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ABSTRACT

Potato plant growth needs to be protected from weeds that grow around it. Currently, the manual spraying of pesticides by farmers is not only precise on weeds but also on cultivated plants. Therefore, we need an intelligent system that can appropriately classify potato plants and weeds. The research contribution combines feature extraction and appropriate classification methods to obtain optimal accuracy. In addition, the small amount of data also contributes to this research. In this research, it is proposed to use a combination of feature extraction using deep learning techniques and classification using machine learning. We use the feature extraction method with the DenseNet201 model because this study's data is not too much. Complex vectors from DenseNet201 were reduced using Principal Component Analysis (PCA). Then we classified it with the Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) classification methods. The experimental results show that the PCA method can reduce the complexity of high-dimensional features into 2 and 3 dimensions. The average of the best classification results using SVM was obtained with a 3-dimensional PCA configuration, but on the contrary, using KNN obtained the best results in a 2-dimensional PCA configuration. The results showed 100% accuracy on the DenseNet201-SVM hybrid. The SVM kernel configuration used is a linear kernel. The results of this study can be an insight into an accurate classification method for separating weeds and potatoes so that agricultural technology can apply this method for classification.

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1. INTRODUCTION

Indonesia is an agricultural country whose livelihoods are primarily farmers. One of the farmers' crops is potatoes [1]. Potato plants are strategic horticultural commodities in providing food to support food security [2]. One factor that affects the quality of potato crop yields is the availability of sufficient nutrients [3]. The cause of nutrient competition is the presence of weeds that grow around cultivated plants [4]. Weeds are plants that are not expected to grow on cultivated land because these plants compete for nutrients that can reduce crop yields. Therefore, Farmer must clean weeds not to seize the nutrients of cultivated plants.

Because the number of weeds growing in the fields increases daily, the right step is to spray pesticides on the fields. Using the pulling weeds manual takes time and effort [5]. Therefore, a special technique is needed to classify weeds with potato plants. Spraying of pesticides uniformly sometimes affects cultivated plants as well. In addition, cultivated plants exposed to pesticides will also affect their growth [6]. So, it requires an appropriate classification system to distinguish between weeds and cultivated plants.

One technique for classification is to use the fields of Artificial Intelligence, such as deep learning [7][8] and machine learning [9]. The use of deep learning usually uses large amounts of data [10]. However, in some instances, the data found are not as abundant as in the case of this weed and potato classification. A deep learning technique that has been previously trained using ImageNet data is called transfer learning [11]. One transfer learning model that produces optimal accuracy is DenseNet201 [12]. The advantage of feature extraction using transfer learning is that features are found in the image automatically and are more robust. In this study, it is proposed to use DenseNet201 as feature extraction. Then the stage after feature extraction is classification. Machine learning techniques often produce less than optimal accuracy in image data classification [13][14]. Therefore, this research proposes a combination of transfer learning and machine learning techniques to improve accuracy results.

Research related to weeds is related to computer vision [15][16] that previous researchers have carried out. Some researchers who classify weeds with cultivated plants use the Support Vector Machine (SVM) and K-Nearest Neighbor (K-NN) methods to classify image data. Researchers Athani and Tejeshwar [17] used the SVM method to classify weeds with corn. The classification results show an accuracy of 82%. Then the researcher by Henrique Yano et al. [18] used the K-NN method to classify weeds with sugarcane. The results showed that the accuracy obtained was 83.1%. Both studies have not produced optimal accuracy. We propose using hybrid DenseNet201 with the classification method, namely SVM or K-NN, to classify weeds with potato plants. We will evaluate the performance of the classification results of the SVM and K-NN methods. It is hoped that this research will obtain a more optimal accuracy. The research contribution combines feature extraction and appropriate classification methods to obtain optimal accuracy. In addition, the small amount of data also contributes to this research.

2. METHOD

The proposed intelligent system for the classification of weeds and potato plants is shown in Fig. 1. The system starts with the training process. The data used in this study is a dataset of weeds and potato plants. The data obtained were pre-processed in the form of resizing. The result of resizing data is then divided into training and validation data. Before entering feature extraction, there is a reduction of the dimensions of the data features using PCA. The result of feature reduction is used for feature extraction and classification using a combination of DenseNet201-SVM or DenseNet201-KNN. The result is the model used for matching using data testing. The matching result is in the form of a classification of whether weed plants or potato plants. The final stage is the evaluation of the system created.

2.1. Data Acquisition

The data used in this study came from the Kaggle dataset [19]. Ali Hassan collected the data on Kaggle, with the data on potato plants being 169 and the number of weeds being 242. The data was shot in the potato field above with the camera above the plants. All data is Red, Green, Blue (RGB). The size of this raw dataset still varies. Fig. 2 shows an example of the dataset used in this study.

2.2. Data Pre-processing

The size of the datasets in this study varied. The DenseNet201 model used in the feature extraction stage requires the input image size to be 224×224 [20]. Therefore, at this pre-processing stage, resize to a size of 224×224. Then the pre-processing data is divided into training and validation data, with a division of 75 % as training data and 25% as validation data.

2.3. Principal Component Analysis

The features of the image object are so many that it makes the dimensions of the features also higher. In this study, Principal Component Analysis will be used to reduce the dimensions of features in the image [21][22]. The PCA method can reduce or reduce the dimensions of the data while maintaining data that has a significant (significant) effect. After the reduction is made, it is hoped that a reduction in the number of dimensions of the image feature data will be obtained, and the data that has a significant influence can be seen [23]. Suppose there is data with an arrangement as shown in equation (1).

$$X = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1n} \\ X_{21} & X_{22} & \dots & X_{2n} \\ \vdots & \vdots & \dots & \vdots \\ X_{m1} & X_{m2} & \dots & X_{mn} \end{bmatrix} \quad (1)$$

Where n is the number of variables/attributes and m is the number of observations. Furthermore, the data is transformed into a column, for example, with a centering technique to reduce each data by averaging each attribute with equation (2).

$$\hat{X} = X - \bar{X} \tag{2}$$

Where $\hat{X}$ is the result vector of entering, and X is the column vector. The process is executed on all columns from $i = 0$ to $i = n$. In this case study, the image features in the PCA method are represented as eigenvectors, namely a collection of characteristic relationships in the image to identify the image specifically.

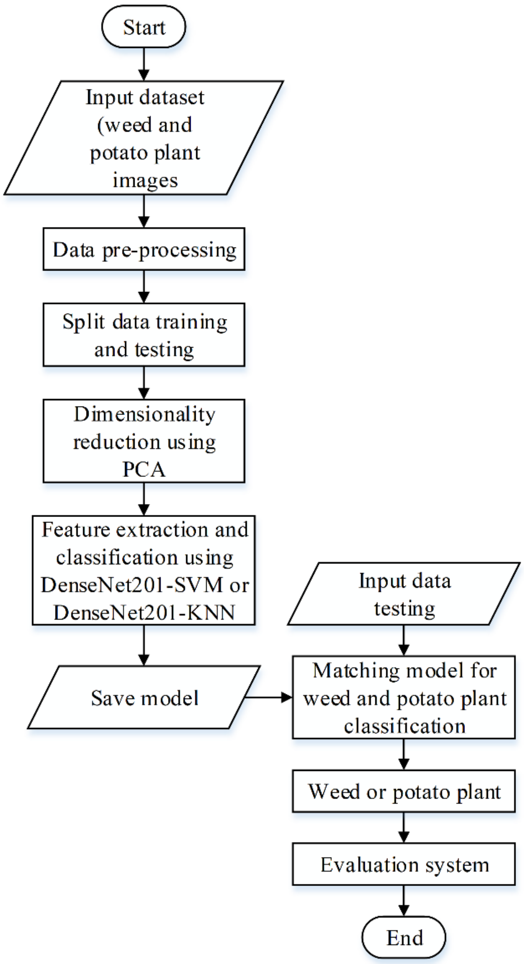


Fig. 1. Stages of the weeds and potato plants classification system

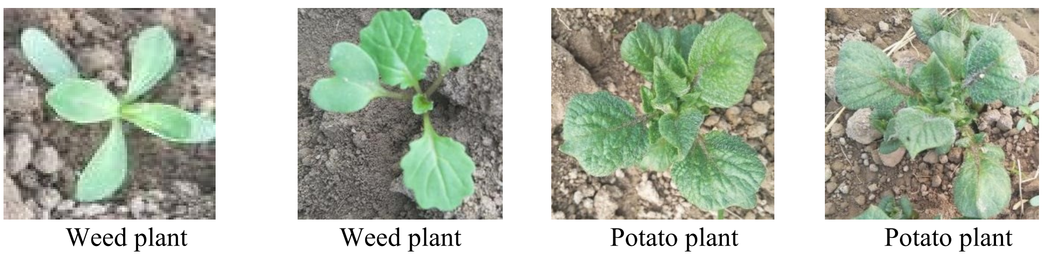


Fig. 2. Samples of data and label

2.4. Feature extraction and Classification

In this study, the feature extraction process uses the DenseNet transfer learning model. DenseNet was first introduced in 2017 [24], which modifies the CNN network structure where each layer will get additional input from the previous layer. In other words, each new layer will receive a feature map from the previous layers [25]. Fig. 3 shows the layers in the DenseNet201 model. DenseNet has higher compute and memory efficiency. DenseNet consists of several types including DenseNet121 [26][27], DenseNet169 [28][29], and DenseNet201 [30][31]. In this study, the DenseNet type used for feature extraction is DenseNet201.

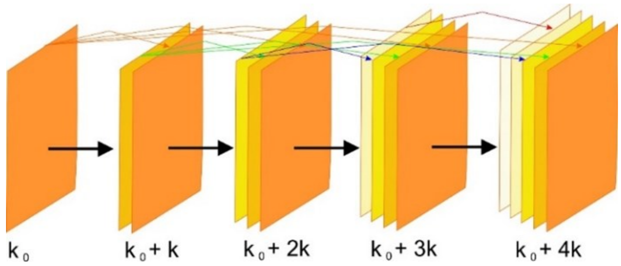


Fig. 3. DenseNet201 layer structure.

Fig. 3 depicts a Dense Block instance with five layers and a growth rate of k. Each successive layer is supplied with feature maps from the preceding layer. DenseNet supports the concatenation of all previous layer feature maps, which means that all feature maps propagate to succeeding layers and are coupled with newly generated feature maps. The newly developed version of DenseNet has several advantages, including the ability to reuse features and reduce gradient vanishing or explosion issues. DenseNets are subdivided into DenseBlocks, in which the dimensions of the feature maps remain constant within a block, but the number of filters varies between blocks. These layers are referred to as Transition Layers and are responsible for downsampling by applying batch normalization, 1×1 convolution, and 2×2 pooling layers.

Then, the classification stage uses the Support Vector Machine (SVM) [32] or K-Nearest Neighbor (KNN) [33] method. SVM is a classification method that is now widely developed and applied [34][35]. This method is derived from a promising statistical learning theory and gives better results than other methods [36]. SVM works very well on high-dimensional datasets. The basic idea of SVM is to maximize the hyperplane boundary described in Fig. 4. SVM must map the original data from its original dimension to another relatively higher dimension using the kernel technique. The reduced vector using PCA is used for classification in SVM. In Fig. 4, suppose that the potato class vector is red, and the weed class vector is yellow. SVM will look for a hyperplane with a maximum margin of both classes to separate it into two area classes. The new dataset will be placed according to the position of the vector so that the results fall into the potato or weed class region.

KNN is a method for classifying objects based on learning data closest to the object [37]. An object will be classified based on the choices of its neighbors. Near or far neighbors are usually calculated based on the Euclidean distance [38]. The use of KNN, in this case, is illustrated in Fig. 5. For example, the PCA result vector for the potato class is red, while the weed class is green. For example, the three closest neighbors will vote using the value of K = 3. The classification result is weed class because the number of neighbors is more than potato class.

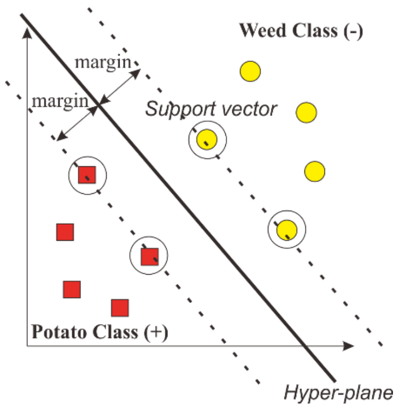


Fig. 4. Illustration of the SVM method

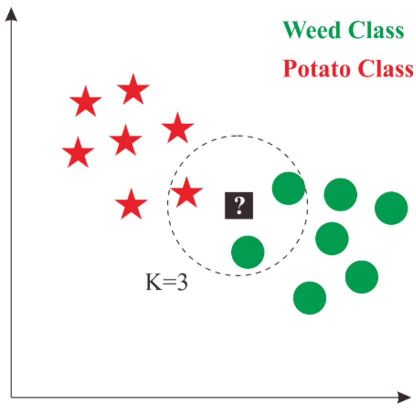


Fig. 5. Illustration of the KNN method

2.5. System Evaluation

This study will evaluate the performance of the hybrid DenseNet201-SVM and DenseNet201-KNN. We will calculate the value of precision, recall, and accuracy of the resulting matching process. Equations (3), (4), and (5) show the equations of precision, recall, and accuracy [39][40]. The test scenario for the DenseNet201-SVM method is to use linear, polynomial, and RBF kernels. Then the DenseNet201-KNN method will test various K values, namely 1, 3, 5, 7, and 9. The odd K values are used because the number of classes is even, namely weed and potato.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

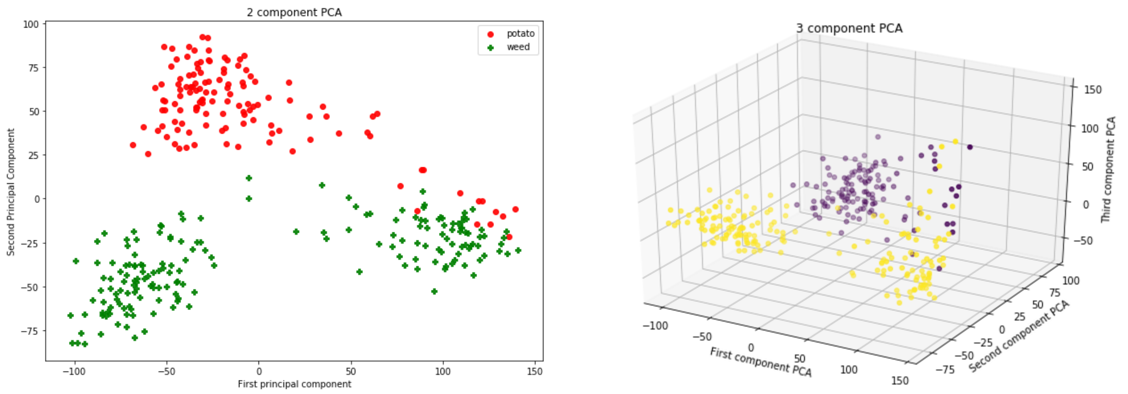
$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{5}$$

3. RESULTS AND DISCUSSION

In this research, we ran an experiment to evaluate the hybrid DenseNet201-SVM and DenseNet201-KNN networks. The images are fed into pre-trained Densely Connected Convolutional Networks with the top layer deleted. All convolutional layers are frozen during the feature learning phase. Finally, the collected features were classified using both Support Vector Machine and K-Nearest Neighbor classifiers, and the results were presented. Principal Component Analysis (PCA) was used to transform characteristics into a 2D (two-dimensional) and 3D (three-dimensional) feature space for SVM and K-NN. In this section, we will discuss the PCA result, feature extraction result, and classification.

3.1. PCA Result

The feature extraction process in this study uses the DenseNet201 model. The results of feature extraction are features in many dimensions. This study uses Principal Component Analysis (PCA) to reduce the features generated in the feature extraction process. In PCA, an image matrix is converted into a high-dimensional vector matrix, which helps calculate the covariance matrix of a high-dimensional vector space. However, the main obstacle is that the covariance matrix becomes large, resulting in a large number with small samples, making it difficult to evaluate accurately. In addition, it takes much time to calculate the next eigenvector. To overcome this difficulty Two Dimensional - Principal Component Analysis (2D-PCA) and Three Dimensional - Principal Component Analysis (3D-PCA) provide a way to deal with this limitation. The PCA results are shown in Fig. 6. 2D-PCA produces 2-dimensional features with x and y dimensions. Meanwhile, 3D-PCA produces 3-dimensional features with dimensions of x, y, and z. The features between potatoes and weeds appear to be distinguished in colors representing the features' location in a coordinate.



(a) (b)

Fig. 6. PCA result a) 2D, b) 3D

3.2. Feature extraction and Classification

This research's feature extraction and classification process use DenseNet201 as the base feature extraction model. Then the classification using SVM or KNN. The programming used in this system uses Python language with Keras and Sklearn libraries.

3.2.1. DenseNet201-SVM

In the SVM method, a kernel contains mathematical functions to separate data between classes. The kernel in SVM will convert the input data into a specific format so that class data will be separated from one another.

In this study, the use of 3 kernels in SVM will be tested, namely linear, polynomial, and RBF. Table 1 shows the results of the Hybrid DenseNet201-SVM experiment. The recall and precision values were obtained from the average yield of weed and potato plant classes.

Table 1. The experiment results using DenseNet201-SVM

Kernel	PCA 2D			PCA 3D		
	Recall	**Precision**	**Accuracy**	**Recall**	**Precision**	**Accuracy**
linear	0.99	0.99	0.99	1.00	1.00	1.00
polynomial	0.96	0.97	0.97	0.99	0.99	0.99
RBF	0.96	0.97	0.97	0.97	0.96	0.97

Based on Table 1, the best results in the experiment were obtained using 3D PCA with recall, precision, and accuracy values of 100%. In using 2D PCA, the best result is using a linear kernel. Using a linear kernel produces optimal accuracy because the number of classes only consists of two classes, so it is easy to separate them linearly. The SVM classification experiment resulted in high recall, precision, and accuracy values, so it can be said that the model produced using feature reduction is very good.

3.2.2. DenseNet201-KNN

In this research, the distance algorithm used is Euclidean Distance. The KNN method calculates the shortest distance between the new testing data and the training data in the database. There are two classes in this study, so the K values used in the experiment are odd, namely 1, 3, 5, 7, and 9. Table 2 shows the experimental results using the combination of DenseNet201 feature extraction with the KNN classifier.

Table 2. The experiment results using DenseNet201-KNN

K	PCA 2D			PCA 3D		
	Recall	**Precision**	**Accuracy**	**Recall**	**Precision**	**Accuracy**
1	0.98	0.98	0.98	0.96	0.95	0.96
3	0.98	0.98	0.98	0.95	0.93	0.94
5	0.98	0.98	0.98	0.96	0.95	0.95
7	0.97	0.96	0.97	0.95	0.94	0.94
9	0.96	0.97	0.97	0.95	0.94	0.94

Based on Table 2, the best results were obtained using a value of K=1 in both 2D PCA and 3D PCA experiments. The use of more K values will calculate recall, precision, and accuracy to decrease. The more neighbors are taken for voting, and the more neighbors are chosen. Then, the results of the recall, precision, and accuracy values are also as good as the experimental results using the SVM classifier. It shows that KNN also produces a reasonable classification, as evidenced by the recall and precision values that are not much different.

3.3. Analysis and Discussion

The transfer learning model is a deep learning-based method suitable for processing fewer data. This study uses the DenseNet201 transfer learning model because the previous research [41] produced excellent accuracy. Likewise, the results of this study, the use of image data that a little requires a suitable feature extraction method. We added PCA to reduce the features obtained from the feature extraction so that only the main features are used. The accuracy results obtained in this study are also excellent, reaching 100% when using the DenseNet201-SVM combination with a linear kernel configuration. Table 3 shows a comparison of the proposed method with previous studies, in previous studies using deep learning and machine learning methods. The results of the proposed research are still superior to several previous studies. PCA affects the accuracy results obtained because the results of feature extraction using DenseNet201 have high dimensions. After the dimensions are reduced to two or three, they can be classified using the SVM method properly.

Table 3. Comparison of the proposed method with previous studies

Classification Model	Accuracy
R-CNN [42]	83.33%
YOLOv5 + Random Forest [9]	87.5%
HSV, shape + ANN [14]	95.46%
InceptionV3 [43]	97.7%
Proposed Method (DenseNet201 +SVM)	100%

Fig. 7 shows the prediction results with the actual data in this research. Prediction results with actual data show all the same, so there is no error in the prediction results. These results indicate that machine learning methods can produce optimal accuracy with the right feature extraction methods. The weakness in this study is that it does not consider the time taken from the feature extraction process to classification. In future research, it is possible to apply these methods to video data so that speed testing can be carried out on real-time data. The use of video data can also be applied to IoT devices. The existence of integration with IoT devices can produce a precise weed sprayer that only hits weeds.

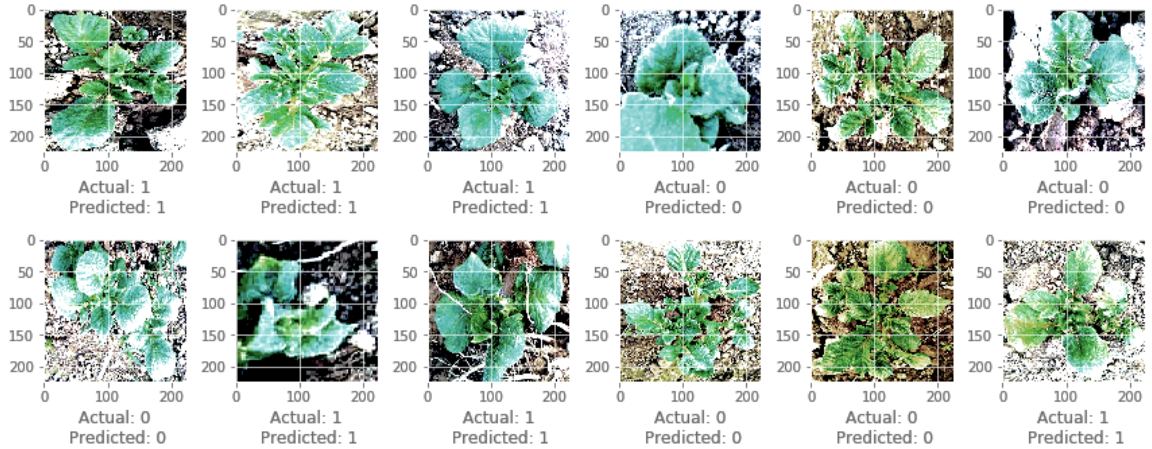


Fig. 7. Prediction results of weeds and potato plants

4. CONCLUSION

Weeds interfere with cultivated plants to compete for nutrients contained in the soil. This research focuses on the use of feature extraction methods and the classification of weeds and potato plants. This research uses Artificial Intelligence, especially deep learning to classify weeds and potato plants. In previous studies, machine learning has not produced optimal accuracy. So, we propose a combination of deep learning and machine learning for this classification. The proposed method uses DenseNet201 with SVM or KNN. In addition, we also use PCA to reduce the dimensions of the feature extraction results. The results showed 100% accuracy for classifying weeds and potato plants. We hope this research can be developed for video data so that the speed of this method can be tested. Future research recommendations can integrate with IoT devices to test the use of real-time video data.

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