Identification of Flowers as Balinese Hindu Ritual Offerings Using Convolutional Neural Network (CNN)

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Abstract. Flowers play a crucial role as elements in Hindu ceremonies in Bali. In the Balinese Hindu tradition, flowers serve as ritual instruments that carry spiritual significance and profound symbolism. Many of the younger generation in Bali today struggle to identify various types of flowers used in Balinese Hindu ceremonies. The utilization of machine learning technology can provide a solution to overcome the limited knowledge faced by the younger generation in Bali when identifying flower types for Balinese Hindu ceremonies. Convolutional Neural Network (CNN) is one highly effective machine learning method for image classification. One efficient CNN model for identification is the ResNet152 architecture. In this study, image data consists of flowers used in Balinese Hindu ceremonies, encompassing five types of flowers. The test results demonstrate an accuracy rate of 98%, with precision at 94%, and recall at 93%. The detection outcomes of flowers used in Balinese Hindu ceremonies through the Convolutional Neural Network (CNN) method yield a satisfactory accuracy value.

Keywords: Identification, flowers, CNN.

1 Introduction

Flowers play a highly significant role as elements in Hindu ceremonies in Bali. In Balinese Hindu tradition, flowers are utilized as ritual instruments with deep spiritual meaning and symbolism. Flowers are often arranged and beautifully organized to create aesthetically pleasing and meaningful appearances in these ceremonies. They are used in the creation of canang sari, daksina, and other elements of the ceremonies. The choice of flower types can carry specific meanings depending on the type of ceremony taking place.

In conducting religious ceremonies, the Hindu community in Bali uses flowers to create prayer instruments, perform rituals, prepare holy water, kumkuman water, and to adorn sacred dances. The utilization of flowers in these ceremonies reflects the cultural acculturation process between traditional and modern influences, showcasing the dynamic nature of life. However, with the passage of time, knowledge about the identity and meanings of the flowers used in ceremonies has become limited. This is because the knowledge passed down from previous generations is primarily oral, transmitted through verbal communication. Additionally, information is acquired through practical

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experience during the preparation, implementation, and post-implementation of religious ritual activities [1].

Most of the young generation in Bali today struggle to recognize various types of flowers used in Balinese Hindu ceremonies. This is influenced by social and technological changes, with many young people being more exposed to modern and digital culture than the traditions and religious rituals that contain knowledge about these flowers. Additionally, the lack of documentation and written sources specifically explaining the types of flowers and their meanings in Balinese Hindu religious ceremonies further limits this knowledge. On the flip side, the younger generation in Bali is challenged to understand and preserve cultural heritage while maintaining the continuity of Balinese Hindu ceremony traditions.

The utilization of machine learning technology can be a solution to address the limited knowledge faced by the younger generation in Bali when identifying flower types for Balinese Hindu ceremonies. With machine learning technology, the younger generation can easily and accurately identify the types of flowers used in Hindu ceremonies in Bali. Furthermore, this technology allows for better documentation, making information about the types of flowers used in religious ceremonies easily accessible to future generations and assisting in preserving Balinese Hindu culture.

Studies on plant identification using machine learning technology have been conducted extensively. One such study involves the application of machine learning technology for the recognition of medicinal plants. The use of machine learning in the classification phase enables the development of an automatic classification system that can identify various types of medicinal plants with high accuracy. The use of machine learning technology in the feature extraction phase is crucial as it allows for the extraction of features that can be compared among various types of medicinal plants [2].

Machine learning plays a role in addressing challenges in the identification and classification of plants. This is because human abilities in identifying plant species have diminished from generation to generation. Limited knowledge and weaknesses in manual identification form the basis for the development of this machine learning model. The development of a plant identification system with machine learning can enhance the efficiency and accuracy of identifying various plant species [3].

Convolutional Neural Network (CNN) is one highly effective machine learning method for object image classification. CNN is specifically designed to handle image data and has the ability to identify complex patterns in images. The CNN architecture consists of convolution layers that can extract hierarchical features from images, followed by pooling layers to reduce dimensions. Using deep learning techniques, CNN can automatically understand and classify objects in images, allowing its application in various fields such as face recognition, object detection, and medical image processing [4].

One effective CNN model for identification is the ResNet152 architecture. ResNet152 is a variant of CNN with 152 layers, designed to handle complex image recognition tasks [5]. The use of ResNet152 in flower identification provides advantages in recognizing fine details and characteristics in flowers, which may be challenging for models with simpler architectures to identify. By leveraging the deep learning capabilities of ResNet152, the identification process can become more accurate.

Based on this background, this research will develop the identification of flowers as elements in Balinese Hindu ceremonies using the Convolutional Neural Network (CNN) method with the ResNet152 architecture, allowing for the measurement of its accuracy.

2 Method

In this study, an experimental research method was conducted with the following stages:

2.1 Data Collection

The data used in this research involves digital images. Digital images were collected from various sources and referred to as the dataset. This dataset was gathered through direct capture using a smartphone camera and also through images found in internet media searches. The images used in this study are images of flowers used in Balinese Hindu ceremonies consisting of 5 types, namely: images of angsoka, sandat, cempaka, kamboja, and lotus flowers.

2.2 The method used

Deep learning algorithms, with their ability to process large-scale datasets, are well-suited for solving object identification problems [6]. One of the deep learning algorithms is the use of Convolutional Neural Network (CNN). CNN is a class of artificial neural networks that has become dominant in various computer vision tasks. CNN is designed to automatically and adaptively learn spatial hierarchies of features through backpropagation by using various building blocks such as convolution layers, pooling layers, and fully connected layers [7]. CNN is similar to other types of neural networks, such as artificial neural networks, where both have elements like bias, weight, and activation function. However, what distinguishes CNN from other types of neural networks is the inclusion of a special layer called the Convolutional Layer. In the processing of flower images, there is the use of kernel features that function to obtain fractions (strides) from the image, and this process is known as convolution.

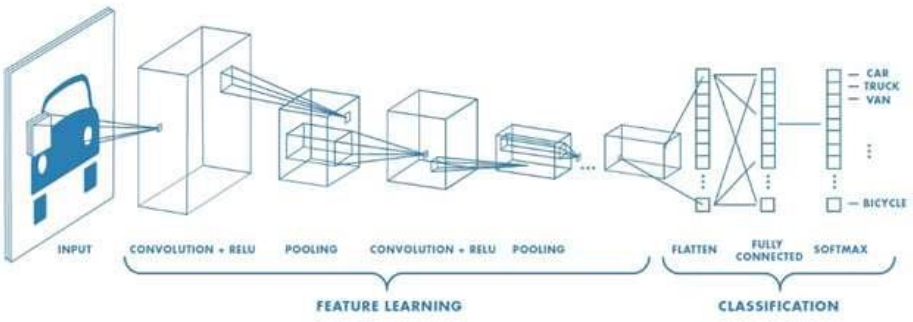

Fig. 1. Stages of the process in CNN [8]

ResNet-152 is one of the many CNN architectures that can be used in the process of identifying an object in an image. One advantage of this CNN structure lies in the thickness of the convolution filter adjusted to the image [9]. The architecture of the CNN network is described in Figure 1. The CNN Architecture structure includes the steps of input, feature extraction, classification process, and output. CNN consists of two main components, namely Feature Learning and Classification. In the feature extraction process in CNN, there are several hidden layers, including convolution layers, activation function (ReLU), and pooling. Meanwhile, the classification process involves fully connected layers and activation function (softmax), producing output in the form of classification result [8].

2.3 Experiment and evaluate results

In this study, the Tensorflow framework, developed by Google to advance machine learning development, was utilized. One aspect found in Tensorflow is the capability of image recognition. Tensorflow utilizes CNN and ResNet-152 architectures [10]. Metode evaluasi yang diterapkan adalah validasi dengan metode presisi dan akurasi. The applied evaluation methods include validation using precision and accuracy. Precision and accuracy methods are processes to assess the extent to which a measurement method provides consistent (precision) and close-to-truth (accuracy) results in testing or evaluation conducte [11]. The following is the model diagram in this research:

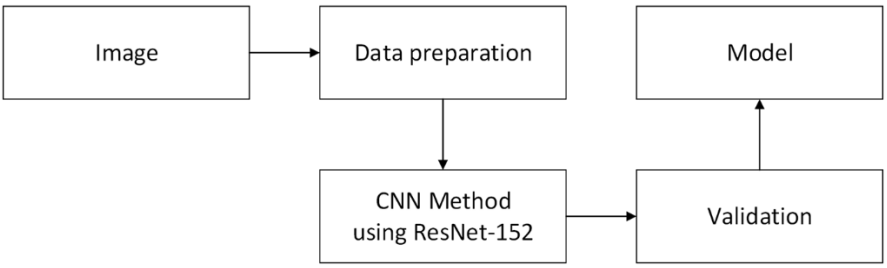

Fig. 2. Research model diagram

3 Results and Discussion

3.1 Data Preparation

The collected dataset consists of 947 images for 5 types of flowers used in Balinese Hindu ceremonies: angsoka, sandat, cempaka, kamboja, and teratai. Each dataset for each type of flower is divided into 80% images for training, 10% images for validation, and 10% images for testing. Classification is performed using the CNN method with the ResNet-152 architecture. The main stage of this system is the training phase, which forms the model for use in the testing phase.

Fig. 3. Example Flower Dataset

3.2 Training Result

The first process conducted is to input the images into the convolution layer. The convolution process aims to maintain the relationship between image pixels by analyzing image features using a set of input data. In this study, the images used have dimensions of 224x224x3 and are colored. The number 3 here indicates that the image has 3 color channels: Red, Green, and Blue (RGB).

During the training phase, a learning process is carried out on the images, resulting in a model that will be saved for use in the testing phase. Model formation involves training the training image data to identify and categorize objects according to their classes. In this study, the applied method is one variant of deep learning algorithms, namely CNN using the ResNet-152 architecture.

ResNet-152 is a model architecture consisting of 152 layers. In the training system phase, there is an initial layer with a kernel size of 7×7 and 64 filters, followed by max pooling with a kernel size of 3×3. The ResNet-152 architecture consists of five main convolution processes with multiple convolution blocks and one fully connected layer.

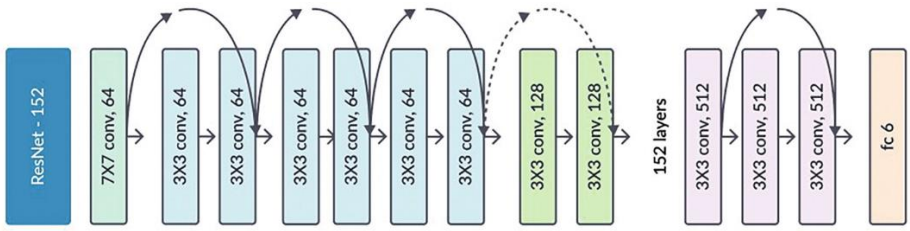

Fig. 4. Stages of Training ResNet-152

After going through the CNN algorithm process using ResNet-152, the training results are obtained. In this process, the learning rate is set to 0.001, and the number of epochs (training cycles) is set to 100. The following is the training process in flower identification:

```
epochs =100

history=model.fit(x=train_gen, epochs=epochs, validation_data=valid_gen)

Epoch 1/100
12/12 [==============================] - 24s 1s/step - loss: 1.6509 - accuracy: 0.5288 - val_loss: 0.5184 - val_accuracy: 0.8298
Epoch 2/100
12/12 [==============================] - 6s 484ms/step - loss: 0.4746 - accuracy: 0.8091 - val_loss: 0.2695 - val_accuracy: 0.9149
Epoch 3/100
12/12 [==============================] - 6s 502ms/step - loss: 0.2334 - accuracy: 0.9258 - val_loss: 0.2349 - val_accuracy: 0.9362
Epoch 4/100
12/12 [==============================] - 6s 489ms/step - loss: 0.1416 - accuracy: 0.9615 - val_loss: 0.2775 - val_accuracy: 0.9149
Epoch 5/100
12/12 [==============================] - 6s 502ms/step - loss: 0.0880 - accuracy: 0.9753 - val_loss: 0.2582 - val_accuracy: 0.9255
Epoch 6/100
12/12 [==============================] - 6s 494ms/step - loss: 0.0642 - accuracy: 0.9849 - val_loss: 0.2460 - val_accuracy: 0.9149
Epoch 7/100
12/12 [==============================] - 7s 501ms/step - loss: 0.0445 - accuracy: 0.9849 - val_loss: 0.2893 - val_accuracy: 0.9043
Epoch 8/100
12/12 [==============================] - 6s 510ms/step - loss: 0.0360 - accuracy: 0.9918 - val_loss: 0.2753 - val_accuracy: 0.9255
Epoch 9/100
12/12 [==============================] - 6s 496ms/step - loss: 0.0410 - accuracy: 0.9959 - val_loss: 0.2532 - val_accuracy: 0.9043
Epoch 10/100
12/12 [==============================] - 6s 509ms/step - loss: 0.0268 - accuracy: 0.9931 - val_loss: 0.2552 - val_accuracy: 0.8936
Epoch 11/100
12/12 [==============================] - 6s 500ms/step - loss: 0.0139 - accuracy: 1.0000 - val_loss: 0.2369 - val_accuracy: 0.9149
Epoch 12/100
```

Fig. 5. Training Process of ResNet-152

3.3 Testing Result

During the training stage explained earlier, learning is carried out using the ResNet-152 algorithm to identify the dataset and form a model based on the training results. The testing stage will then test the previously formed model. The testing process will assess the model that was formed earlier. The following is the application interface for identifying flowers used in Balinese Hindu ceremonies.

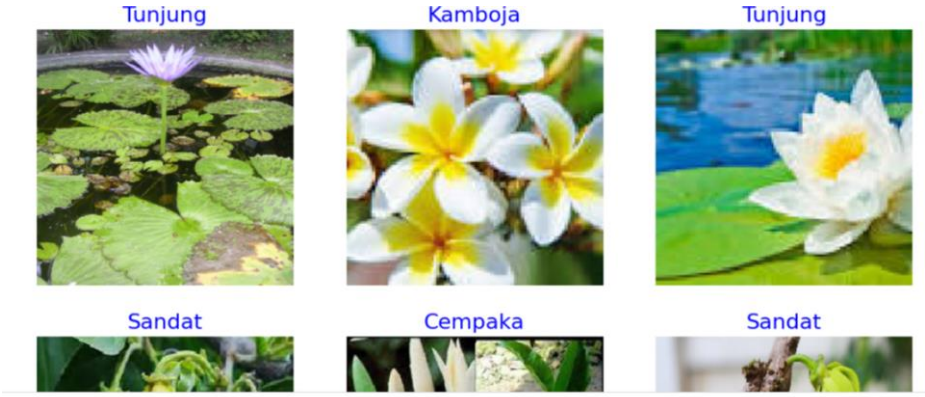

Fig. 6. Application Interface for Flower Identification

The designed system will be assessed for its performance based on the system's performance adequacy. To measure system performance, the evaluation method used is validation with precision and accuracy methods. The test results indicate good model performance, with an accuracy rate of 98%, precision value of 94%, and recall value of 93%. The following are the test results using precision and accuracy:

Classification Report:

	precision	recall	f1-score	support
Asoka	1.00	1.00	1.00	22
Cempaka	1.00	0.79	0.88	14
Kamboja	0.80	0.92	0.86	13
Sandat	1.00	1.00	1.00	20
Tunjung	0.91	0.95	0.93	22
accuracy			0.95	91
macro avg	0.94	0.93	0.93	91
weighted avg	0.95	0.95	0.95	91

Fig. 7. Test Results

4 Conclusion

The image data used in this study consists of flower images used in Balinese Hindu ceremonies, comprising 5 types of flowers. In this research, Convolutional Neural Network with ResNet-152 architecture is employed. The testing results in this study show an accuracy of 98%, with a precision value of 94% and a recall value of 93%. The detection of flowers as part of Balinese Hindu Ritual Offerings using the Convolutional Neural Network (CNN) method yields a quite good accuracy.

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