Convolutional Neural Network in Image SPIE-ISPhOA 2019

by Kestrilia .

Convolutional Neural Network in Image Analysis for Determination of Mangrove Species

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ABSTRACT

Information on mangrove species plays crucial role for sustainable management of coastal ecosystems. However, the current in-depth data acquisition for sustainable management of coastal ecosystems is still collected manually. The increased demand to obtain mangrove environmental data in a short time and at affordable cost has encouraged our research to develop an automatization method for determining the species based on the images of mangrove leaf. In this paper the authors used a deep learning method that uses the Convolutional Neural Network (CNN) to overcome manual leaf sample identification during image recognition process. CNN is used to process the machine learning on a personal computer. Stages on CNN were data input, preprocessing and training. CNN was implemented by using tensorflow libraries through the transfer learning process to recognize three mangrove species of northern coast of Probolinggo, East Java, Indonesia. The recognition process is based on images of the mangrove leaf shape. This method was simple and can be reproduced by anyone without the need for in-depth computer programming knowledge. In a relatively short time, the method has been proven to give high accuracy of predicted results. Field test showed that this method can determine and distinguish the leaves of the three species of mangrove well. In the future this method will be developed to identify mangrove plants using Unmanned Aerial Vehicle (UAV).

Keywords: Deep learning, mobile device, mangrove determination, tensorflow, transfer learning.

1. INTRODUCTION

In sustainable tropical coastal ecosystems, mangroves are keystone species that provide a wide range of ecological services. Ecological services provided by mangroves include shelter, feeding grounds and breeding grounds for marine organisms such as fish, shrimp and crab, other services such as water filtration and protection against erosion by ocean waves. In fact, sustainable aquacultures are mostly developed in the mangrove area [1]. Due to the important role of mangroves, the availability of information on these keystone species becomes crucial for the sustainable management of coastal ecosystems. Ecological information collection on mangrove plants is generally consisting of species identification, species distribution, health level and above ground biomass. Such information can be reprocessed into mangrove biodiversity data that can provide in-depth information on coastal ecosystems sustainability [2]. In general practice, the collection of information about mangrove is conducting manually by human, it is usually time, energy and funds consuming. The increasing need to obtain environmental data such as species identity, species distribution and other biotic or abiotic information in a relatively short time at affordable cost in recent years, encourage the growth of research in the field of automatic ecological information collection. One method of automatic ecological information collection is the identification of plant species using a combination of digital image processing technology and artificial intelligence involving deep learning algorithms [3,4,5]. This paper will discuss a simple method of applying deep learning on android based mobile devices using tensorflow libraries through the transfer learning process for determination of mangrove species based on leaf shape.

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2. MATERIAL AND METHODS

2.1 Data collection

Mangrove leaves were collected from the mangrove community on the north coast of Probolinggo, East Java, Indonesia (7°44'04.6"S 113°13'23.8"E, figure 1). The mangrove community on Probolinggo north coast is dominated by 3 species, i.e. Rhizopora sp, Avicennia sp and Sonneratia sp (figure 2). Images of mangrove leaf were taken by a mobile phone Xiaomi Mi A1 with 2.0 8-core processor and 4 GB RAM, using custom android application provided by tensorflow. To enrich variation of dataset and ease of image acquisition process, mangrove leaf image were taken by video recording process from different angle position. The leaf image was extracted by FFMPEG library at 60 frame per second rate from video. 500 unique mangrove leaf images were choosen as dataset for each species. in total, 1500 mangrove leaf images were collected.

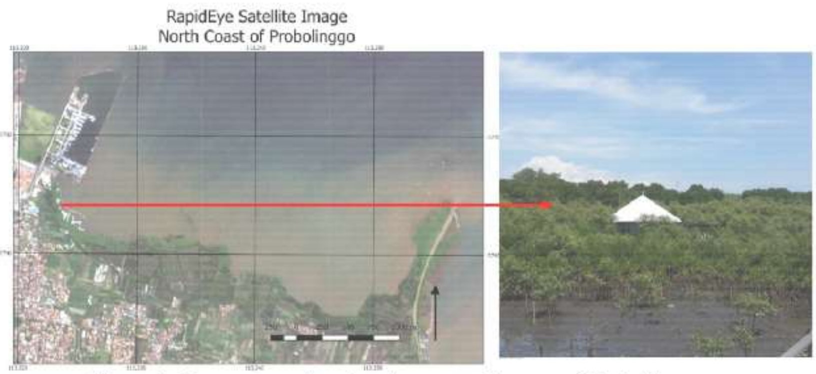

Figure 1. Research project location at north coast of Probolinggo

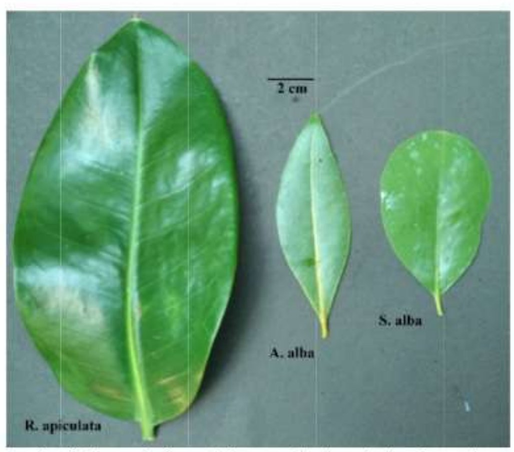

Figure 2. Typical shape of mangrove leaf. From left to right are depicted the 3 species collected from Probolinggo, i.e. *R. apiculata*, *A. alba* and *S. alba*, respectively

2.2 Deep learning method

Deep Learning is a part of Machine Learning which consists of many layers (hidden layers) and forms a stack. The layer is an algorithm or method that performs classification of commands inputted to produce output. Recent Deep Learning technology is in form of Convolutional Neural Network. This deep learning network uses images as input, then goes through the convolution layer and it is processed based on the specified filter, each of these layers produces a pattern of key feature that facilitate the classification process [6,7].

The development of deep learning now is facilitated by the number of libraries and Application Program Interface (API). Tensorflow was used in this research for the library. Tensorflow has an interface for expressing machine learning algorithms easily and also could execute commands by using information about the object or target to distinguish objects from other different objects. Tensorflow has a feature to run model training using the Central Processing Unit (CPU) and Graphic Processing Unit (GPU). Recently, Google as a developer of Tensorflow also releases the Tensorflowlite (TFlite) for mobile implementation of Tensorflow.

In this research, a personal computer with i7 12-core processor and 16 GB RAM was used as to conduct the deep learning training. Deep learning inference technique was implemented on android based mobile devices using tensorflow libraries through the transfer learning process. The learning and determination process was based on the shape of mangrove leaf as in the image. In transfer learning process, the last layer of pre-trained mobilenet v0.5 deep neural network was trained using 1500 mangrove leaf images for 4000 iterations and 0.01 learning rate. Deep learning model (pb) produced by tensorflow library on PC was transferred into android mobile phone by using Tensorflowlite procedure described in [8]. Implementation of Deep Learning on mobile environment was very smooth without any lag.

2.3 Evaluation metrics of deep learning training

Accuracy as an evaluation metric was calculated based on the definition as described on equation 1.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

In addition, we used cross entropy to quantify the difference between two probability distributions of predicted and true class label of the sample. Cross entropy is a generalization of log loss to multi-class classification problems. Cross-entropy quantifies the difference between two probability distributions. Cross entropy can be used to define the loss function in machine learning and optimization as described on equation 2.

$$H_{y'}(y) := -\sum_i y_i' \log(y_i) \tag{2}$$

Where y_i is the predicted probability value for class i and y_i' is the true probability for that class.

3. RESULT AND DISCUSSION

3.1 Convolutional Neural Network (CNN) process

Convolutional Neural Network (CNN) is one of the latest developments of artificial neural networks inspired by human neural networks and commonly used in image data to detect and recognize an object in an image. CNN consists of neurons that have weights, biases and activation functions. CNN process flow that is shown in figure 3.

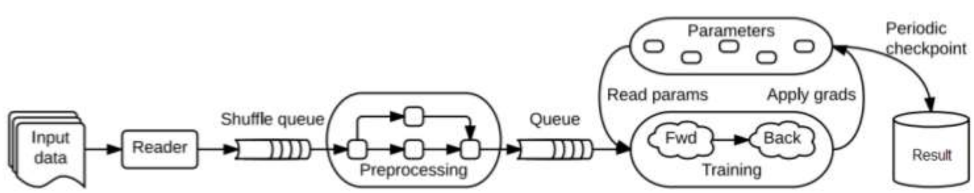

Figure 3. Convolutional Neural Network Process adapted from [9]

Convolutional layer

Convolutional layer section performs convolution operations by using linear filters on local areas. This layer is the first step to receive an image feeded into the deep learning architecture. This layer is a filtered with specific filter matrix with certain length (pixel), width (pixel) and dimension according to image channel/band of the feeded data. These filters will shift throughout the image according stride parameter. Filter direction is from left to the right and from top to the bottom of matrix image. This shift will do a "dot" operation between the input and the value of the filter so that it will produce an output called the activation map or feature map. Figure 4 shows the convolution process in the convolution layer and Figure 5 is how to calculate the convolution value.

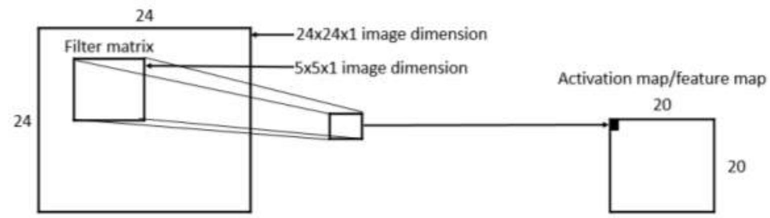

Figure 4. Convolution process

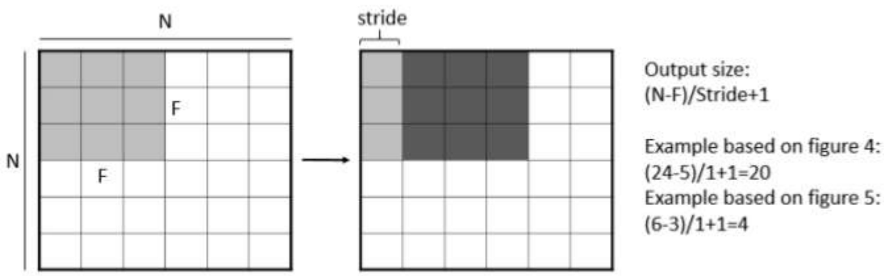

Figure 5. Formula for Calculating Convolution

Pooling Layer

Pooling layer receives output from the convolution layer, at this layer the image data size will be reduced. The principle is that the pooling layer consists of filters of a certain size and stride/steps then shifts throughout the feature map area. Most of the CNN architecture used max pooling. Max pooling divides output of convolution layers into several grids then shift filters will take the largest value from each grid. Depending on the length of the stride/step, the resulting image is reduced from its original size which is useful for reducing the dimensions of the data, thereby reducing the number of parameters in the next step. Figure 6 shows the process in the pooling layer.

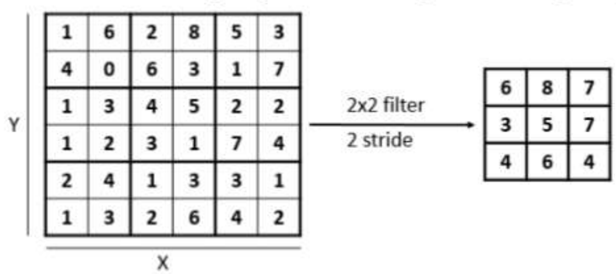

Figure 6. Process of Pooling Layer

Fully Connected Layer

Fully connected layer takes input from the output pooling layer in the form of a feature map. The feature map is still in the form of a multidimensional array so it will reshape the feature map and generate n-dimensional vectors where n is the number of output classes that the program must choose. For example, the layer consists of 500 neurons, softmax will be applied which returns the list of greatest probabilities for each of the 10 class labels as the final classification of the network. Figure7 shows the process in the fully connected layer.

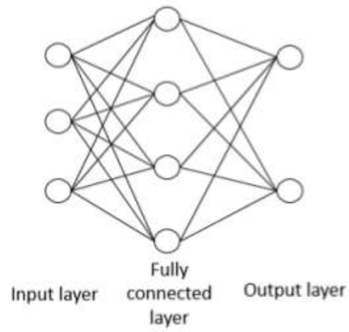

Figure 7. Fully Connected layer process

3.2 Training evaluation process

The results of convolutional neural network (CNN) training showed good results. Accuracy values from the training and validation process show that the training process can achieve convergence of less than 4000 steps. Exactly in the training process, convergence is achieved after 800 steps and the convergence validation process is achieved after 1,800 steps. Although the training process is not carried out using a PC with high convergence specifications until accuracy reaches 100 percent on the training and validation process can be achieved. This shows that the implementation of simple deep learning is very likely to be done using commercially available equipment on the market. Train and validation accuracy is shown in figure 8 and 9.

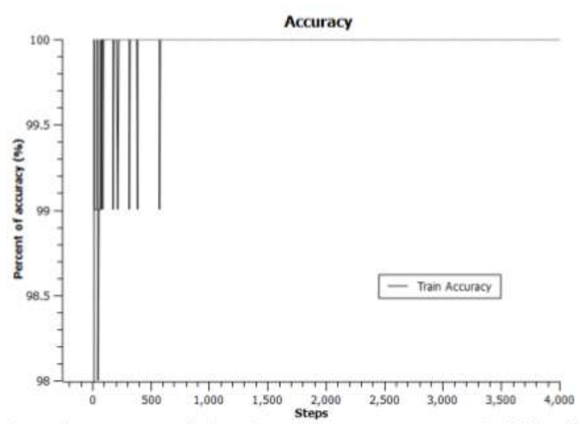

Figure 8. Train accuracy of deep learning mangrove tree leaf identification

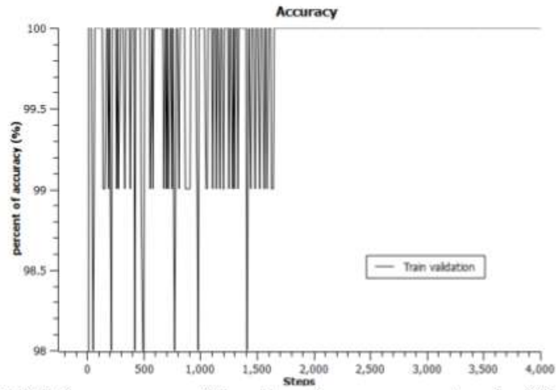

Figure 9. Validation accuracy of deep learning mangrove tree leaf identification

Figures 10 and 11 show that cross entropy training and validation of deep learning models in tensorflow hidden layers continue to decrease gradually in each iteration. In the initial iteration the value of the training error and error validation ranges from 0.1 and continues to decrease until it reaches a value less than 0.05 at the end of the iteration. From these results, it shows that the use of the tensorflow library can produce quite good performance in determining mangrove leaves. This is because tensorflow has a simple configuration and initial parameters that allow the classification process to run well without significant changes.

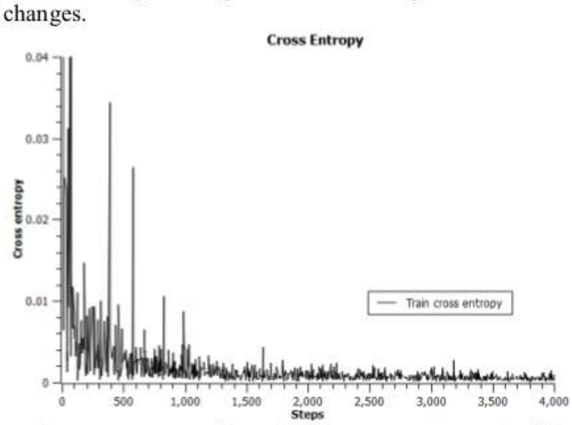

Figure 10. Train cross entropy of deep learning mangrove tree leaf identification

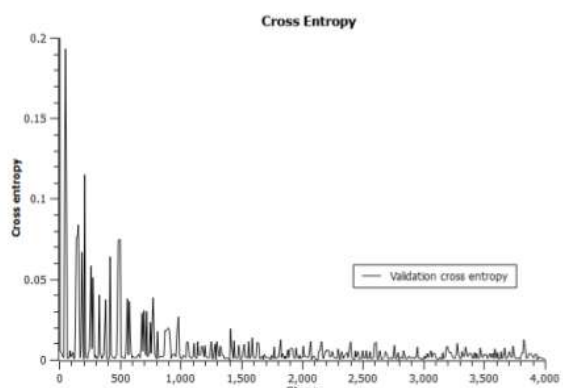

Figure 11. Validation cross entropy of deep learning mangrove tree leaf identification

3.3 Field validation

Field validation using the tensorflow has been conducted by transfer the model into custom android application transferred to Xiaomi Mi A1 device. Field validation process shows the same results as the validation of the PC training process. From experiments carried out at the location of the research project showed that the tensorflow model inside android application was able to distinguish the entire sample of mangrove leaves given as input. Accuracy obtained from the experiment was 99 percent. Accuracy cannot reach 100 percent because some of A. alba and R. apiculata mangroves have almost the same leaf shape, which is the needle shape. Deep learning models experience confusion if the image acquisition is not done at the same distance at the initial data collection. Unequal image acquisition distance causes the leaf size to be relative, to improve recognition accuracy it is recommended that the mangrove leaf image is taken at a distance that is still the same with initial data collection. Screenshoot of android application with tensorflow deeplearning model is shown in figure 12.

Figure 12. Field test of mangrove leaf species determination

4. CONCLUSIONS

Based on research result, due to its simple configuration, this method can be reproduced by anyone without the need for in-depth computer programming knowledge in a relatively short time with high accuracy of predicted results. The result from deep learning neural network training process shown that this method can reach 100 percent accuracy and less than 0.05 cross-entropy loss only with 4000 steps of iteration process. Field test show that this method can determine and distinguish the leaves of the three species of mangrove well. In the future this method will be developed to identify mangrove plants using Unmanned Aerial Vehicle (UAV).

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