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Application of PSO in CNN attribute weighting for banana tree classification based on leaf images

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Abstract - Banana (Musa paradisiaca) is a very popular fruit in Indonesia. Banana production in Indonesia, with more than 200 types of bananas, accounts for more than 50% of banana production in Asia. Differences in how to consume Ambon bananas and Kepok bananas and their various benefits encourage cultivators to be careful in choosing seeds to avoid mistakes. Distinguishing the seeds of Ambon bananas and kepok bananas is more difficult than distinguishing between Ambon bananas and kepok bananas. This is because the leaves and stems of the seeds look the same. The purpose of this study is to use an optimization algorithm to improve the performance of the image classification algorithm on the image of kepok banana leaves and Ambon bananas to assist in the selection of banana plant seeds that can be used by banana cultivators to get the maximum benefit according to the desired type of banana. The results of this study are used as the basis for making a decision support system to assist in the selection of banana plant seeds that can be used by banana cultivators in order to get the maximum benefit according to the desired type of banana.

Keywords - Image classification; Banana leaf; CNNs; CNN+PSO

1. INTRODUCTION

Bananas (Musa paradisiaca) are a fruit that is very popular with Indonesian people. Banana production in Indonesia, with more than 200 types of banana, reaches more than 50% of banana production in Asia [1]. Therefore, it is necessary to develop quality banana cultivation to meet domestic consumption needs and meet export demand. Bananas are grouped into 2 groups based on how they are consumed, namely bananas (consumed directly) and plaintain (consumed after cooking) [2]. One type of banana that is often consumed directly is Ambon banana. Meanwhile, Kepok bananas are bananas that are widely used for processed foods.

Apart from containing various vitamins, Ambon bananas have several other benefits, namely antihypertensive, wound healing and antidiabetic [3]. Kepok bananas are often used as a raw material for several food snacks, apart from that they are also proven to be useful for preventing anemia [4], the banana peel can be used as a biosorbent for iron [5], anti-acne [6] and kepok banana weevil can also be used for making biodegradable plastic [7].

Differences in how to consume Ambon bananas and Kepok bananas and their various benefits encourage cultivators to be careful in choosing seeds to avoid mistakes. Differentiating Ambon banana seeds and Kepok bananas is more difficult than differentiating Ambon bananas and Kepok bananas. This is because the shape of the leaves and stems of the seeds look the same.

Current advances in science and technology have given rise to various ways to help and make things easier for humans. One of them is digital image classification which can be used to help differentiate Ambon banana seeds and kepok bananas based on leaf images. The images of Ambon banana leaves and Kepok bananas are processed and then classified so that they can be differentiated.

The purpose of this study is to use an optimization algorithm to improve the performance of the image classification algorithm on kepok and ambon banana leaf images to assist in the selection of banana plant seeds that can be used by banana cultivators to get the maximum benefit according to the desired type of banana.

Several researchers have conducted research on the topic of image classification, using the Support Vector Machine (SVM) [8], K-Nearest Neighbors (KNN) [9], and Convolutional Neural Network (CNN) [10][11][12] algorithms. The leaf images of kepok banana and ambon banana trees have similar shapes and colors, so a good feature extraction method is needed to classify them. CNN has the advantage of using a high level of computation to extract many features and at the same time, provides detail and fast detection so that it is more resistant to unnecessary noise [13]. And in 2020 KNN has proven superior to SVM for classification of banana leaves[14], then in 2021 there have been researchers who have proven that the CNN method is superior to SVM and KNN for weather image classification [15]. Then several hybrid method researchers used optimization algorithms to develop attribute selection or attribute weighting. As in research on the classification of diabetes using Principal Dimensionality Reduction (PCA) and Particle Swarm Optimization (PSO) [16], for multi-label classification [17] [18] using PSO.

By paying attention to some of these things, the researcher proposes to solve the problem using image classification techniques using the CNN + PSO algorithm so that it can be proven that PSO optimization increases the accuracy of CNN. Henceforth, the results of this study can be used as a basis for making a decision support system to assist in the selection of banana plant seeds that can be used by banana cultivators in order to get the maximum benefit according to the desired type of banana. Also contributes to the image classification method in comparing or comparing several classification algorithms for different cases or in the same case and using different algorithms.

The combination of the CNN classification algorithm and the PSO optimization algorithm on image data of Kepok and Ambon banana leaves offers significant novelty in solving the problem of classifying Kepok and Ambon banana tree seedlings. Several previous studies in research on the classification of banana types still used images of bananas [19][20], while novice farmers found it difficult to differentiate kepok and Ambon banana tree seeds for planting. Then for the classification of banana leaf images, optimization methods have not been used.

By using these two techniques together, researchers can produce a model with maximum performance as a basis for creating a decision support system to assist in selecting banana plant seeds.

2. RESEARCH METHOD

To achieve the objectives of this research, the steps that must be carried out are as follows:

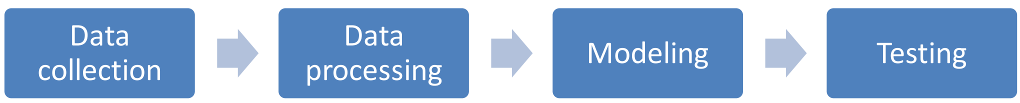

Figure 1. Research Stages

2.1. Data collection

This study will use data on banana leaves from clove plantations owned by the people in the Semarang Regency area. Based on references from previous studies, CNN is superior for large data, so 200 banana leaves will be taken from 20 different trees, 100 images for each type of banana, namely kepok and ambon. Every 1 tree, the 2nd and 3rd youngest leaves are taken from the shoot. What researchers do at this stage is as follows:

1. Take banana leaves from people's banana plantations.
2. Cut the banana leaves into A4 size pieces to prepare for scanning.
3. Scan the banana leaves for each type. Scans were carried out on the upper and lower surfaces of the leaves according to reference [21][22] for scanned images. The white color was chosen to contrast with the green color of the leaves.
4. The leaf scanned softfile is then uploaded to Google Drive.
5. Then the image is cropped automatically using Google Colab with the Python programming language. Cutting is done to the size 512 x 512.
6. The results of cutting the leaf image are saved in a folder as follows:
    a. Ambon_Top, contains 128 files
    b. Ambon_Bawah, contains 115 files
    c. Kepok_Top, contains 105 files
    d. Kepok_Bawah, contains 113 files

The target in this stage is to collect 100 Kepok banana leaf image data and 100 Ambon banana leaf image files that have been stored in Google Drive.

2.2. Data Processing

In this stage, the leaf image data which is already in the form of a soft file is divided into 2 parts for each type, namely training data and testing data. The comparison of training data and testing data is 8:2.

In this stage, the leaf image data is resized to 224 x 244 and then the format is changed to type_bananaleaf_224x224px.pkl so that modeling can be directly carried out using Google Colab with the Python programming language as follows:

```python
    # read all images in PATH, resize and write to DESTINATION_PATH
    for subdir in os.listdir(src):
        if subdir in include:
            print(subdir)
            current_path = os.path.join(src, subdir)

            for file in os.listdir(current_path):
                if file[-3:] in {'jpg', 'png'}:
                    im = imread(os.path.join(current_path, file))
                    im = resize(im, (width, height)) #[:,:,::-1]
                    # data['label'].append(subdir[:-4])
                    data['label'].append(subdir)
                    data['filename'].append(file)
                    data['data'].append(im)

        data['target']=np.unique(data['label'])
        joblib.dump(data, pklname)

# modify path to fit your system
data_path = '/content/drive/MyDrive/CNNPSO/dataset'
os.listdir(data_path)

base_name = 'type_bananaleaf'
width = 224

include = {'Ambon_Atas', 'Ambon_Bawah', 'Kepok_Atas', 'Kepok_Bawah'}

#resize for first prepare dataset, next just skip with comment
resize_all(src=data_path, pklname=base_name, width=width, include=include)
```

Figure 2. Data processing scripts using the Python programming language.

The result of this data processing stage is that the dataset is ready for modeling.

2.3. Modeling

There are 2 models used, namely the CNN model, and CNN+PSO. The proposed CNN model is the ResNet50 transfer learning model to overcome the vanish gradient in the Residual Network architecture [23].

1. CNNs

   Three popular CNN models—Inception_v2, Mobilenet_v3_small_075_244 and Resnet_v1_50—are used in the current research. Training was done over 100 epochs with a learning rate of 0.001 and momentum of 0.9. The subsequent experiment will be based on the three models' best outcomes.

2. CNN+PSO

   With the parameter value n_particles = 10, dimensions = trainable param of CNN model, options = 'c1': 0.5, 'c2': 0.5, 'w': 0.5, and iterations = 50, PSO is used to replace the weight parameter on CNN. The parameter values used refer to in a study conducted by Hariri M, et al [4]. The algorithm of the proposed cnnpso model is as follows:

   a. Start
   b. Determination of learning rate, batch size, number of epochs, PSO iteration, convergence value
   c. CNN training with resnet50 model
   d. Capture weights tensor
   e. Train tensors with PSO
   f. Update weights of CNN
   g. CNN based testing
   h. Prediction accuracy and results
   i. end

The target for this stage is the CNN and CNN+PSO modeling scripts with the Python programming language on Google Colab ready to run.

2.4. Testing

Testing and measuring the accuracy of the results achieved by the model using the confusion matrix technique. At this stage it will be known the maximum accuracy value of the proposed 2 model experiments. Then the accuracy results are compared to find out which model has the best performance with the highest accuracy.

The target of this stage is that the results of the accuracy of each experiment are well documented so that they can be compared.

3. RESULTS AND DISCUSSION

3.1. CNN Model with Transfer Learning ResNet50 (100 Epochs):

Inception_v2, Mobilenet_v3_small_075_244 and Resnet_v1_50 are three widely utilized CNN models that are used in this study. With a learning rate of 0.005 and a momentum of 0.9, training was conducted over 100 epochs. The graph below displays the findings from the three models.

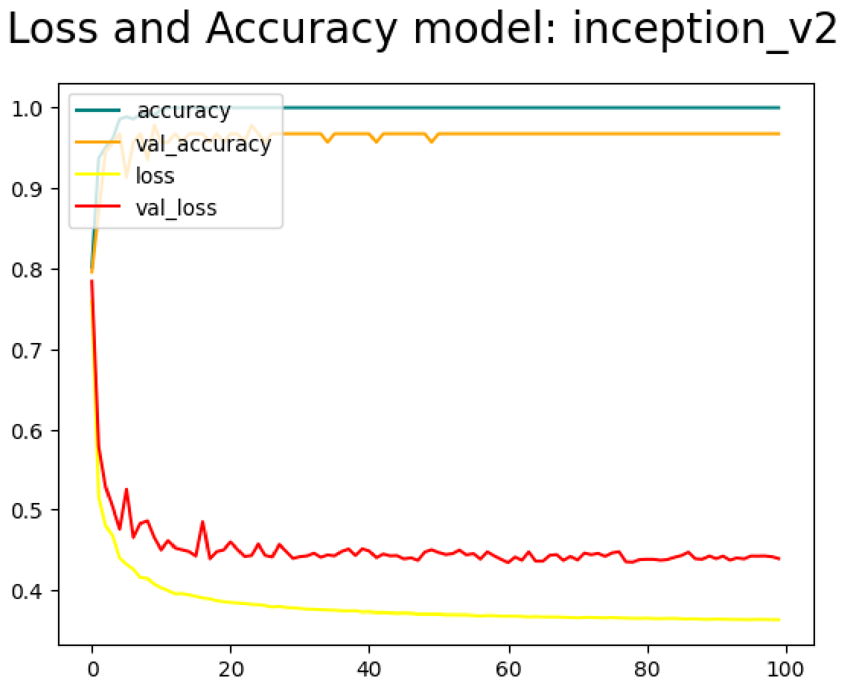

Figure 3. The loss and accuracy model inception_v2

The above illustration represents the result of the inception_v2 model. It appears that val_accuracy increases and val_loss decreases. That proves that the model runs well for classification on the banana leaf dataset. The maximum accuracy generated is 100% and the maximum loss is 43.3%. At the 30th epoch the Accuracy starts to stabilize at 100% while the loss is in the range of 43.3%-45%.

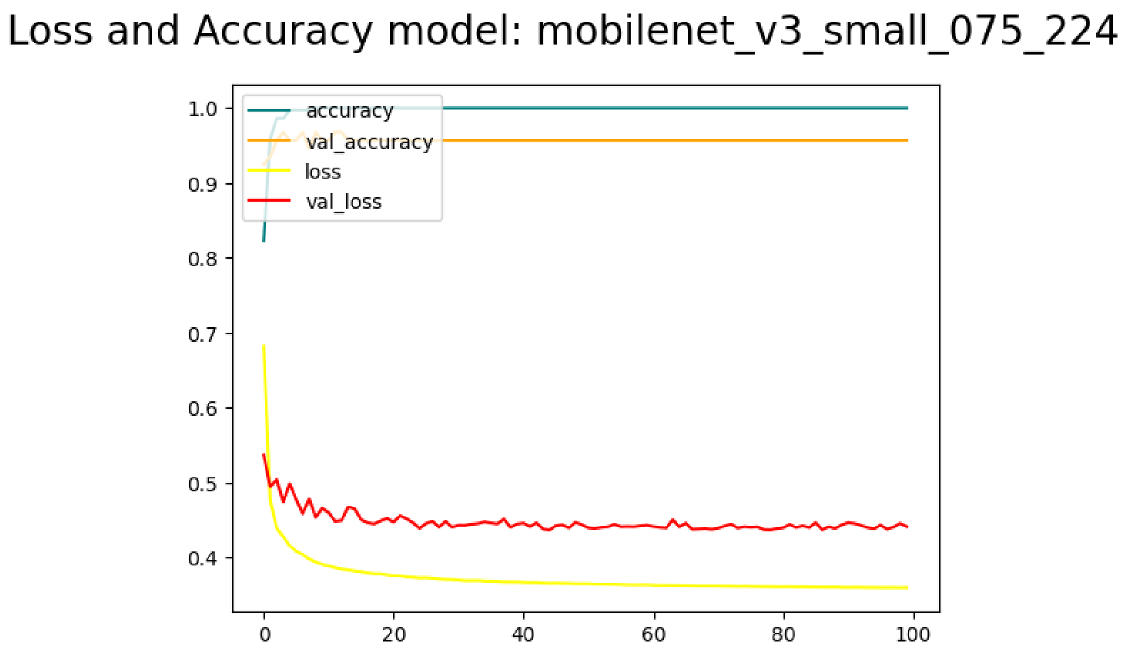

Figure 4. The loss and accuracy model mobilenet_v3_small_075_244

The output of the mobilenet_v3_small_075_244 model is shown in the image above. Val_accuracy seems to rise while Val_loss seems to fall. This demonstrates that the model performs well for classification on the dataset for banana leaves. The maximum loss generated is 43.75%, and the maximum accuracy is 100%. The accuracy begins to stabilize at 100% in the 10th epoch, whereas the loss is between 43.75% and 45.5%.

Figure 5. The loss and accuracy model resnet_v1_50

The resnet_v1_50 model's output is depicted in the image above. Val_accuracy seems to rise while Val_loss seems to fall. This demonstrates that the model performs well for classification on the dataset for banana leaves. The greatest loss generated is 51.1%, and the maximum accuracy generated is 100%. The accuracy begins to stabilize at 100% in the 18th epoch, whereas the loss is between 51.1% and 53.5%.

Figure 6. Comparison of the three model's loss values

The performance of any CNN model in use is really high. The inception_v2 model yields the lowest loss value, 43.3%, and the resnet_v1_50 model yields the highest loss value, 51.1%. Therefore, in the experiment that follows, we will use the inception_v2 model.

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 keras_layer_5 (KerasLayer)  (None, 1024)              10173112

 dense_5 (Dense)             (None, 4)                 4100

=================================================================
Total params: 10177212 (38.82 MB)
Trainable params: 4100 (16.02 KB)
Non-trainable params: 10173112 (38.81 MB)
```
Figure 7. The total number of parameters generated by the inception v2 model

Of the total params of 10177212, only 4100 are trainable. So the dimensions that will be used to apply PSO on CNN are filled according to the value of trainable params that is 4100.

3.2. CNN + PSO (inception_v2)

The second modeling involves using the Particle Swarm Optimization (PSO) algorithm to optimize the weight parameters in the second layer of the CNN model after keras layer. The number of particles (n_particles) is 10, and the dimensions are adjusted according to the number of parameters that need to be optimized. Other PSO parameters such as 'c1', 'c2' and 'w' are set according to the research you mean, namely 0.5, 0.5 and 0.5 respectively. Testing was carried out 5 times with a number of iterations of 3, 5, 10, 30, and 50. The highest accuracy results were achieved in the 5th iteration of 41.94%.

As previously stated, the number of parameters that can be trained from the inception_v2 model, as well as 4100, will be utilized as the dimension parameter value to train the CNN+PSO model.

Then, while setting the second layer in the reshaping best parameters, it is filled with 1024 parameters, which is one-quarter of the trainable parameters.

```
# # Set the best weights found by PSO
# first_layer_weights = best_params[:32].reshape((4, 8))
second_layer_weights = best_params[4:].reshape((1024, 4))
# best_model.layers[0].set_weights([first_layer_weights, np.zeros(8)])
best_model.layers[1].set_weights([second_layer_weights, np.zeros(4)])

# # Compile the best model
best_model.compile(
            optimizer=SGD(learning_rate=0.001, momentum=0.9),
            loss=CategoricalCrossentropy(from_logits=False, label_smoothing=0.1),
            metrics=["accuracy"]
            )
# # Evaluate the best model on the test set
loss, accuracy = best_model.evaluate(X_test, y_test, verbose=0)

print("Test evaluation with best.params[PSO] set accuracy: {:.2f}%".format(accuracy * 100))
```

Figure 8. Scritpt python for CNNPSO

Table 1. CNNPSO accuracy achievement data based on number of iterations

Iteration	Accuracy
3	13.98%
5	**41.94%**
10	22.58%
30	33.33%
50	35.48%

From such results proves that the application of PSO on parameter weigthing is less effective. In addition to decreasing accuracy, the computing time required to train the model is longer.

The CNN model used already has a perfect accuration of 100% with a relatively short computation time compared to CNN+PSO.

4. CONCLUSION

These findings demonstrate that adding PSO to the CNN model's weighting variables does not enhance model performance; rather, it makes it worse. In this instance, the CNN model's performance for the job of classifying images of banana leaves does not appear to be enhanced by the application of PSO. Numerous things, including a possible inappropriate PSO setting or not enough iterations, can contribute to this. When employing optimizations like PSO, it's crucial to experiment with various settings and methodologies to make sure they're suitable for the task at hand and the relevant data set.

Several different classification methods' parameter values can be optimized for further study using PSO or other optimization models.

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