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A new CNN model integrated in onion and garlic sorting robot to improve classification accuracy

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ABSTRACT

The profit share of the vegetable market, which is quite large in the agricultural industry, needs to be equipped with the ability to classify types of vegetables quickly and accurately. Some vegetables have a similar shape, such as onions and garlic, which can lead to misidentification of these types of vegetables. Through the use of computer vision and machine learning, vegetables, especially onions, can be classified based on the characteristics of shape, size, and color. In classifying shallot and garlic images, the CNN model was developed using 4 convolutional layers, with each layer having a kernel matrix of 2x2 and a total of 914,242 train parameters. The activation function on the convolutional layer uses ReLu and the activation function on the output layer is softmax. Model accuracy on training data is 0.9833 with a loss value of 0.762.

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1. INTRODUCTION

The profit share of the vegetable market which is quite large in the agricultural industry needs to be equipped with the ability to classify types of vegetables quickly and accurately [1-4]. Some vegetables have a similar shape, such as onions and garlic. This can lead to misidentification of the type of vegetable. The ever-developing technology allows humans to use it as a solution to problems in everyday life, one of which is in terms of differentiating these types of spices.

The agricultural industry is one of the sectors that can apply artificial intelligence technologies [5-7]. This technology offers users a variety of benefits through various learning and optimization techniques, including machine learning and cluster intelligence concepts [8]. By using computer vision and machine learning, vegetables can be divided into many groups, depending on external characteristics such as shape, size, and color [9], [10].

One of the artificial intelligence systems that has the ability to classify images is a deep learning technique with the Convolutional Neural Network (CNN) algorithm [11-13]. CNN methods are considered appropriate for the identification of vegetable types because they are more effective in extracting features, provide significant accuracy, are suitable for non-structural data such as images, and are widely used in image data [14], [15].

Previous research on the classification of seasoning imagery has been carried out by Wulandari et al. [16] in his research entitled "Digital Image Classification of Seasonings and Spices with the Convolutional Neural Network (CNN) Algorithm". The accuracy value obtained from this test is 98.75% for training data, 85% for testing data and 88.89% for new data. The model used is the CNN model with 2 convolutional layers with each layer having 10 filters and in each filter there is a 3x3 kernel matrix. The activation function used in the convolutional layer and the hidden layer is tanh, while the output layer uses softmax.

Other studies regarding image classification using the CNN method have also been carried out: (1) for hyperspectral classification of fruits and vegetables with an average accuracy of 92.23% [17]; (2) classification of garlic images using multi-label and multi-class achieved a classification accuracy of 91.8% and 98.0% respectively [12]; (3) classification among 10 different leaf categories of tomato plants using the novel TomConv model which achieved an accuracy of 98.19% [14], and (4) classification of families or species of plant seeds based on two different datasets, the resulting accuracy reached 95, 65% for the first and 97.47% for the second [18].

Based on these studies, image classification using the CNN method has a high accuracy value, exceeding 90%, and is suitable for image classification. However, this research still needs to be improved, so this paper proposes a research entitled "Image Classification Using Convolutional Neural Networks on Shallots and Garlic". This research aims to help communities identify shallots and garlic quickly and accurately. In addition, research into the potential of CNN algorithm exploration as a general image classification system can open up and broaden the scope of the public, especially to develop artificial intelligence-based systems in the technology industry as a starting point for research, as one of the objectives of support for industrial innovation. The SDGs for 2030.

2. METHOD

Tools and Dataset

The Garlic and Shallot dataset used in this study is part of the "Fruit and Vegetables Image Recognition Dataset" taken on the kaggle.com page [19]. This dataset consists of 200 images (each class consists of 100 images) which have a red, green, blue (RGB) light spectrum. The dataset is then processed using the Python programming language on the Kaggle site.

Steps

The flow of this research work begins with the selection of sample data used as training data, validation as well as testing with a ratio of 90:10. Then, pre-processing training data and validation data, followed by network design using CNN method, is done to train models. If the onion type is distinguished, a good result is obtained, and the network is tested with validation data. If validation data also shows good results, the network can be used to classify test data. The results of the model test will generate an accuracy value that indicates the accuracy of the model for classifying garlic and shallots. The research process is shown in Figure 1.

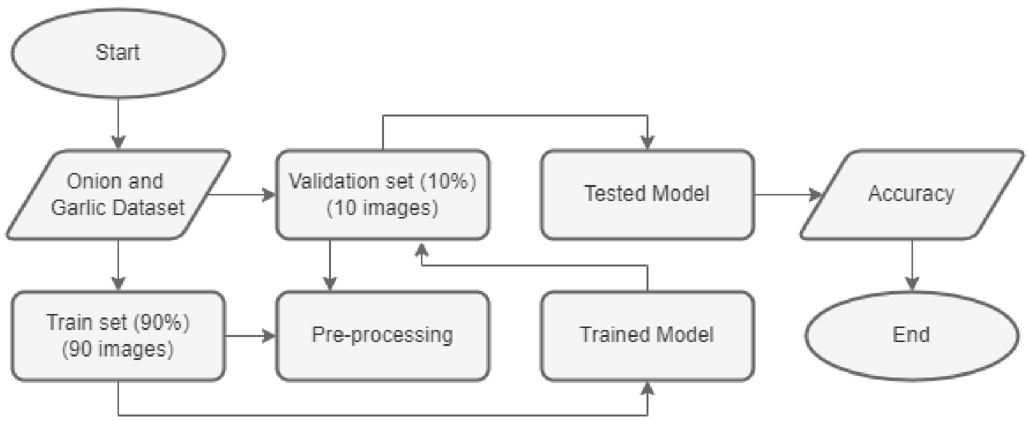

Figure 1. Classification workflow with CNN

Convolutional Neural Network

Convolutionary neural networks (CNNs) are part of deep-learning machine learning because of the depth of the network. Machine learning is a process of training that teaches computers to perform human tasks [20]. CNN is a combination of multiple processing and multiple processing elements that work simultaneously, inspired by the biological nervous system, each neuron represented in two dimensions [21], [22]. CNN structures consist of inputs, feature extraction processes, classification processes, and outputs. In the process of extracting functions, there are several hidden layers, including convolutionary layers, activation functions (ReLu), and pooling. The output from the first level of the convolution is used as the input from the next level of the convolution. The classification process is composed of a fully connected layer and a softmax activation function, which produces an output in the form of a classification result [23].

CNN Model Structute

The proposed CNN model structure is shown in Table 1. The network consists of an input layer, four convex layers, one flat layer, two dense layers and one output layer. The input layer uses training data. The input data is then processed in the first curve layer using the Max Pooling and ReLU activation functions. The output of the first convolution layer is used as the input of the second convolution process. The process of convolution continues until the fourth convolution. In addition, the results of the rotation process are collected in fully connected layers (including flats and dense layers). In this layer, the properties determined with a specific class are correlated, and the final result of this process is a property divided into two classes.

Table 1. New CNN models

Layers	Output size	Parameter
Input		
Conv1	32 x 32 x 32	896
Max Pool 1	16 x 16 x 32	
Conv2	16 x 16 x 64	18496
Max Pool 2	8 x 8 x 64	
Conv3	8 x 8 x 128	73856
Max Pool 3	4 x 4 x 128	
Conv4	4 x 4 x 256	295168
Max Pool 4	2 x 2 x 256	
Flatten	1024	
Dense1	512	524800
Dense2	2	1026
Output	32 x 32 x 3	

3. RESULTS AND DISCUSSIONS

CNN Pre-processing and Implementation

The first step before making the CNN model was pre-processing the garlic and shallot dataset. This is done to equalize the pixel size of each image in the dataset, which is changed to 32 x 32 pixels. Then, at this stage, the distribution of training and data validation is carried out with a ratio of 90%: 10%. After the data is divided into training and validation data, the dataset is labeled which is divided into two classes, garlic and shallots. At this pre-processing stage, the Keras library in the Tensorflow framework is used.

Furthermore, in implementing CNN there are 3 stages carried out, namely training, validation, and testing. At the training stage, model training has been carried out by studying the input data. Then, the model is tested on validation data. After obtaining good accuracy results, the model is used for image classification on test data.

Training, Validation, and Testing

The training and validation results are presented in Table 2. The training data used is taken 90% of the total data so that there are 180 images with each class there are 90 samples. The training process uses the categorical cross-entropy sparse loss function, the Adam optimization function with a learning rate of 0.001, and a maximum of 15 epochs. Based on these results, the highest accuracy value in the training model is 98.33% at the fifteenth epoch. The validation process for the CNN model that has been trained uses 20 data to test the model with 10 images for each class. Based on these results, the accuracy obtained was good

.

Table 2. CNN model training and validation results

Epoch	Train_loss	Train_accuracy	Val_loss	Val_Acc
1	46.6908	0.5167	14.8319	0.5
2	8.9520	0.4667	1.8674	0.5
3	1.0631	0.5556	0.5318	0.85
4	0.5963	0.7167	0.6774	0.6
5	0.5499	0.7222	0.3727	0.85
6	0.4405	0.8056	0.3272	0.8999
7	0.3539	0.8667	0.2364	0.9499
8	0.3229	0.8778	0.1976	0.9499
9	0.2584	0.9056	0.1476	0.9499
10	0.2289	0.9111	0.1347	0.9499
11	0.1784	0.9444	0.1180	0.9499
12	0.1612	0.9410	0.1058	1.0
13	0.1367	0.9611	0.1034	0.9499
14	0.1011	0.9611	0.0861	1.0
15	0.0762	0.9833	0.0547	1.0

Furthermore, the accuracy and error graphs of the training process are presented in Figures 2 and 3 together with the accuracy and error graphs of the validation process.

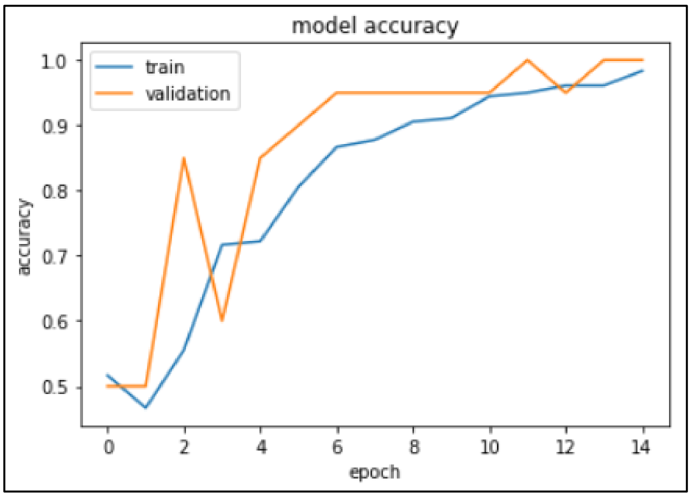

Figure 2. Training and validation model accuracy chart

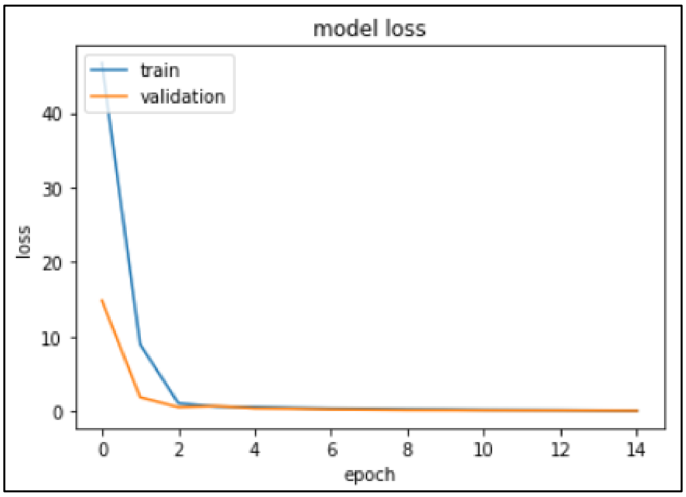

Figure 3. Training and validation model loss chart

At the testing stage, there were 20 data used to conduct an onion type classification experiment using a model that had been trained and validated. The image used in data testing is the same as the image in data validation. The model that has been made is able to classify all the images used in this test. There are 10 images which are garlic and 10 images which are shallots. The results of the testing process are shown in Figures 4.1 to Figure 4.6.

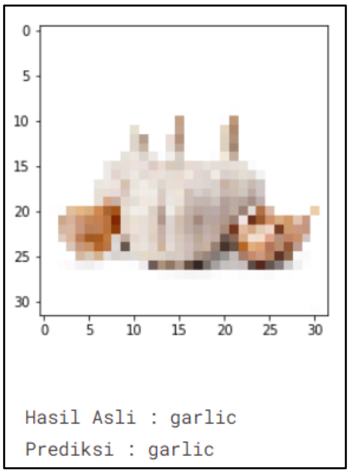

Figure 4.1. Garlic 1

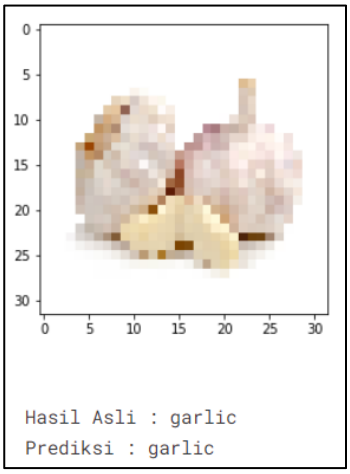

Figure 4.2. Garlic 2

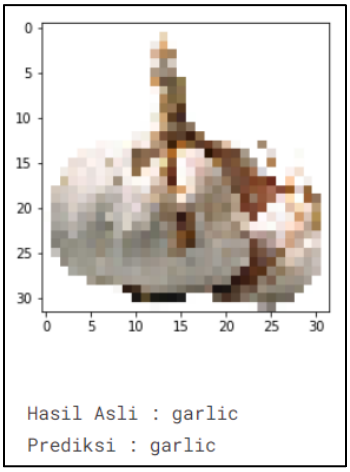

Figure 4.3. Garlic 3

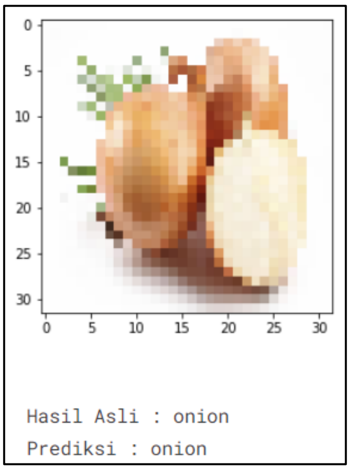

Figure 4.4. Onion 1

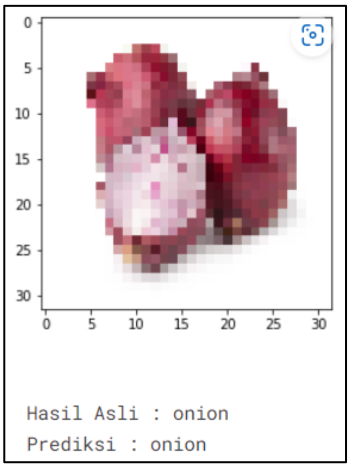

Figure 4.5. Onion 2

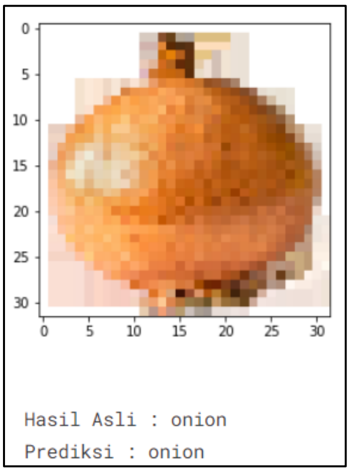

Figure 4.6. Onion 3

4. CONCLUSION

The CNN model created for the garlic and shallot image classification consists of 4 convolutional layers with each layer having a kernel matrix with a size of 2x2 and a total of 914,242 train parameters. The activation function on the convolutional layer uses ReLu and the activation function on the output layer is softmax. Model accuracy on training data is 0.9833 with a loss value of 0.762.

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