANN | (Shrestha et al. 2016) |
| 9 | Wheat | 88.33% | 6400 | 40 | SVM | (Olgun et al. 2016) |
| 10 | Wheat | 99.93% | 200 | 2 | ANN | (Sabanci et al. 2017) |
| 11 | Soybean | 95.90% | 4366 | 5 | SVM | (Naik et al. 2017) |
| 12 | Rice | 95.50% | 7399 | 3 | DCNN | (Lin et al. 2018) |
| 13 | Rice | 93.02% | 3810 | 2 | LR | (Cinar & Koklu 2019) |
| 14 | Wheat | 93.46% | 3000 | 2 | ANN | (Kaya & Saritas 2019) |
| 15 | Rice | 88.07% | 200 | 3 | CNN | (Ahmed et al. 2020) |
| 16 | Drybean | 93.13% | 13,611 | 7 | SVM | (Koklu & Ozkan 2020) |

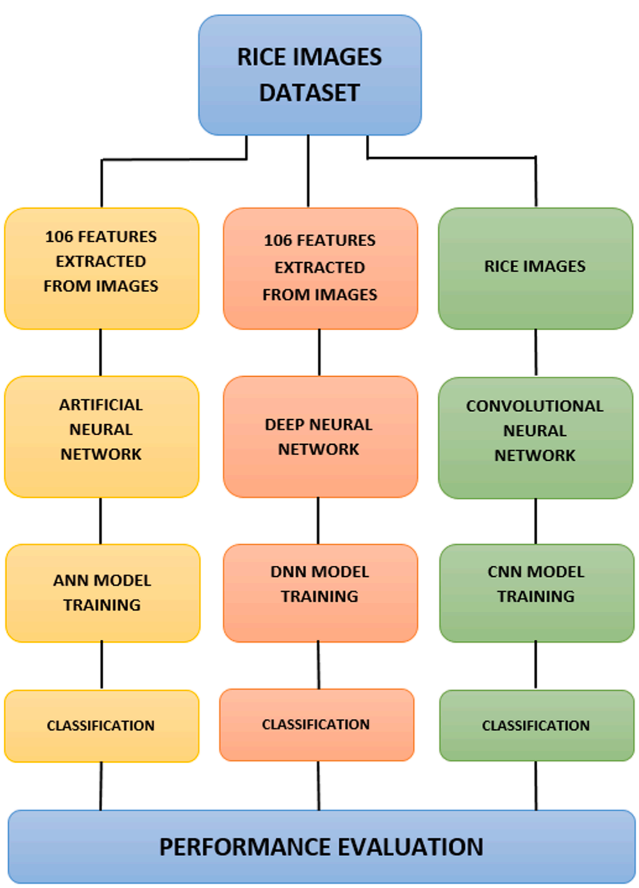


**Fig. 1.** Flow chart of evaluation of classification performances of rice varieties.

achieved with the deep CNN algorithm (Lin et al. 2018). In another study conducted with three different types of rice and 200 pieces of data, the researchers used CNN for classification procedures after feature extraction and achieved 88.07% success (Ahmed et al. 2020).

The aim of this study is to develop a non-destructive model to increase classification success by using images of rice varieties. In the proposed models, 106 morphological and color features obtained from rice images were given as input to ANN and DNN and classification was carried out. In addition, 75,000 rice images from 5 different classes even distribution to the CNN method, which has the ability to classify raw images without requiring pre-processing, were given as input and the classification process was carried out. Later, the classification successes of ANN, DNN, CNN methods were compared.

This study is organized as follows. In the second section of the paper, the dataset, performance metrics, cross validation and methods used in the study were described. In the third section, the experimental results obtained in the study were described. In the last section, experimental results were evaluated and recommendations were presented.

## 2. Material and methods

Models were created using ANN, DNN and CNN algorithms to perform classification operations with the image and feature datasets used in the study. The flow chart of the proposed models for the classification of rice varieties is given in Fig. 1.

### 2.1. Datasets

Datasets belonging to five rice varieties as Arborio, Basmati, Ipsala, Jasmine and Karacadag, which are often cultivated in Turkey, were used in the study. The first image dataset consists of 75,000 rice grain images, 15,000 from each varieties. In RGB images contained in this dataset, the size of the image in which each grain of rice is located is 250 $\times$ 250 pixels. Furthermore, there is a second feature dataset with a total of 106 features, including 12 morphological, 4 shapes and 90 color features obtained from each rice grain using these images (Cinar 2019). The rice varieties used in the study and the obtained features are shown in Fig. 2.

The 12 morphological features found in the dataset are given in Table 2, and the 4 shape features and formulas obtained using these morphological features are given in Table 3. In addition, after converting from RGB (red, green, blue) color space to HSV (hue, saturation, value), L*a*b* (L*: lightness, a*: red/green value, b*: blue/yellow value), YCbCr (y: luminance, cb: chroma blue, cr: chroma red) and XYZ color spaces, list of 90 different color features obtained from five different color spaces is given in Table 4 (Cinar 2019).

The data set obtained from rice images and containing 106 features was used in the classification process performed with ANN and DNN algorithms. Using this data set of 75,000 images, classification process was carried out with the CNN algorithm.

### 2.2. Performance metrics

The confusion matrix is used to measure the classification performance of machine learning methods. This matrix makes it easier to find connections between the classifier's performance and test results. The confusion matrix provides information about the correct and incorrect classification of positive samples and the correct and incorrect classification of negative samples (Sokolova & Lapalme 2009). In Table 5, a two-class confusion matrix is given.

The rice dataset in this study consists of five classes. For this reason, a five-class confusion matrix was used in classification processes. The representation of confusion matrix TP, FP, FN, TN values is given in Table 6.

Using TP, FP, FN and TN values in the confusion matrix, statistical calculations are performed and the performance of classifiers can be analyzed in detail (Martínez et al. 2018). The metrics obtained from

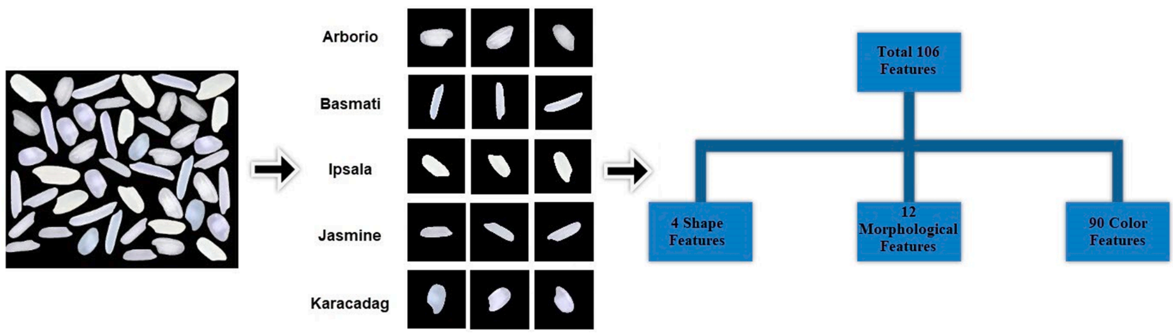


**Fig. 2.** Rice varieties used in the study and obtained features.

**Table 2**
List of morphological features.

| Morphological Features | | | | | |
|---|---|---|---|---|---|
| 1 | Area | 5 | Eccentricity | 9 | Extent |
| 2 | Perimeter | 6 | Equivalent Diameter | 10 | Aspect Ratio |
| 3 | Major Axis Lenght | 7 | Solidity | 11 | Roundness |
| 4 | Minor Axis Lenght | 8 | Convex Area | 12 | Compactness |

**Table 3**
List of shape features and formulas.

| Shape Features | | Formulas |
|---|---|---|
| 1 | Shape_Factor_1 | $\frac{\text{Major Axis Lenght}}{\text{Area}}$ |
| 2 | Shape_Factor_2 | $\frac{\text{Minor Axis Lenght}}{\text{Area}}$ |
| 3 | Shape_Factor_3 | $\frac{\text{Area}}{\left(\frac{\text{Major Axis Lenght}}{2}\right)^2 x\ \pi}$ |
| 4 | Shape_Factor_4 | $\frac{\text{Area}}{\frac{\text{Major Axis Lenght}}{2} x \frac{\text{Minor Axis Lenght}}{2} x\pi}$ |

statistical calculations for two-class confusion matrix, the formulas used to calculate these metrics, and information about the purpose for which the metrics are used are shown in Table 7. Calculation of TP, TN, FP and FN values in a five-class confusion matrix is shown in Table 8.

There are also different metrics in the literature to evaluate the performance of classification algorithms, apart from the metrics given in Table 7. But because the data set is regular, that is, there is an equal number of data belonging to each class, and the success of classification is high, there is no need to use other metrics. The metrics used range from 0 to 1. But since the classification success of the 3 models used is high, a healthy comparison cannot be made when these values are rounded. For this purpose, the values of these measurements are shown as percentages.

### *2.3. Cross validation*

Cross validation is a method used to objectively measure the accuracy of classification models. In this method, the dataset is divided into equal number of parts according to the specified number value. The specified numerical value is named as *k*. *1 / k* part of the dataset is reserved for testing, *k-1* part is reserved for training. This process continues until each part of the dataset is used as a test part. So this process is repeated *k* times. The general classification success of the model on the test set is obtained by taking the arithmetic average of the classification successes obtained as a result of these operations (Arlot & Celisse 2010).

**Table 5**
Confusion Matrix.

| | | Predicted Class | |
|---|---|---|---|
| | | Positive | Negative |
| Actual Class | Positive | *TP* (True Positive) | *FN* (False Negative) |
| | Negative | *FP* (False Positive) | *TN* (True Negative) |

**Table 6**
Five-class Confusion matrix.

| | | Predicted Class | | | | |
|---|---|---|---|---|---|---|
| | | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
| Actual Class | $C_1$ | $T_1$ | $F_{12}$ | $F_{13}$ | $F_{14}$ | $F_{15}$ |
| | $C_2$ | $F_{21}$ | $T_2$ | $F_{23}$ | $F_{24}$ | $F_{25}$ |
| | $C_3$ | $F_{31}$ | $F_{32}$ | $T_3$ | $F_{34}$ | $F_{35}$ |
| | $C_4$ | $F_{41}$ | $F_{42}$ | $F_{43}$ | $T_4$ | $F_{45}$ |
| | $C_5$ | $F_{51}$ | $F_{52}$ | $F_{53}$ | $F_{54}$ | $T_5$ |

**Table 4**
List of color features.

| Color Space | Mean | Standard Deviation | Skewness | Kurtosis | Entropy | Wavelet Decomposition |
|---|---|---|---|---|---|---|
| RGB | Mean_RGB_R | StdDev_RGB_R | Skewness_RGB_R | Kurtosis_RGB_R | Entropy_RGB_R | Daub4_RGB_R |
| | Mean_RGB_G | StdDev_RGB_G | Skewness_RGB_G | Kurtosis_RGB_G | Entropy_RGB_G | Daub4_RGB_G |
| | Mean_RGB_B | StdDev_RGB_B | Skewness_RGB_B | Kurtosis_RGB_B | Entropy_RGB_B | Daub4_RGB_B |
| HSV | Mean_HSV_H | StdDev_HSV_H | Skewness_HSV_H | Kurtosis_HSV_H | Entropy_HSV_H | Daub4_HSV_H |
| | Mean_HSV_S | StdDev_HSV_S | Skewness_HSV_S | Kurtosis_HSV_S | Entropy_HSV_S | Daub4_HSV_S |
| | Mean_HSV_V | StdDev_HSV_V | Skewness_HSV_V | Kurtosis_HSV_V | Entropy_HSV_V | Daub4_HSV_V |
| L*a*b* | Mean_LAB_L | StdDev_LAB_L | Skewness_LAB_L | Kurtosis_LAB_L | Entropy_LAB_L | Daub4_LAB_L |
| | Mean_LAB_A | StdDev_LAB_A | Skewness_LAB_A | Kurtosis_LAB_A | Entropy_LAB_A | Daub4_LAB_A |
| | Mean_LAB_B | StdDev_LAB_B | Skewness_LAB_B | Kurtosis_LAB_B | Entropy_LAB_B | Daub4_LAB_B |
| YCbCr | Mean_ YCbCr_Y | StdDev_ YCbCr_Y | Skewness_ YCbCr_Y | Kurtosis_ YCbCr_Y | Entropy_ YCbCr_Y | Daub4_ YCbCr_Y |
| | Mean_YCbCr_Cb | StdDev_ YCbCr _Cb | Skewness_ YCbCr_Cb | Kurtosis_ YCbCr_Cb | Entropy_ YCbCr_Cb | Daub4_ YCbCr_Cb |
| | Mean_ YCbCr_Cr | StdDev_ YCbCr_Cr | Skewness_ YCbCr_Cr | Kurtosis_ YCbCr_Cr | Entropy_ YCbCr_Cr | Daub4_ YCbCr_Cr |
| XYZ | Mean_XYZ_X | StdDev_XYZ_X | Skewness_XYZ_X | Kurtosis_XYZ_X | Entropy_XYZ_X | Daub4_XYZ_X |
| | Mean_XYZ_Y | StdDev_XYZ_Y | Skewness_XYZ_Y | Kurtosis_XYZ_Y | Entropy_XYZ_Y | Daub4_XYZ_Y |
| | Mean_XYZ_Z | StdDev_XYZ_Z | Skewness_XYZ_Z | Kurtosis_XYZ_Z | Entropy_XYZ_Z | Daub4_XYZ_Z |

**Table 7**
Performance Metrics.

| Metrics | Formula | Evaluation Description |
|---|---|---|
| Sensitivity *(SNS)* | $TP/(TP + FN)$ | Gives the number of positive estimates that are correctly classified. |
| Specificity *(SPC)* | $TN/(TN + FP)$ | Gives the number of negative estimates that are correctly classified. |
| Precision *(PRE)* | $TP/(TP + FP)$ | Gives a positive estimate value. |
| F1-Score *(F1S)* | $(2{*}TP)/(2{*}TP + FP + FN)$ | It is the harmonic mean of Precision and Sensitivity values. Informs you whether the model is incorrect in data sets that are not evenly distributed. |
| Accuracy *(ACC)* | $(TP + TN)/(TP + TN + FP + FN)$ | Gives the classification success of the model. |
| False Positive Rate *(FPR)* | $FP/(TN + FP)$ | Gives false classified positive estimates. |
| False Negative Rate *(FNR)* | $FN/(TP + FN)$ | Gives negative estimates that are misclassified. |

**Table 8**
Calculation of TP, TN, FP and FN values in a five-class confusion matrix.

| CLASS | TP | TN | FP | FN |
|---|---|---|---|---|
| C1 | $TP_1 = T_1$ | $TN_1 = T_2 + T_3 + T_4 + T_5 + F_{23} + F_{24} + F_{25} + F_{32} + F_{34} + F_{35} + F_{42} + F_{43} + F_{45} + F_{52} + F_{53} + F_{54}$ | $FP_1 = F_{21} + F_{31} + F_{41} + F_{51}$ | $FN_1 = F_{12} + F_{13} + F_{14} + F_{15}$ |
| C2 | $TP_2 = T_2$ | $TN_2 = T_1 + T_3 + T_4 + T_5 + F_{13} + F_{14} + F_{15} + F_{31} + F_{41} + F_{51} + F_{34} + F_{35} + F_{43} + F_{45} + F_{53} + F_{54}$ | $FP_2 = F_{12} + F_{32} + F_{42} + F_{52}$ | $FN_2 = F_{21} + F_{23} + F_{24} + F_{25}$ |
| C3 | $TP_3 = T_3$ | $TN_3 = T_1 + T_2 + T_4 + T_5 + F_{12} + F_{14} + F_{15} + F_{21} + F_{24} + F_{25} + F_{41} + F_{42} + F_{45} + F_{51} + F_{52} + F_{54}$ | $FP_3 = F_{13} + F_{23} + F_{43} + F_{53}$ | $FN_3 = F_{31} + F_{32} + F_{34} + F_{35}$ |
| C4 | $TP_4 = T_4$ | $TN_4 = T_1 + T_2 + T_3 + T_5 + F_{12} + F_{13} + F_{15} + F_{21} + F_{23} + F_{25} + F_{31} + F_{32} + F_{35} + F_{51} + F_{52} + F_{53}$ | $FP_4 = F_{14} + F_{24} + F_{34} + F_{54}$ | $FN_4 = F_{41} + F_{42} + F_{43} + F_{45}$ |
| C5 | $TP_5 = T_5$ | $TN_5 = T_1 + T_2 + T_3 + T_4 + F_{12} + F_{13} + F_{14} + F_{21} + F_{23} + F_{24} + F_{31} + F_{32} + F_{34} + F_{41} + F_{42} + F_{43}$ | $FP_5 = F_{15} + F_{25} + F_{35} + F_{45}$ | $FN_5 = F_{51} + F_{52} + F_{53} + F_{54}$ |

In our study, the value of $k$ was determined as 10. Fig. 3 shows how the cross validation method works.

### 2.4. Development of modelling

#### 2.4.1. Artificial neural network (ANN)

Artificial neural networks are a system modeled on the basis of the human brain. They try to solve problems that cannot be solved by classical methods in methods similar to the working system of the human brain. Artificial neural networks are complex systems formed by connecting artificial neurons, which are formed similar to neurons in the human brain, with different connection geometry (Ebrahimi et al. 2014; Ozkan 2020).

In artificial neural networks, artificial neurons are simply clustered in layers. Then, these layers are associated with each other. Basically, all artificial neural networks have a similar structure. In this structure, some neurons are connected to receive inputs, and some neurons to transmit outputs. All the remaining neurons are found in hidden layers (Singh et al. 2009). The ANN structure is shown in Fig. 4.

#### 2.4.2. Deep neural network (DNN)

High classification successes are achieved by using deep neural networks in classification processes using data sets containing a large number of data and complex data. Because DNN contains a large number of hidden layers and neurons, it can increase classification success by extracting interesting and hidden features from the data contained in the dataset. Because of the advantage of the large number of hidden layers and neurons, it can perform rapid learning. Another advantage is that the dropout method, which will prevent the over-learning (overfitting) problem that may occur in the training of neural networks, can be applied in deep neural networks. With the dropout method, a more realistic learning can be performed by disabling neurons so that they are random at each iteration (Dahl et al. 2013; Liu et al. 2017). The DNN structure used in this study is shown in Fig. 5.

#### 2.4.3. Convolutional neural network (CNN)

CNN is a deep learning method that is often used in areas such as image processing, natural language processing, voice recognition, and data sets that contain a high number of data (Albawi et al. 2017). The

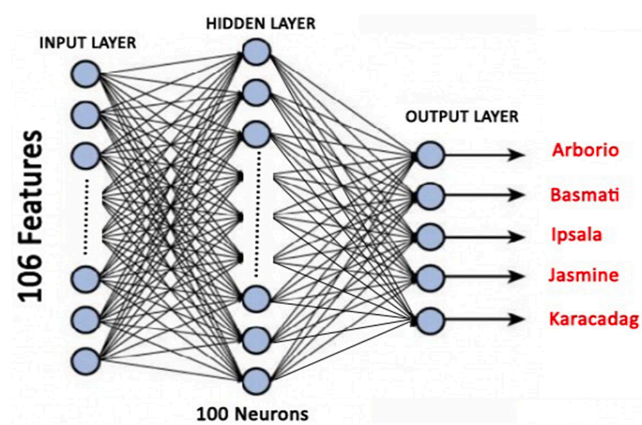


**Fig. 4.** ANN structure.

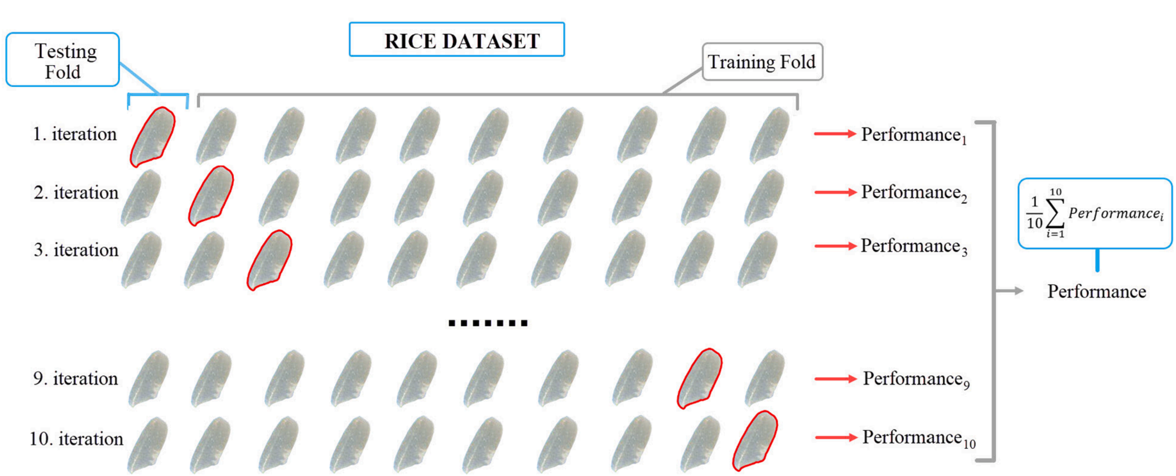


**Fig. 3.** Cross validation process.

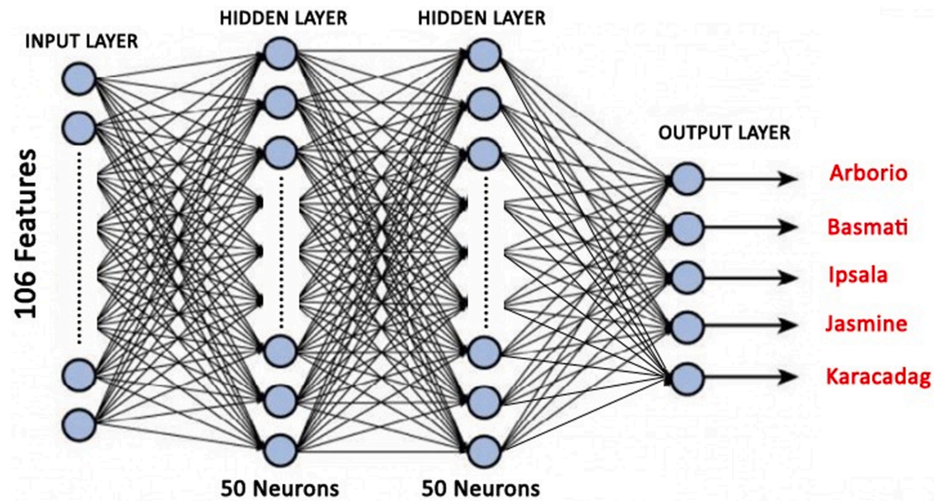


**Fig. 5.** DNN structure.

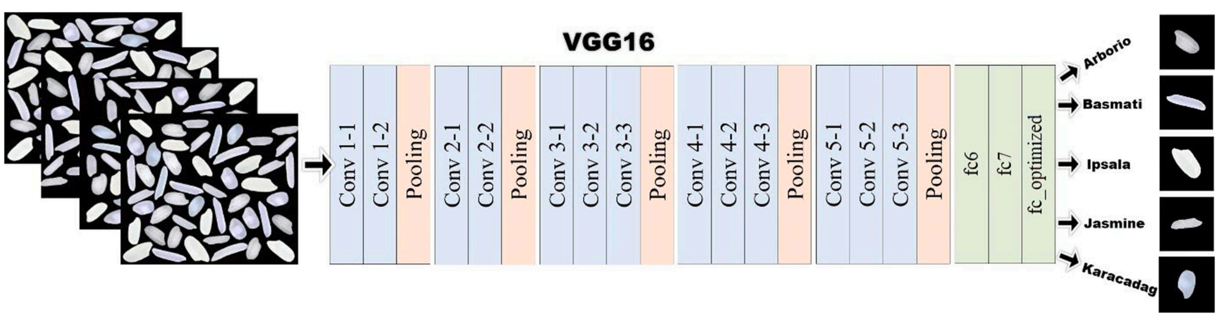


**Fig. 6.** VGG16 network structure.

**Table 9**
Layers and parameters of VGG-16 based transfer learning.

| Layer Name | Layer Type | Filter Size | Stride | Padding | Output Channel | Activation Function |
|---|---|---|---|---|---|---|
| conv1_1 | convolution 2d | 3 × 3 | 1 | 1 | 64 | relu |
| conv1_2 | convolution 2d | 3 × 3 | 1 | 1 | 64 | relu |
| pool1 | max pooling 2d | 2 × 2 | 2 | 0 | 64 | – |
| conv2_1 | convolution 2d | 3 × 3 | 1 | 1 | 128 | relu |
| conv2_2 | convolution 2d | 3 × 3 | 1 | 1 | 128 | relu |
| pool2 | max pooling 2d | 2 × 2 | 2 | 0 | 256 | – |
| conv3_1 | convolution 2d | 3 × 3 | 1 | 1 | 256 | relu |
| conv3_2 | convolution 2d | 3 × 3 | 1 | 1 | 256 | relu |
| conv3_3 | convolution 2d | 3 × 3 | 1 | 1 | 256 | relu |
| pool3 | max pooling 2d | 2 × 2 | 2 | 0 | 256 | – |
| conv4_1 | convolution 2d | 3 × 3 | 1 | 1 | 512 | relu |
| conv4_2 | convolution 2d | 3 × 3 | 1 | 1 | 512 | relu |
| conv4_3 | convolution 2d | 3 × 3 | 1 | 1 | 512 | relu |
| pool4 | max pooling 2d | 2 × 2 | 2 | 0 | 512 | – |
| conv5_1 | convolution 2d | 3 × 3 | 1 | 1 | 512 | relu |
| conv5_2 | convolution 2d | 3 × 3 | 1 | 1 | 512 | relu |
| conv5_3 | convolution 2d | 3 × 3 | 1 | 1 | 512 | relu |
| pool5 | max pooling 2d | 2 × 2 | 2 | 0 | 512 | – |
| fc6 | fully connected | – | – | – | 4096 | relu |
| fc7 | fully connected | – | – | – | 4096 | relu |
| fc_optimized | fully connected | – | – | – | 5 | softmax |

CNN method can work as an end-to-end classifier. From the data given as an input to the CNN network, it can extract features with layers within itself, and with these features, it can learn and classify. CNN is a deep learning method consisting of five main layers: the convolution layer, the pooling layer, the activation layer, the fully connected layer, and the softmax layer (Lin et al. 2018; Ahmed et al. 2020).

In the convolution layer, various filters are applied step by step in the regions on the image to extract image features from each region. In this layer, the number of desired steps and the number of filters can be determined and the number of features can be increased and reduced. However, the optimum adjustment should be made as the emergence of many features will make it difficult for the network to learn (Guo et al. 2016).

At the pooling layer, operations are performed to reduce the large

**Table 10**
Specifications of hardware used in the study and network parameters of classifiers.

| HARDWARE UNIT | SPECIFICATIONS | | |
|---|---|---|---|
| **Central Processing Unit** | Intel i7 10875H 2.3 GHz | | |
| **RAM** | 16 GB | | |
| **Graphic Card** | Nvidia RTX 2070 | | |
| **Operating System** | Windows 10 | | |
| **Programming Language** | Python 3.6 | | |
| **DNN, CNN Framework** | Tensorflow 2.0 | | |
| **CLASSIFIER** | **ANN** | **DNN** | **CNN** |
| **Batch Size** | 16 | 1 | 10 |
| **Learning Rate** | 0.0001 | 0.002 | 0.0003 |
| **Iteration** | 200 | 200 | 200 |

number of data comes from the convolution layer and reduce complexity. The image feature is intact, reducing its size and transferring it to the next layer. In this layer, it is also necessary to make optimal adjustments so as not to affect the classification (Scherer et al. 2010).

After the other layers, the activation layer is added, which allows data to be drawn to certain ranges. After these operations, in the fully connected layer as a classification layer, features are reduced to the level of the neural network, and learning operations are performed to make inferences. At the end of this process, the softmax activation function is used to parse classes. In this layer, the tagging process is also performed and output is taken (Sainath et al. 2013).

In this study, the CNN network was trained by the transfer learning method using a previously trained model (Deepak & Ameer 2019). VGG16 network structure and trained VGG16 were used. The VGG16 network structure used is shown in Fig. 6.

Features were extracted from rice images using the modified VGG16 architecture. The last fully connected layer of VGG16, the fc8 layer, has been removed, the features are taken from the fc7 layer. Classification was also performed with five outputs from the fully dependent fc_optimized layer, which was later added to the network. The modified VGG-16 architecture layers and parameters are given in Table 9.

## 3. Experimental results

Classification results made by ANN, DNN and CNN methods are given in this section. The data set used in the study contains features obtained from 75,000 rice grain images. In ANN and DNN methods, this data was used as input. Arborio, Basmati, Ipsala, Jasmine and Karacadag rice classes were given as classification outputs. The images contained in the data set used were used as an introduction to CNN. The hardware specifications used to run these algorithms and the network structures used in the algorithms are shown in Table 10.

In Table 10, the parameter values for which classification success is highest are given. Confusion matrix was used to evaluate the results obtained from the performance measurements of the classification algorithms used in the study. A confusion matrix was created for each classification algorithm, and performance evaluations were realized by using values on the confusion matrix (TP, TN, FP, FN). *SNS, SPC, PRE, F1S, ACC, FPR, FNR* metrics were used in performance evaluation. The cross validation method was used to objectively evaluate the classification success of the models. In the cross validation method, the $k$ value was determined as 10.

In the model created by the ANN method, 106 features obtained from rice images was used as input. Classification success as a result of the ANN method was found to be 99.87%. The resulting confusion matrix is given in Table 11.

According to the results of the ANN method, statistical results of *SNS, SPC, PRE, F1S, ACC, FPR* and *FNR* were given in Table 12.

After training using 106 features of 75,000 data and using the DNN method, tests were conducted to achieve classification success. As a result of the classification, 99.95% success was achieved. The values obtained from the classification result are given in Table 13.

According to the results of the DNN method, statistical results of *SNS, SPC, PRE, F1S, ACC, FPR* and *FNR* were given in Table 14.

In the model in which the CNN method is used, 15,000 images from each rice variety are given as input to CNN. In order to achieve higher success in the CNN method, the weights of the VGG16 network were used to train the network using the transfer learning method. In addition to this network structure, dropout was used to avoid the overfitting problem of the trained CNN model. In this way, classification success has been increased and overfitting problem has not occurred. Close to 100% classification success has been achieved in the CNN method. The confusion matrix obtained as a result of this classification process is shown in Table 15.

According to the results of the CNN method, statistical results of *SNS, SPC, PRE, F1S, ACC, FPR* and *FNR* were given in Table 16.

A 10-fold cross validation value was used in the training of algorithms. In this way, an attempt was made to achieve a more accurate classification result. The average classification accuracy of the ANN, DNN and CNN methods used in the study are shown in Table 17.

## 4. Conclusions

In this study, performance measurements of 3 different machine learning algorithms were obtained using rice images and features extracted from these images. Statistical measurements of confusion matrix as a result of classification were used as performance metrics. *SNS, SPC, PRE, F1S, ACC, FPR, FNR* values were obtained and compared for each method and each class. With the help of these metrics, information about the training and testing success of algorithms has been calculated. Looking at average classification success, the highest rate belongs to the CNN method with 100%. Because the CNN method directly processes images and use many hidden features such as size, color and so on, classification success is thought to be high. After this

**Table 12**
Statistical results based on results from ANN method (%).

| | Arborio | Basmati | Ipsala | Jasmine | Karacadag |
|---|---|---|---|---|---|
| ***SNS*** | 99.59 | 99.66 | 99.95 | 99.51 | 99.72 |
| ***SPC*** | 99.89 | 99.92 | 99.97 | 99.89 | 99.93 |
| ***PRE*** | 99.55 | 99.68 | 99.91 | 99.57 | 99.73 |
| ***F1S*** | 99.57 | 99.67 | 99.93 | 99.54 | 99.73 |
| ***ACC*** | 99.83 | 99.87 | 99.97 | 99.82 | 99.89 |
| ***FPR*** | 0.11 | 0.08 | 0.02 | 0.10 | 0.06 |
| ***FNR*** | 0.41 | 0.34 | 0.05 | 0.49 | 0.28 |

**Table 11**
ANN confusion matrix.

| ANN | | Predicted Class | | | | |
|---|---|---|---|---|---|---|
| | | Arborio | Basmati | Ipsala | Jasmine | Karacadag |
| **Actual Class** | **Arborio** | **14,939** | 0 | 5 | 16 | 40 |
| | **Basmati** | 0 | **14,949** | 7 | 44 | 0 |
| | **Ipsala** | 3 | 0 | **14,993** | 4 | 0 |
| | **Jasmine** | 23 | 48 | 2 | **14,927** | 0 |
| | **Karacadag** | 42 | 0 | 0 | 0 | **14,958** |

**Table 13**
DNN confusion matrix.

| DNN | | Predicted Class | | | | |
|---|---|---|---|---|---|---|
| | | Arborio | Basmati | Ipsala | Jasmine | Karacadag |
| Actual Class | Arborio | **14,993** | 0 | 0 | 0 | 7 |
| | Basmati | 0 | **14,985** | 0 | 15 | 0 |
| | Ipsala | 0 | 0 | **15,000** | 0 | 0 |
| | Jasmine | 29 | 23 | 0 | **14,948** | 0 |
| | Karacadag | 7 | 0 | 0 | 0 | **14,993** |

**Table 14**
Statistical results based on results from DNN method (%).

| | Arborio | Basmati | Ipsala | Jasmine | Karacadag |
|---|---|---|---|---|---|
| ***SNS*** | 99.95 | 99.90 | 100 | 99.65 | 99.95 |
| ***SPC*** | 99.94 | 99.96 | 100 | 99.98 | 99.99 |
| ***PRE*** | 99.76 | 99.85 | 100 | 99.90 | 99.95 |
| ***F1S*** | 99.85 | 99.87 | 100 | 99.78 | 99.95 |
| ***ACC*** | 99.94 | 99.95 | 100 | 99.91 | 99.98 |
| ***FPR*** | 0.06 | 0.38 | 0 | 0.03 | 0.01 |
| ***FNR*** | 0.05 | 0.10 | 0 | 0.35 | 0.05 |

method, the highest average classification success rate belongs to the DNN method with 99.95%. The DNN method has a high classification success, as it can perform a wide range of learning in large data sets. The ANN method, which is a traditional method, has also achieved quite high success. With a classification accuracy rate of 99.87%, the ANN method achieved success close to the other methods used in the study. *SNS, SPC, PRE, F1S, ACC, FPR, FNR* values are observed as the best classifier CNN method when examined. The *SNS* mean of ANN method was found to be 99.69%, the *SNS* value mean of DNN method was found to be 99.89%, and the CNN method was found to be 100%. The *SPC* value of the ANN method was found to be 99.92%, the *SPC* value of the DNN method was found to be 99.97%, and the *SPC* value of the CNN method was found to be 100%. According to these values, where we can get information that positive samples are correctly classified in correct and negative samples, it can also be said that the best classification method is the CNN method. When Table 9 is examined, it is observed that there are misclassified classified varieties in all types of rice as a result of classification made by ANN method. In total, 234 rice was misclassified out of 75,000 rice images. A total of 81 rice were misclassified as a result of the classification by the DNN method when Table 11 was examined. When Table 13 is examined, it is seen that only 3 pieces of rice were misclassified as a result of the classification by CNN method. These erroneous classifications are thought to be due to the fact that some of the rice varieties are very similar to each other. It has been observed that the Jasmine rice variety is the rice variety that is most mixed with other rice varieties.

There are many studies with rice in the literature. Similar studies with rice before and comparison of these studies are given in Table 18.

Looking at the studies with rice in Table 18, the highest classification success were achieved by the algorithms used in this study. But it should be noted that each data set in Table 18 is different from each other, and the number of features of rice contained in the data set is different. This data has been shared for information purposes only.

Algorithms used in classification can be examples of other studies. In other studies, new studies can be done using different machine learning algorithms. Different varieties of rice can also be tested with these models, using. It can be used by adapting to traditional rice classification machines to achieve effective and fast results. It can also be effective in identifying pure rice phenotypes.

**Table 17**
Average accuracy rates of the methods used.

| | ANN | DNN | CNN |
|---|---|---|---|
| **Average Accuracy** | 99.87% | 99.95% | 100% |

**Table 18**
Studies with rice in literature and comparison of this study.

| References | Data Pieces | Class | Classifier | Accuracy |
|---|---|---|---|---|
| (Liu et al., 2016b) | 843 | 16 | SVM | 87.18% |
| (Ahmed et al., 2020) | 200 | 3 | CNN | 88.07% |
| (Cinar and Koklu, 2019) | 3810 | 2 | LR | 93.02% |
| (Lin et al., 2018) | 7399 | 3 | DCNN | 95.50% |
| (Sun et al., 2014) | 1700 | 2 | SVM | 98.50% |
| **This Study** | 75,000 | 5 | ANN | 99.87% |
| **This Study** | 75,000 | 5 | DNN | 99.95% |
| **This Study** | 75,000 | 5 | CNN | 100% |

**Table 15**
CNN confusion matrix.

| CNN | | Predicted Class | | | | |
|---|---|---|---|---|---|---|
| | | Arborio | Basmati | Ipsala | Jasmine | Karacadag |
| Actual Class | Arborio | **14,999** | 0 | 0 | 1 | 0 |
| | Basmati | 0 | **14,999** | 0 | 1 | 0 |
| | Ipsala | 0 | 0 | **15,000** | 0 | 0 |
| | Jasmine | 0 | 1 | 0 | **14,999** | 0 |
| | Karacadag | 0 | 0 | 0 | 0 | **15,000** |

**Table 16**
Statistical results based on results from CNN method (%).

| | Arborio | Basmati | Ipsala | Jasmine | Karacadag |
|---|---|---|---|---|---|
| ***SNS*** | 99.99 | 99.99 | 100 | 99.99 | 100 |
| ***SPC*** | 100 | 100 | 100 | 100 | 100 |
| ***PRE*** | 100 | 99.99 | 100 | 99.99 | 100 |
| ***F1S*** | 100 | 99.99 | 100 | 99.99 | 100 |
| ***ACC*** | 100 | 100 | 100 | 100 | 100 |
| ***FPR*** | 0 | 0 | 0 | 0 | 0 |
| ***FNR*** | 0.01 | 0.01 | 0 | 0.01 | 0 |

## Declaration of Competing Interest

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

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