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Stepping up Onion Classification Model using CNN Algorithm

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Abstract
Traditional shallot classification methods, relying on visual inspection or conventional image processing, face limitations in dataset identification. To address the issues, we propose a CNN model for classifying shallot types. The study involves collecting a large dataset, preprocessing, and training the model with optimized parameters to maximize accuracy. By adjusting hyperparameters, we achieve a balance between accuracy and performance time. With 50 epochs and a batch size of 64, the model achieves over 80% accuracy in classification tests. These results demonstrate the effectiveness of CNN in shallot classification, outperforming traditional methods. Future work could explore advanced architectures like Generative Adversarial Networks (GAN) and Graph Convolutional Networks (GCN) to further enhance the model's performance.

Keywords
Onion, Classification, Deep Learning, CNN

1. Introduction

Plants are helpful as traditional medicine and have been in high demand as an alternative source of therapy by the general people [1]. Shallots are a valuable plant for herbal medicine that we commonly encounter daily. Shallot is a generic term for a group of plants in the genus Allium that is essential to humans. In general, shallot bulbs, leaves, and blossoms are employed in the culinary industry as vegetables or spices. Choosing the shallots based on attributes is simple for people but difficult for computers. Human perception of an object is usually subjective, owing to the color composition element, shape, or texture that the entity owns. As a result, a system is needed to detect and classify the different types of shallots automatically. Shallots are the most important crop on the globe. Global shallot output reached a record high in the first quarter of 2020, with 19 tons exported compared to the previous year's same period [2].

Various diseases and pests threaten shallot production, resulting in considerable losses and a deterioration in quality, thus increasing shallot production prices [3]. The fungus Helminthosporium solani causes silver scurf; Colletotrichum coccodes causes black patches; Rhizoctonia solani causes black dandruff, and the common scab is caused by the pathogenic bacterium Streptomyces spp. Moldy tubers result from these diseases, which impair the market's selling process [4].

The leaves of some plants, such as shallots, can be consumed by humans. Shallots are frequently used to sauté vegetables as whole or mashed ingredients. In addition, powdered shallot spices are commonly used to make sauce thickeners and baked goods [5]. This

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vegetable is easy to digest and contains vitamin B6 (pyridoxine), necessary for the nervous and immune systems to function correctly. Vitamin B9 (folic acid) is found in shallots and is required for cell division, DNA synthesis, and red cell production. Shallots also contain vitamin C and vitamin A, two essential vitamins with many health benefits. Shallots contain quercetin, a flavonoid (vegetable pigment) that strengthens and lowers the permeability of small blood arteries (capillaries). This molecule aids in the prevention of cerebrovascular illness and a variety of inflammatory conditions. People believe quercetin can help in the reduction of harmful cholesterol. Furthermore, shallot peptide isolates have exhibited antimicrobial and antifungal activities in studies. These qualities have yet to be proven in shallot-eating humans [6].

Shallots are one of Indonesia's most valuable horticultural products. Farmers examine the state of the leeks to determine the condition of the shallots. Choosing the shallots based on attributes is simple for people but difficult for computers. Human perception of an object is usually subjective, owing to the color composition element, shape, or texture that the entity owns. A system is required to classify the types of shallots automatically. The manual classification of shallots is done through visual analysis, which involves paying attention to color, shape, and texture. The human eye does not easily recognize the physical condition and color. The application of shallot-type classification with the CNN approach can be used to identify various kinds of shallots in supermarkets by users. Developers can use an image processing solution to help grocery personnel classify the many sorts of shallots. As a result, users require a system that can aid in the classification of shallots. In this application, we use the CNN method to categorize different types of shallots seen in supermarkets using an image processing methodology [7].

Farmers are increasingly aware of the engineering science and technology in agricultural management. Farmers require sophisticated technology to grow their crops. Typically, crop health and growth are influenced by environmental conditions, which are likely to be unpredictable at times. As a result, enormous initiatives are required to accelerate the development of agriculture's life cycle. The application of technology in agriculture has always assisted in adopting profitable, environmentally sound, and high-quality farming practices. On the other hand, farmers have particular obstacles requiring technology and training to ensure their success [8].

In the current year, the communities have developed various approaches to construct image classification using deep learning to incorporate the most recent scientific advances and design tools into their daily operations. This method produces classification results, enhancing efficiency, reducing losses, and increasing profitability [9]. Deep learning is a machine learning technique that teaches computers to do what people do naturally: learn by example. A computer model knows how to execute categorization tasks directly from images, text, or sound in deep learning. The precision of its results can outperform human capability. The author uses a large dataset with labels and multi-layer neural network architecture to train the model. Fully connected layers are an essential part of CNN, particularly effective at recognizing and classifying pictures in computer vision. Convolution and pooling are the first steps in the CNN process, which breaks down the image into features and analyzes them separately. This procedure is fed into a fully connected neural network structure, used to make the final classification decision [10].

In this paper, we propose CNN to classify shallot kinds by constructing the number of layers and filters to produce faster calculation time. In the shallot classification, we have several contributions, especially in the classification technique as follows:

1. We provide a new method for categorizing fruit types that combines training fruit features with the CNN algorithm and then uses the image set to construct a viable model. The concept separates the many sorts of fruit that need to be categorized. We acquired great accuracy and a low loss rate to prove the model.
2. The testing procedure is a classification procedure that employs weights and biases derived from the outcomes of the training procedure. The classification accuracy, the data that was unable to be classified, the number of images that we're unable to organize, and the form of the network produced from the

feedforward process will all be the results of this operation. The user uses the feedforward process with updated weights and biases to build an output layer. The system entirely connects the output layer to the accessible labels. The system categorizes the outcomes of failed data connection attempts.

3. As a result of our research, we can produce more accurate and efficient models based on classification using deep learning techniques, particularly CNN, which have lately gained popularity due to their improved accuracy over traditional machine learning approaches.

2. Related Works

Before developing deep learning technology, traditional technology was used to recognize plant classification images. Researchers started using deep learning to add plant pictures after inventing the technique, and they have made much progress in recent years. Image recognition is substantially more efficient and effective than older approaches [11]. A study looked into a method for classifying shallots that would allow users to classify shallots faster than humans. However, there are still flaws with this strategy. In articles evaluating various algorithms, researchers make recommendations that personalize data based on form and color attributes. Another study that uses the KNN approach to classify objects in digital photos by extracting GLCM features has been shown to have 100% accuracy [12].

Learning techniques such as SVM, KNN, RNN, and ANN are often used to classify objects. The classification problem involves establishing new classes or data groups based on the previously classified data. SVM and ANN are well-known methods for monitoring and classification methods. In recent years, many studies have used SVM to solve classification and identification difficulties. The most suited algorithm in a multilayer setting is ANN feedforward. The back-propagation neural network has many applications because of its simplicity and precision. The primary purpose of ANN training is to generate output from input data [14]. The KNN algorithm classifies objects based on neighboring training samples in the feature space of pattern recognition. It determines the distance between the query scenario and the dataset collection of scenarios [15]. The KNN algorithm belongs to instance-based group learning and is one of the top 10 classification algorithms. However, the KNN technique has a flaw: the variable value must be essential to achieve maximum accuracy while selecting the variable at k [16].

The classification problem involves establishing new classes or data groups based on the previously classified data. Classification techniques such as SVM and ANN are well-known to keep an eye on. In recent years, many studies have used SVM to solve classification and identification difficulties. The most appropriate approach in a multilayer setting is NN feedforward. The back-propagation neural network has many applications because of its simplicity and precision. The primary purpose of NN training is to generate output from input data [17].

Humans most widely used learning technique is the ANN computational model, which consists of several components, simple processing parts called nodes or neurons. Each neuron is connected to the others via communication links. Association weights in neurons represent the information studied by the neural network. This paper provides a CNN approach for shallot type which enables to building of a model for shallot type classification based on size, weight, and RGB mean values [18]. The CNN method is currently the most commonly utilized for extracting and classifying objects that can perform an independent learning process. It can be employed in high-resolution photographs using nonparametric distribution models [13].

3. Proposed Method

This section will provide a formal definition of the research problem and some of the concepts in this journal

3.1 Problem Definition

This study focuses on the categorization of shallots using the CNN method using dataset features based on the RGB average value. As a benchmark data set, we suggest a model for training features. To finish the classification process, the data is supplied to the function along with arguments. The weight of each characteristic in the vector is calculated by multiplying it by the parameter.

$$f(x) = xw + b \tag{1}$$

$$f(x) = x_1 w_1 + x_2 w_2 + \cdots x_N w_N + b \tag{2}$$

3.2 Proposed Method

We use the CNN method in this study to develop a classification model for shallots. The CNN algorithm model is structured and operated similarly to the human brain. As a hot subject of study, deep learning is becoming a more popular method for resolving numerous research difficulties. Numerous research employs the CNN algorithm to address classification issues. We also calculate the accuracy and loss of training and testing to achieve the optimum results [5].

To address the issue of overfitting during the training process, which is a frequent occurrence in CNN training, we use a regularizer. It enables the approximate combination of an exponentially large number of distinct network configurations. Dropout is a strategy used during the training phase to create a thinner network. Dropout regularization is used in this research for the training sample but not for the prediction technique.

Dropout is a cutting-edge regularizer that is simple and works with a wide variety of training methodologies and models. It determines the neuron's contribution to the output based on the measured value. Consider a network with l hidden layers for the function. We develop they_train training technique using the dropout function for elements such as input x and Bernoulli probability p. z^l signifies the vector of inputs to layer l, y^l denotes the vector of outputs from layer l, r^l denotes an independent vector of Bernoulli random variables with probability p equal to 1, and 〖ỹ〗^l denotes the thinned outputs described by 〖ỹ〗^l= r^l * y^l in the traditional feed-forward. As a result, the dropout regularizer computes the following:

$$z_i^{(l+1)} = z_i^{(l+1)} \, y^l \theta + z_i^{(l+1)} \tag{3}$$

$$y_i^{(l+1)} = f(z_i^{(l+1)}) \tag{4}$$

The regularizer is calculated using the following formula feed-forward operation:

$$z_i^{(l+1)} = z_i^{(l+1)} \tilde{y}^l \theta + z_i^{(l+1)} \tag{5}$$

$$y_i^{(l+1)} = f(z_i^{(l+1)}) \tag{6}$$

The regularizer calculates the next layer using the thinning outputs y_i^((l+1)). The process is repeated for each layer of the hidden layer. This value differentiates between a sub-network and a more extensive network. During training, it propagates the derivatives of the loss function backward through the sub-network.

To improve training and testing accuracy, a study can utilize several parameters in the DL algorithm, including epoch, regular, and optimizer. Figure 1 illustrates the CNN topology for training the book lending recommendation model.

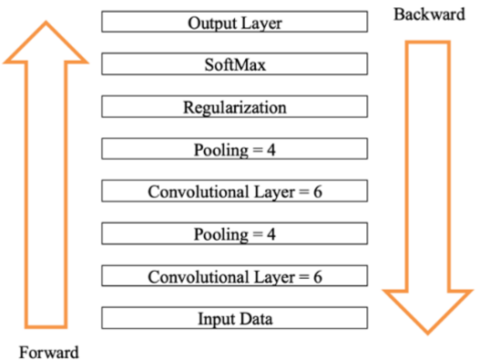

Figure 1. The proposed CNN topology for training the shallots dataset.

The proposed CNN employs a Deep Neural Network with several hidden layers to train and test the model. It also utilizes a gradient descent to minimize the objective function with the model's parameters. The model updates the settings in the opposite direction of the gradient of the objective function. Different from the regular pooling layer, this study adopts a pooling layer to optimize and accelerate training time in a neural network. By using the proposed CNN topology, we calculate the accuracy and loss of the training and testing process to achieve the best result with the diverse input vector. We establish a supervised learning model by defining calculation over NN as follows:

Input features$x^{(i)} \in R$
Outputs $x^{(i)} \in Y\ (e.g. R, \{0,1\}, \{1, \ldots, p\})$
Model parameters $\theta \in R^k$
Hypothesis function$h_{\theta:} : R^n \rightarrow R$
Loss function $l : R \times Y \rightarrow R_{+:}$

4. Experimental Setup

4.1 Main Idea

The objective of this paper is to develop a shallots classification model using CNN based on the size of the RGB value. CNN is used to classify labeled data using a supervised learning approach, categorizing the data using training data and targeted variables. In this paper, we present CNN to classify and identify objects. Due to the high level of accuracy that the CNN algorithm achieves, it is very good at dealing with classification problems.

4.2 Dataset

The diameter, weight, and average RGB values of shallots were collected in this study. The data is partitioned into training and testing datasets. Training data sets are used to create learning models, whereas test data sets are used to develop machine performance or accuracy models. For our experiment, we gathered a sample of 200 datasets containing 100 garlic and 100 onions. We divide the dataset distribution into 80% for training and 20% for testing. The distribution of the training and testing datasets is shown in Table 1. The following table summarizes the dataset distribution table used in the study:

Table 1. Details distribution of the dataset

Dataset Label	Deep Shallots Features	
	Training 80%	Testing 20%
Garlic	100	20
Onion	100	20

4.3 Data Pre-Processing

Preprocessing is carried out in this phase by examining the data type of each variable in the dataset and determining whether there are any empty values. When data is missing values, it is necessary to handle them. Each variable is initialized with the appropriate data type. The following step is to generate a vector by employing label coding and feature scaling techniques. The label coding method converts raw data to vectors, whereas feature scaling normalizes the data to conserve storage space [19].

4.4 Classification Method

We gathered a dataset of shallots labeled with two distinct varieties to conduct our study. After collecting the dataset, the raw data is vectorized using label coding and feature scaling methods. After preprocessing, we compute the acquired features to train the classifier model. The dataset is divided into two parts during the feature extraction process: training and testing. The training dataset is used to develop or train a model capable of classifying various types of shallots. In contrast, the test dataset is used to assess the model's performance or accuracy. We changed some parameters to obtain the optimal training accuracy of the model classifier. Following that, the CNN algorithm feeds the model [20].

5. Result and Analysis

5.1 Classification Test

In this experiment, we achieve a trade-off between accuracy and performance time. We adjust various hyperparameters to optimize network performance. During the training and testing phases, we set the epoch to 50 and the batch size to 64. Our proposed model can classify with an accuracy of 80% based on the classification test, as shown in Fig. 2 depicts accuracy and Fig. 3 depicts loss of the model.

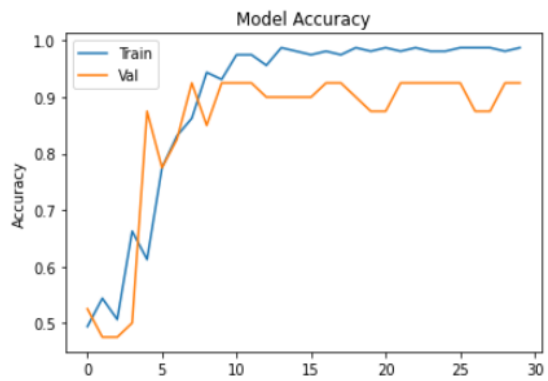

Figure 2. Training Accuracy

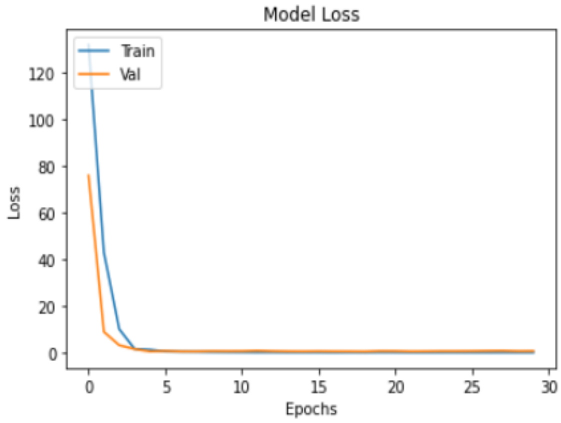

Figure 3. Training Loss

5.2 Evaluation Metrics

Evaluation metrics are used to assess the classification algorithm's predictive ability. This study's accuracy, precision, and recall are 0.92, 0.90, and 0.90, respectively. As illustrated in the following confusion matrix, the model correctly recognizes 100% of the garlic class and 80% of the onion class. The model correctly classifies 20% of the images in the onion class as garlic. Figure 4 displays the evaluation metrics of the proposed model of this paper.

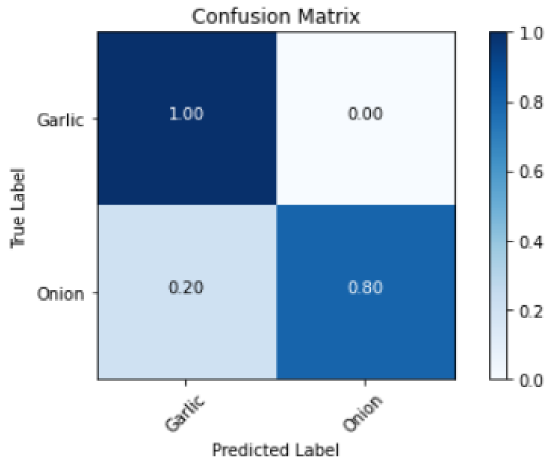

Figure 4. Confusion Matrix

6. Conclusion

Traditional classification techniques for shallots have relied on visual capabilities or conventional image processing methods. However, there are still shortcomings in the process of identifying datasets. In this paper, we test a new classification model using the CNN to classify the shallot types to solve this problem. In this experiment, we collect large amounts of data, preprocess, train our model using parameters optimized for maximum accuracy, and test the model. Based on the experimental result, we gain a trade-off between accuracy and performance time by adjusting hyperparameters to optimize network performance. During the training and testing phases, we set the epoch to 50 and the batch size to 64. Our proposed model can produce an accuracy of more than 80% based on the classification test. In future work, modern algorithms such as GAN and GCN architectures could be used to improve this model.

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