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CONVOLUTIONAL NEURAL NETWORK OPTIMIZATION FOR DEEP WEEDS

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Abstract: Precision agriculture is critical in ensuring food availability while maintaining environmental sustainability. Weeds are a serious threat to crops because they can inhibit plant growth and absorption of nutrients and infect nearby plants. Reduction in agricultural production can reach 20-80% if weeds are not handled quickly and precisely. In this study, four Convolutional neural network architectures were implemented to identify weeds based on images. The total number of images in the dataset used is 17,509 images grouped into nine classes which are divided into 80% for training data and 20% for test data. The training process uses a transfer learning scheme and operates several different optimization functions. The test results show that the best performance is achieved by the GoogleNet architecture using the stochastic gradient descent with momentum optimization function with a classification accuracy of 92.38%. Testing also shows that the ShuffleNet architecture classifies images faster than the other architectures used in this study, although its performance is slightly lower than GoogleNet.

Keywords: Convolutional Neural Network, Weeds Classification, Transfer Learning, CNN Optimization

INTRODUCTION

In agriculture, AI (Artificial Intelligence) can make sound predictions for planning the planting of certain types of plants, harvesting, and maintenance to increase yields and reduce maintenance costs (Eli-Chukwu, 2019). AI (Artificial Intelligence) also encourages the development of precision agriculture, allowing for more accurate and controlled agricultural handling (Dharmaraj & Vijayanand, 2018). Precision agriculture has a significant role in ensuring food availability while maintaining environmental sustainability. Precision agriculture can increase agricultural production simultaneously as efforts to reduce the negative impact of using hazardous chemicals in the agricultural field. An important part of precision farming is identifying factors that reduce agricultural production, such as pests and weeds. Weeds seriously threaten crops because they can inhibit growth and nutrition and infect nearby plants (Mounashree et al., 2021). If not handled quickly and appropriately will reduce production yields by 20-80% (Asad & Bais, 2020). Early identification of these two factors will facilitate their handling while reducing the use of pesticides (Le et al., 2020). Handling weeds using herbicides requires excellent attention and costs. In Australia, it is estimated that weed control costs AUD$1.5 billion annually, and agricultural production losses due to weeds amount to AUD$2.5 billion (Olsen et al., 2019). Handling weeds using herbicides is also wrong because herbicides can contaminate crops (Jogi et al., 2020).

CNN (Convolutional Neural Network) has the advantage of identifying weeds and distinguishing backgrounds from well-recognized objects (Jiang et al., 2020). Many image features, such as color, shape, and texture, can be used. Still, some things have abstract features that require different techniques to solve. With the presence of CNN (Convolutional Neural Network), it can be a solution because CNN can extract many abstract features that exist in an image. An example of one of the CNN models is VGG16 which can recognize 1000 different classes from millions of prints. However, to produce good accuracy, the CNN model requires large datasets and computer resources (Sawada et al., 2016). In a previous study, (Wu et al., 2021) Zhangnan Wu and Yajun Chen classified weeds with an accuracy of 95.1 (inception-v3)% & 95.7% (resnet-50), and resnet got a speed of 53.4 ms per image, so research is needed to find the most optimum CNN architecture for handling weeds. The results of this study are expected to be used in further research in Indonesia, particularly in weed identification. It is hoped that early detection will make weed control more effective, increasing the production and quality of crops in Indonesia.

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LITERATURE REVIEW

Deep Learning

One suitable method for handling weeds in the field is deep learning because it can extract perfect features. This method has attracted a lot of attention from researchers. In controlling weeds, the deep learning method shows good accuracy and grass detection results. wild (Wu et al., 2021), Deep Learning is a development of ANN (Artificial Neural Network). Deep learning is also a field of machine learning that utilizes artificial neural networks to be able to solve cases with large datasets. Deep learning can classify images and sounds using feature extraction from training data and special learning algorithms, but speed and accuracy are still a challenge in deep learning (Lecun et al., 2015).

Convolutional Neural Network

CNN (Convolutional Neural Network) is one of the deep learning architectures that can identify information from an image or object in two dimensions (Liu et al., 2015)CNN is currently used in many areas of life to solve many cases, such as system recommendations (Zheng et al., 2019)medical image analysis (Lundervold & Lundervold, 2019), and others. Weeds are one of the agricultural problems that researchers continue to focus on.
Feature Learning and Classification are the two fundamental components of CNN architecture. An activation function, convolution layer, and pooling are the components of feature learning. Depending on the architectural requirements, this layer is frequently divided into many levels. After that, Flatten, Fully Connected, and Softmax make up the classification part (Ghosh et al., 2019). Convolution is an image multiplication technique with a kernel. The kernels in the convolution layer are in charge of extracting features. The kernel size must be smaller than the size of the input image. Filters are two-dimensional arrays of odd sizes, such as 3 x 3, 5 x 5, 7 x 7, and others. Filters are made to know the feature is present, not where the filter is located. For example, when determining whether an image contains a face, it is not necessary to know the location of the eye with pixel-perfect accuracy. We only need to know that the eye is on the left side of the face and there is an eye on the right of the face (Won, 2018).

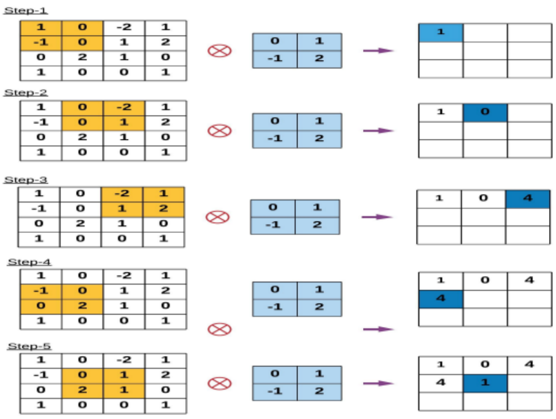

Fig 1 Illustration of the Convolution Process (Ghosh et al., 2019)

As shown in Figure 1, the input image with three channels of 4 x 5 pixels is filtered with one channel output. The number of multiplications between the input images on the first channel produces 2. On the second channel, it has -2, and on the third channel, it makes 0. The convolution output is the sum of each channel plus the bias, namely 2 + (-2) + 0 + 1 = 1.

Optimization Function

The performance of the CNN learning process can be affected by applying optimization methods for CNN training (Dogo et al., 2018). Some often used optimization methods include ADAM, SGDP, RMSPROP, and others.

ADAM Optimization

ADAM (Adaptive Moment Estimation) is a learning speed optimization algorithm specifically designed for deep neural networks. ADAM was first introduced in 2014. in his research detailing a better increase in gradient descent, Adam is a combination of RMSPROP and SGDM, a development of RMSPROP. (Kingma & Ba, 2015)

SGDM Optimization

The stochastic gradient descent momentum (SGDM) method uses several randomly chosen data samples and is connected to random probability. This helps lower the significant computational expenses associated with CNN training (Chee & Li, 2020).

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Optimization of RMSPROP

RMSPROP (Root Mean Square Propagation) is the most successful method in many cases. RMSPROP is a learning speed method adapted for each parameter by dividing a weight's learning speed by the average of the most recent gradient for that weight (Kingma & Ba, 2015).

Transfer Learning

Two ways to train the CNN model are: by creating a network from Scratch (Scratch) or transfer learning (Transfer Learning). To be able to do Scratch, it takes a lot of objects to find solutions in the image. Even though we still have complete control over the network that is created, it is a matter of time to do model training, which takes a very long time. Overfitting and convergence are problems that very often arise in the training process. The solution to overcome this problem can be used by using Transfer learning. In the process, the convolution layer is used as a fixed feature extractor, but only the fully-connected layer is adapted to the task to be carried out (Altuntaş et al., 2019).

METHOD

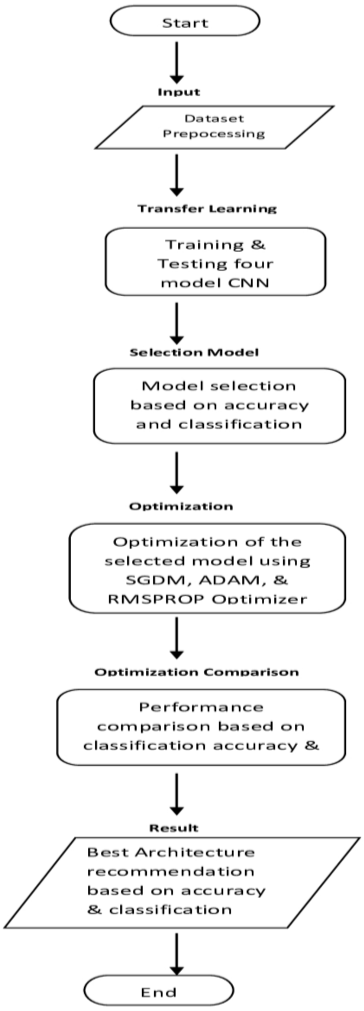

Fig 2 Flowchart model

Datasets

The collection consists of 17,509 color images of weeds divided into nine types. An example of the image utilized in this study is shown in Figure 2

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Fig 3 Datasets

Table 1 lists the number of images in the dataset utilized in this investigation for each class. The dataset will be split into 20% for testing and 80% for training. For each CNN architecture that will transfer learning, the size of the input image is altered by the default image size for that CNN architecture.

Table 1 Datasets

Class	Total Images
Chinee apple	1.126
Lantana	1.064
Parkinsonia	1.031
Parthenium	1.024
Pricky acacia	1.062
Rubber vine	1.008
Siam weed	1.074
Snake weed	1.014
Another	9.106

Dataset preprocessing
The dataset's used images each have a 256 x 256-pixel size. Each of these photos has been adjusted to fit the input size of the respective CNN. For instance, the image will be downsized to 224 by 224 pixels when used for ShuffleNet, MobileNet V3, or GoogleNet architectural training. Other image modifications were not done, such as converting RGB to GrayScale, eliminating noise, or segmenting the image.

CNN Architecture Transfer Learning
The initial stage is to use transfer learning on each existing CNN architecture with a relatively small number of parameters. Transfer learning is done by changing the size of the last fully connected layer of the CNN architecture used according to the number of classes in the dataset, namely, nine categories. After changing the size of this last layer, the CNN is retrained on this research dataset. Still, all the CNN layers before the previous layer are frozen, so the actual training only occurs in the last layer, and the training results for all previous layers are still used. After this transfer learning, This will evaluate which architecture gets the best accuracy for recognizing patterns in the dataset. This study will also explore the effect of several different optimization functions to see the optimal combination. Several optimization functions will be used: ADAM optimizer, SGDM optimizer, and RMSPROP optimizer.

Performance evaluation of the CNN architecture
Performance measurement of CNN in Transfer Learning uses parameters of accuracy, loss, classification time, and the number of learnable parameters. The accuracy used is top-1 accuracy which is measured during training and testing. The accuracy value will be compared to each epoch's training and testing loss values . Classification time is estimated based on the time required by CNN to determine the label of a test image. In practice, several

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images will be tested, and then the average time for image testing will be measured to obtain the test time per image.

RESULT

The data obtained in this study are data obtained based on the four architectures that were tested initially. Figure 3 shows the accuracy trend of the four architectures in 20 training epochs, and table 2 compares test accuracy and classification time per image for each architecture. From Figure 3, it can be concluded that the GoogleNet architecture has a good trend of accuracy while exceeding the accuracy of the others. Then followed by MobileNet and then ShuffleNet. The trend in SqueezeNet's accuracy is far below the other three accuracies and is also unstable. The time factors used to classify the four architectures are shown in Table 2 The two architectures with the quickest categorization times are ShuffleNet and SqueezeNet, then GoogleNet. The most time-consuming for classifying an image is MobileNet. The conclusion drawn from the classification accuracy and processing time evaluation is that the GoogleNet and ShuffleNet architectures are suggested for the following optimization stage.

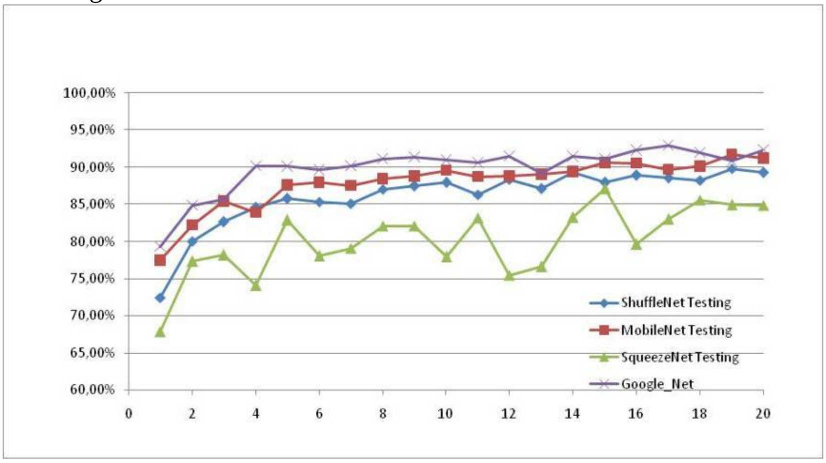

Fig 4 comparison chart of four model

Table 2 Comparison of the performance of the four architectures tested

models	number of parameters	accuracy (%)		Loss		classification time/Images(s)
		training	testing	training	testing	
ShuffleNet	1,4 M	100	89.26%	0.0053	0.3545	0.0220
MobileNet	3,4 M	100	91.21%	0.0386	0.2952	0.0439
SqueezeNet	1,2 M	100	84.87%	0.0173	0.5109	0.0227
GoogleNet	6,8 M	100	92,38%	0,0162	0,4182	0.0365

From the graph shown in Figure 3, the GoogleNet architecture with the SGDM optimization function achieved the best results. The lowest marks were in the GoogleNet architecture with the RMSPROP optimization function. For almost the entire 20 epochs of training, the performance of GoogleNet with the SGDM optimization function exceeded the performance of the GoogleNet architecture using other optimization functions and ShuffleNet

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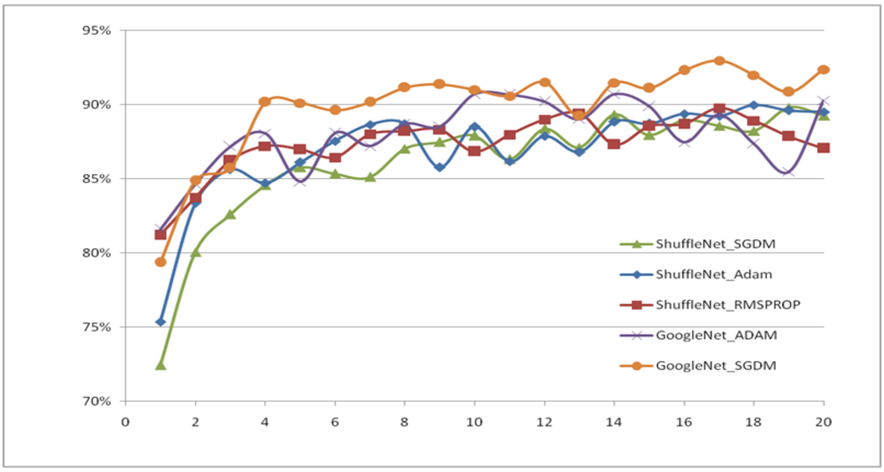

Fig5 Graph of ShuffleNet and GoogleNet architecture optimization results

Then in the next step, GoogleNet and ShuufleNet are optimized using three optimization functions: SGDM, ADAM, and RMSPROP. This optimization produces six architectures, whereas ShuffleNet and GoogleNet each have three architectures. These six architectures were then trained over 20 epochs on the same dataset and computer sequentially. From the graph shown in Figure 4, the best results were achieved by the GoogleNet architecture with the SGDM optimization function, while the lowest results were in the GoogleNet architecture with the RMSPROP optimization function. For almost the entire 20 epochs of training, GoogleNet's performance with the SGDM optimization function exceeded the performance of the GoogleNet architecture using other optimization functions and ShuffleNet.

Table 3 Performance optimization results of ShuffleNet and GoogleNet architectures

models	number of parameters	accuracy (%)		Loss		classification time/Images(s)
		training	testing	training	testing	
ShuffleNet_ADAM	1,4 M	100	89.52	0.0543	0.3984	0.0220
ShuffleNet_RMSPROP		100	87,06	0,0069	0,5793	
ShuffleNet_SGDM		100	89,26	0,0053	0,3545	
GoogleNet_ADAM	6,8 M	100	90,29	0,2474	0,5213	0.0365
GoogleNet_RMSPROP		100	65,16	0,8438	10.261	
GoogleNet_SGDM		100	92,38	0,0162	0,4182	

CONCLUSION

The GoogleNet architecture with the SGDM optimization function is the first recommendation for the weed classification task based on the results of the weed classification experiment using the CNN architecture with the transfer learning scheme and various optimization functions. The results show that the GoogleNet architecture with the SGDM optimization function is the architecture with the best accuracy performance. However, suppose classification time is the primary consideration in choosing the architecture used. In that case, ShuffleNet with the ADAM optimization function is the recommendation because the classification accuracy is also quite good.

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