Classification of good and damaged rice using convolutional neural network

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ABSTRACT

Rice production is massive in Indonesia, therefore maintaining the quality of the product is necessary. Detection and classification of objects have become a very important part in image processing. We performed object detection namely rice. After the object is found, it can be classified into two categories, namely good and damaged rice. We conducted a new study on rice which was carried out per group not per grain to obtain or classify good and damaged rice where we had carried out several steps, namely segmentation process using HSV (hue, saturation, value) color space. HSV is used because of its excellence in representing brightness of the image. We considered evaluating brightness because the tendency of damaged rice is darker or paler compared to good rice. To accomodate environment lighting ambiguity we perform the image acquisition in a controlled environment, so that all the images have the same light intensity. Here we use only channel V of HSV to be used in feature extraction using the gray-level co-occurrence matrix (GLCM) and finally convolutional neural network (CNN) is used for classification. From the test experiments that we have done, we have produced 83% prediction accuracy. Considering how similar the good rice is to the spoiled rice, the results are quite impressive.

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1. INTRODUCTION

Rice was a staple food for most Indonesian people. Rice consumption in Indonesia was increasing every year in line with the increasing population of Indonesia [1]. Image processing is used for better interpretation of images by humans [2] and for analysis, data storage and transfer [3] which is an important research area within the engineering and computing discipline [4], [5].

Object detection has become a very important part in image processing. The object detection system functions to find objects in the real world by utilizing the object model [6]. Object detection involves several main elements such as data sets, algorithms and techniques in assigning classes [7]. Several studies have carried out object detection such as object detection using image precessing for unmanned aerial vehicles (UAV) [8], object detection using deep learning [9], object detection using color image processing [10], automatic car plate recognition using convolutional neural network (CNN) [11], [12], detection for vehicle make and model recognition (MMR) in low light contiditions image processing for human skin detection [13]. After the object is found, it can then be classified into certain categories. Several studies have carried out classifications such as object color classification through the Delta robot [14], image classification and object detection [15], strawberry fruit ripeness identification [16], classification of batik patterns using KNN and SVM [17].

In this paper, we conducted a new study on rice that was carried out per group not per grain to obtain or classify good and demaged rice where we have done some steps i.e., for the segmentation process using the HSV (hue, saturation, value) color space, feature extraction using gray-level co-occurrence matrix (GLCM) while for classification using CNN. We use only the channel V of HSV which is representing brightness of the image. Brightness of the image is evaluated because damaged rice tend to have darker or more pale in term of brightness compared to good rice.

2. METHOD

The detection model of good rice and damaged rice is shown in Figure 1 that consist of image input and then image processing is carried out. In image processing performed several steps while for object detection process by a feature search first, then the rice objects found then will be classified, namely good and damaged rice.

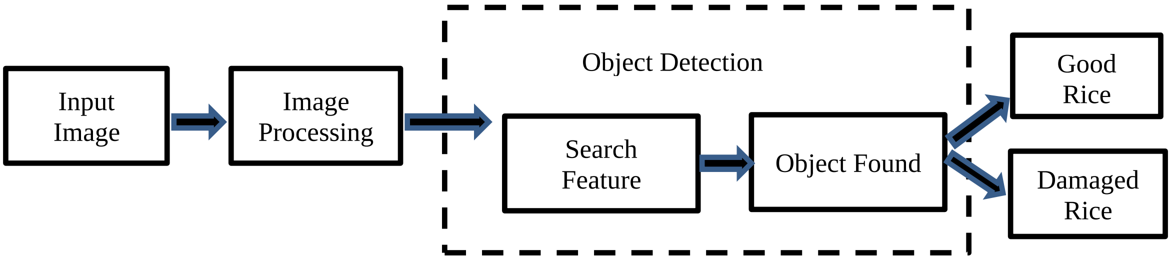
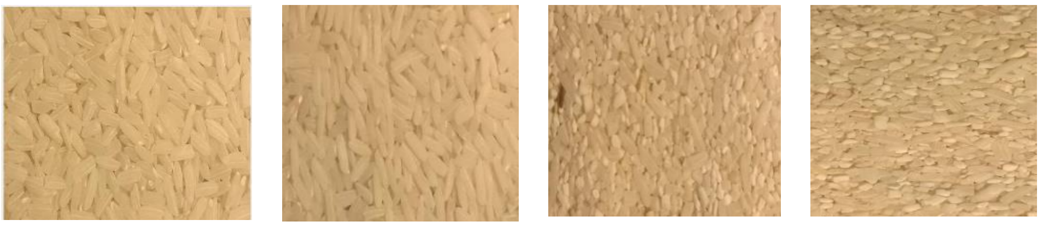


Figure 1. Object detection model for good and damaged rice

2.1. Input rice image

RGB color space is composed of red, green, and blue spectrum components [18]. The input image of rice were 73 images with format RGB that consist of 25 images of good rice while 48 images of damaged rice. We used the image as a dataset. The image of good rice was rice that is whole rice or rice with a minimum size of more than 50% of its original size while the image of damaged rice was black rice or rice with a size of less than 50% of its original size or a combination of good rice and damaged rice in rice group. Examples of good and damaged rice are shown in Figure 2. Figure 2(a) and (b) are the first and second batch sample of good rice respectively, we can see overall the rice are whole and clean. Figure 2(c) and (d) are the first and second batch sample of damaged rice respectively, most of the rice are broken and rotten.



(a) (b) (c) (d)

Figure 2. Images of (a, b) good and (c, d) damaged rice in RGB format

2.2. Preprocessing

At this stage we do the cropping process from the image taken from the webcam in a controlled environment to a size of 500x500 pixels.

2.3. Segmentation

The color segmentation stage is the process of separating areas in an image based on the colors contained in the image [19]. Segmentation begins with the conversion of RGB images into the HSV color space [20], then the HSV image extracted only for channel V. This is performed because of the charasterictic of the damaged rice which is darker and more pale compared to the good rice. Damaged rice also often have more texture because of the broken grain or not whole anymore. From the Figure 3 we can see that channel V performed better to represent brightness and texture of the image as it is more apparent.

Figure 3. Comparison between RGB (left) and channel V of HSV (right) color space

2.4. Feature extraction

The next step is to extract feature from the channel V image. The feature extraction stage is used to obtain information from images for classification [21]. The method used in this study is a texture classification method [22]-[26]. We use GLCM to extract the texture feature. In this GLCM method, it will calculate how often a pixel with a gray level value (gray scale intensity) i appears horizontally adjacent to a pixel with a j value. The pixel values of the image are converted to the gray scale intensity which have 8 level of intensities. After that gray level co-occurrence is calculated and represented in a GLCM matrix as shown in Figure 4.

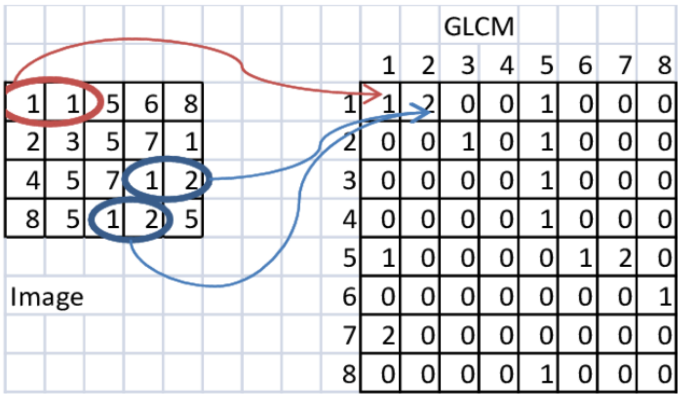


Figure 4. GLCM calculation

2.5. Classification

CNN is a type of neural network commonly used in image data and is included in the supervised deep learning method [27], [28]. CNN is a class of deep, feed-forward artificial neural network [29], [30]. We use GLCM information as the CNN feature. The size of matrix that we use for GLCM operation is 8x8. We then reshape the matrix so that it become only one row. The final form of the matrix size is then become 1x64. We use 5 layers for the CNN, the first layer is the input layer, then continue with 3 hidden layers, and end with output layer. For the input layer we use 64 features as the input, this is because we use 8x8 GLCM matrix which then transformed into 1x64 matrix, so the final result is 64 features. For the first hidden layer we expand the neurons to get more detail of the features, 192 neurons are used in this stage using rectified linear unit (ReLU). For the second hidden layer we shrink the neurons become 64 number of neurons, and the third hidden layer become 21 neurons. Finally, the output layer have 2 neurons as we only want to classify the data into 2 classes. Implemented CNN network shown in Figure 5.

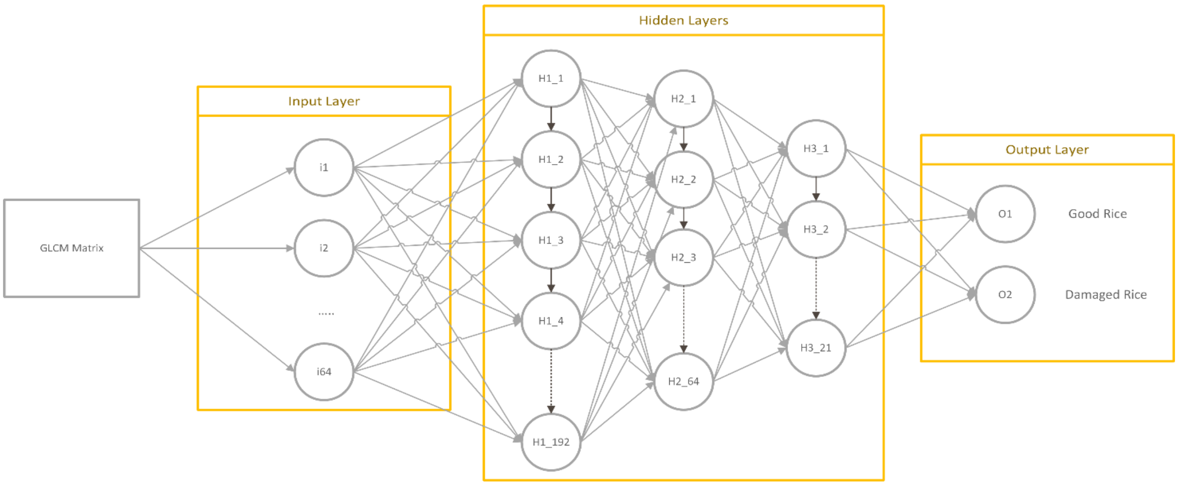


Figure 5. Implemented CNN network

3. RESULTS AND DISCUSSION

Seventy three images are used for the training purpose which is consist of good rice and damaged rice images. Each training images are calculated for the GLCM matrix so that in the end we acquire 73x64 size of data ready to be trained. For the training purpose, we use 73 images consists of 25 images for good rice class and 48 images for damaged rice class. All images are captured with using a webcam with controlled environment. Training is processed in 75 epochs where the data order is randomized in each epoch. The process is split into mini batches where each batch consists of 16 data, the process then run in per batch. Training progress result shown in Figure 6.

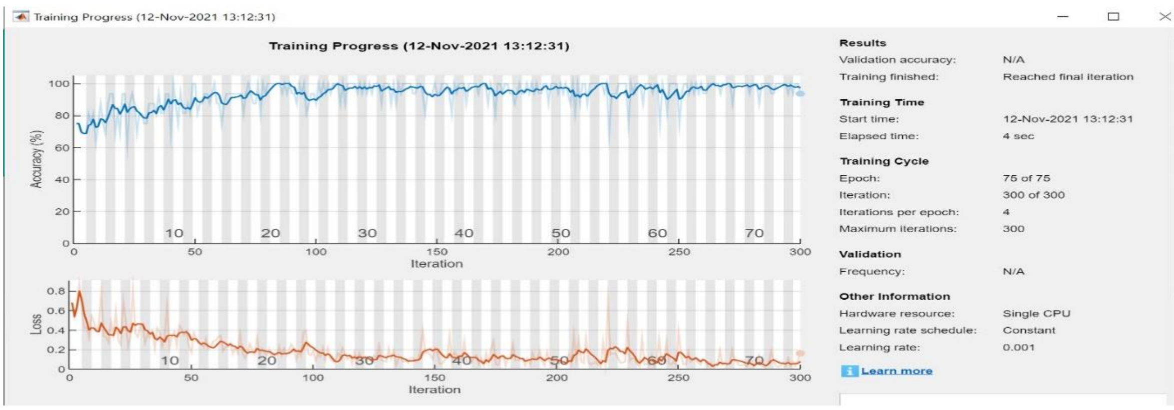


Figure 6. Training progress result

With this training setup we achieve minimum loss at the final iteration, with this result we can conclude that the network that we built is considered good and can be used for the classification or testing stage. The training algorithm can be seen in Figure 7. In testing stage, we use different images from the images we used in training. Each testing images are already labelled according to the class where they are belonging. The testing stage is implemented to test how accurate the program predicting the label or class of the testing images. The testing images are run through the same process as in the training stage, which is, preprocessing, segmentation and feature extraction. Testing result shown in Figure 8.

```
imds = read_image_folder
class = label(imds)
train_im = []
for i = 1 to size(imds)
        img = readImage(imds(i))
        im_hsv = rgb2hsv(img)
        im_v = im_hsv(3) % take the third layer (v)
        im_gray = uint8(255*mat2gray(im_v)) % pixel normalization
        glcms = graycomatrix(im_gray) % 8x8 glcm matrix
        glcm = reshape(glcms,1,[]) % reshape to 1x64 glcm matrix
        train_im = [train_im ; glcm]
end
layers = [
    %input layer (64 Total Features)
        featureInputLayer(64)
    %hidden layer 1 (192 Neurons)
        fullyConnectedLayer(192)
        batchNormalizationLayer
        reluLayer
    %hidden layer 2 (64 Neurons)
        FullyConnectedLayer(64)
        batchNormalizationLayer
        reluLayer
    %hidden layer 3 (21 Neurons)
       fullyConnectedLayer(21)
       batchNormalizationLayer
       reluLayer
    %output neurons (2 classes)
       fullyConnectedLayer(2)
       softmaxLayer
    classificationLayer]
options = trainingOptions(...
    'adam', ... %Optimizer Function
    'MaxEpochs',75, ... %Training Cycle
    'MiniBatchSize',16, ... %Processed data per run
    'Shuffle','every-epoch', ... %Randomize data order every epoch
    )
net = trainNetwork(train_im,class,layers,options);
```

Figure 7. Training algorithm

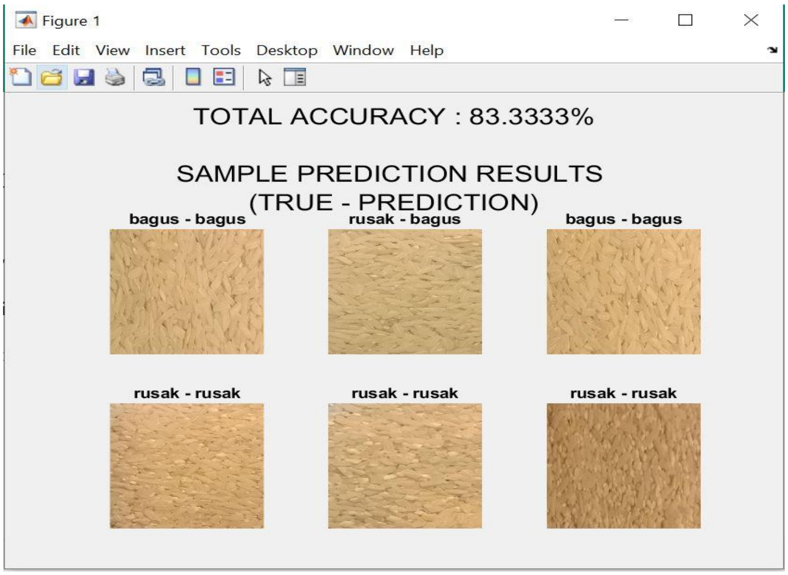


Figure 8. Testing result

From the testing experiment we have done, we have yield 83% of prediction accuracy. Considering how similar it looks between the good and the damaged rice, the result is quite impressive. The testing algorithm can be seen in Figure 9.

```
net = CNN_Network
imds = read_image_folder
class = label(imds)
test_im = []
for i = 1 to size(imds)
img = readImage(imds(i))
        im_hsv = rgb2hsv(img)
        im_v = im_hsv(3) % take the third layer (v)
        im_gray = uint8(255*mat2gray(im_v)) % pixel normalization
        glcms = graycomatrix(im_gray) % 8x8 glcm matrix
        glcm = reshape(glcms,1,[]) % reshape to 1x64 glcm matrix
        test_im = [test_im ; glcm]
end
YPred = classify(net,test_im)
YValidation = class
accuracy = sum(YPred == YValidation)/numel(YValidation)
```

Figure 9. Testing algorithm

4. CONCLUSION

In this paper, we have carried out a classification for good and damaged rice. RGB to HSV image conversion is performed so that it is easier to get brightness information in HSV format. V channel from the HSV is the only channel we used as we only interested in the brightness and texture of the image. GLCM is used as the texture feature and finally a convolutional neural network is implemented to classify the testing data. From this study it is yield with a result of accuracy rate of 83%. It is noted that the result is achieved using the testing and training images which is acquired in the same environment setup.

In future work, we will continue our current research by focusing on identifying good and damage rice in real time using other methods. It is important to implement a new method to tackle the problem of ambiguity of environment lighting to perform better normalization of lighting, therefore image acquisition can be performed in a more flexible environment.

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