Rice Image Classification

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January 2023

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 25,000 grain images, 5,000 from each of these varieties, are included in the dataset. 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 model and the results were given in tables. Classification successes from the model were achieved as 97.85% with CNN.

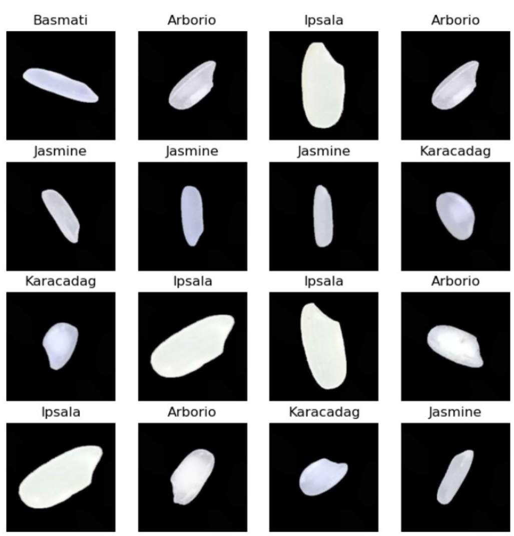

Figure 1: rice varieties

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. Computer vision applications based on image processing offer advantages compared to traditional methods based on manual work. 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.

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. 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.

The aim of this study is to develop a non-destructive model to increase classification success by using images of rice varieties. 25,000 rice images from 5 different classes even distribution were given 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.

2 Related Work

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, SVM, LR, DNN and CNN from machine learning algorithms.

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 [2]. In another study, 843 pieces of data were examined from sixteen classes and 87.16% accuracy was obtained using the SVM algorithm [3]. In the study, which used three classes and 7399 pieces of data, a 95.5% success rate was achieved with the deep CNN algorithm [4]. 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.

3 Data set Description

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 25,000 rice grain images, 5,000 from each varieties [1]. In RGB images contained in this dataset, the size of the image in which each grain of rice is located is 250×250 pixels.
We split the data into 80% training and 20% testing.

For each class, we will have approximately 4000 images in the train set, 800 images in training set and 200 images in validation set.

4 Project Description

We used a Convolution Neural Network model to classify the data, The model is a Sequential model, which means that the layers are added to the model in a linear stack, one after the other. The first layer is a Rescaling layer, this is done to normalize the pixel values of the input image to be between 0 and 1. The second layer is a RandomFlip layer, it randomly flips the input image horizontally. The third layer is a RandomContrast layer, it applies a random contrast to the input image by adjusting the brightness.

The following layers are convolutional layers, which apply filters to the input image. The filters are applied using a sliding window approach and the filters are learned during the training process. We used 3 convolutional layers, the first convolutional layer applies 32 filters of size 3x3 to the input image, the second convolutional layer applies 64 filters of size 3x3 to the input image and the third convolutional layer applies 128 filters of size 3x3 to the input image. All of them used a ReLU activation function

After each convolutional layer, a MaxPooling2D layer is applied which reduces the spatial size of the input while retaining the most important information. The maxpooling layer takes the maximum value of all the pixels in the window. The flatten layer is then used to reshape the data from a 3D tensor to a 1D tensor. The last two layers are fully connected dense layers, which process the output of the previous layers to produce the final output. The first dense layer has 1000 neurons and uses the ReLU activation function, and the last dense layer has 5 neurons and uses a Softmax activation function, which is used for multiclass classification.

```
cnn = keras.Sequential([
    layers.Rescaling(1./255),
    layers.RandomFlip(),
    layers.RandomContrast(0.3),
    layers.Conv2D(filters = 32, kernel_size = 3, activation = 'relu'),
    layers.MaxPooling2D(pool_size = 2),
    layers.Conv2D(filters = 64, kernel_size = 3, padding = 'same', activation = 'relu'),
    layers.MaxPooling2D(pool_size = 2),
    layers.Conv2D(filters = 128, kernel_size = 3, padding = 'same', activation = 'relu'),
    layers.MaxPooling2D(pool_size = 2),
    layers.Flatten(),
    layers.Dense(1000, activation = 'relu'),
    layers.Dense(5, activation = 'softmax')
])
```

Figure 2: CNN model

5 Conclusion

During this project with played with the parameters of the model, changing and/or adding layers, tried different learning rates, batch sizes and number of epochs. We ended up running the model with 10 epochs and a batch size of 50 and got **97.85% accuracy** of classifying the varites of the rice.

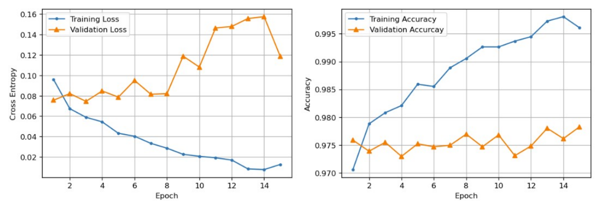

Figure 3: Train Validation history

	precision	recall	f1-score	support
0	0.95	0.94	0.94	985
1	0.99	0.99	0.99	1061
2	1.00	0.99	0.99	970
3	0.98	0.99	0.99	992
4	0.95	0.96	0.95	992
accuracy			0.97	5000
macro avg	0.97	0.97	0.97	5000
weighted avg	0.97	0.97	0.97	5000

Figure 4: Confusion Matrix

As we can see from the confusion matrix above, we had mostly great results with 99% accuracy between classes 1,2 and 3. The accuracy was a bit lower than the rest resulting in lower accuracy score for the model overall. We need to keep in mind that we lowered the amount of data from the original data set due to large amount of running time, from 75000 images with 15000 images for each class to 25000 images with 5000 images for each class. If we had a better computer we could've ran the entire data set so the model could train better on all other classes.

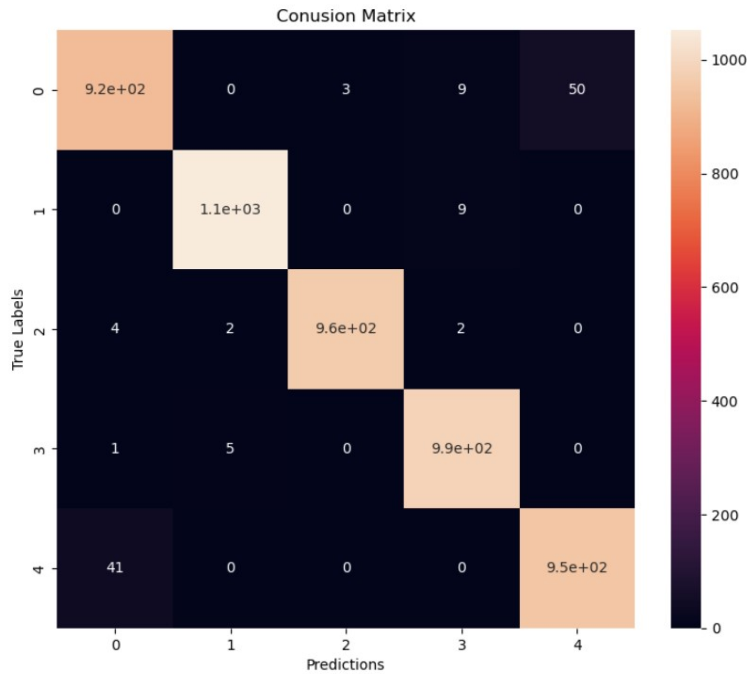

Figure 5: Confusion Matrix heatmap

6 References

1. Rice image dataset
2. Evaluation and analysis the chalkiness of connected rice kernels based on image processing technology and support vector machine
3. A survey of deep neural network architectures and their applications
4. A Deep Convolutional Neural Network Architecture for Boosting Image Discrimination Accuracy of Rice Species