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Deep Learning Implementation Using CNN to Classify Bali God Sculpture Pictures

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Abstract

Efforts to preserve Balinese culture can be carried out by integrating art and technology as new steps that need to be developed. This research is motivated by the existence of various forms of God statues which have a central role in Balinese culture. The Deep Learning method is proposed because it has unique features that can be extracted automatically. The technique used in Deep Learning is Convolutional Neural Network (CNN). The training process is first performed to perform the classification process, and then the testing process is performed. We compared our CNN model with two other models, AlexNet and ResNet, based on the experimental results. Using a data split of 70%- 30%, our CNN model has the highest accuracy in managing statue image data. Specifically, our model achieves 97.14% accuracy, while Alexnet and Resnet achieve 24.44% and 33.33%, respectively. Apart from contributing to introducing the Balinese God Statue, this research can also be a basis for developing more comprehensive applications in culture and tourism.

Keywords: *Deep learning, CNN, God Statue, Bali*

1. Introduction

Image recognition is one of the fields in computer vision that is widely researched. Research on image segmentation, feature extraction, and classification with various types of images are some of the frequently discussed topics. Convolutional Neural Network (CNN) is generally used in image data and to detect images [1], [2]. CNNs are mathematical constructs, typically consisting of three types of layers (or building blocks): convolution layers, joint layers, and fully connected layers. In essence, CNN operates through the convolution process, wherein the Convolutional Multiplier (filter) is applied to an image with a specific size. This procedure allows the computer to derive fresh representative information by multiplying image segments with the applied filter. The evolution of convolutional neural network (CNN) paradigms now encompasses aspects such as transfer learning and the incorporation of ensemble models derived from diverse CNN architectures.

Previously, research had been carried out regarding evaluating the CNN model using three data sets: mammography data, MIAS, DDSM, and CBIS-DDSM. The method suggested in this research involves applying data augmentation using a customized U-Net model and InceptionV3, producing optimal results, mainly when applied to the DDSM dataset [3]. Other experiments on images using CNN achieved high accuracy with minimal memory requirements (718,961 KB) and fast inference time (122,969 ms) during air testing for ESCA and PlantVillage datasets. This supports the feasibility of designing a portable embedded system for plant leaf disease classification [4]. The other research uses CNN to classify rice disease [5] and mammographic image classification for breast cancer [6]. For unique images, a traditional Kekarangan Balinese carving classification system was developed using the Gabor Convolutional Neural Network to help Balinese people identify classes of traditional Balinese carving. As a result of this research, the GaborCNN method can produce the highest image classification accuracy of 89%[7]. Apart from that, several other studies related to images and culture, such as Panchadeva Sculpture Image Classification [8], Traditional Chinese Sculpture and Painting [9], and Dunhuang Cultural Heritage[10], used computer vision and CNN techniques in the research.

God Statues have high artistic and spiritual value for Balinese people. These statues depict gods (Brahma, Vishnu, Shiva, Ganesha), goddesses (Saraswati), and other icons, which in the spiritual mythology of Balinese culture are believed to be spiritual balancing elements. This God statue is firmly applied to spirituality and symbolism and has an essential sacred function in the spiritual life of Balinese Hindu society. Statues of Gods are usually found in holy places or temples where Hindus worship. In them, statues generally symbolize the gods worshipped at that place. A. A. Gde Bagus, a Balinese statue craftsman, explained that the sculptors tried to create tools for worshipping the gods by drawing as beautifully as possible. With the increasing use of digital technology, the recognition and classification of Balinese God Statues automatically become increasingly important.

Classification of Balinese deity statues is an exciting challenge because the variations in shape, texture, and color that each statue has can be complicated to recognize precisely using traditional methods [11]. Using a Deep Learning approach, we hope to build a model to identify and classify Balinese God Statues accurately. Deep learning (DL) assumes a progressively crucial role in daily life, substantially influencing diverse domains, including arts and culture[12]. Deep learning is also used to improve algorithm methods, such as the reliability of biometric systems, and comparative analysis will be carried out using the SVM method [13]. In deep learning, numerous Convolutional Network Architectures (CNN) exist for image classification, including but not limited to AlexNet (Krizhevsky et al. 2017), GoogleNet, VGG16, and ResNet, all employing advanced deep learning techniques [14]. To classify God's Statues in Bali, the first step is to identify the pattern in each image. Next, an image classification process is carried out by utilizing the details obtained from the pattern. The ultimate goal of this classification process is to group patterns into different categories based on their characteristics, making it easier to differentiate images. This is particularly important when visiting temples in Bali where statues of Gods with various patterns can be found [15],[16]. Research related to feature selection with Balinese culture by taking images manually to be used as research material [15], [16], [17]

Research using deep learning using the CNN algorithm aims to classify God Statues by applying authentic private datasets, considering computational efficiency aspects, and applying CNN techniques in model training. This research's contribution lies in the selection and performance of unique models and datasets by comparing the results of testing and comparing the proposed model with CNN models AlexNet and ResNet. There are two popular CNN models besides VGG [18], [19]. Apart from contributing to introducing Balinese God Statues, this research can also be a basis for developing more comprehensive applications in culture and tourism.

2. Research Methods

The stages in this study begin with preprocessing in the form of image resizing. Resizing images is an essential initial step in computer vision preprocessing [20], [21]. The acquired images have different pixel sizes, which may lead to poor classification accuracy. The resized data will be divided into training and testing data. The data development category consists of 75% training data and 25% testing data, 50% training data and 50% testing data, 40% training data and 60% testing data.

Furthermore, the image will be trained first using the CNN model that has been made so that the accuracy results are obtained, and then the same will also be done on the testing data so that the accuracy results are also known. The CNN model is constructed through the feature learning process, wherein this feature learning aims to capture distinct characteristics for each classification of sculptures. The outcome of this research endeavor manifests as the accuracy level or precision of deep learning in identifying the specific category of sculptures. Here are the stages of this research process:

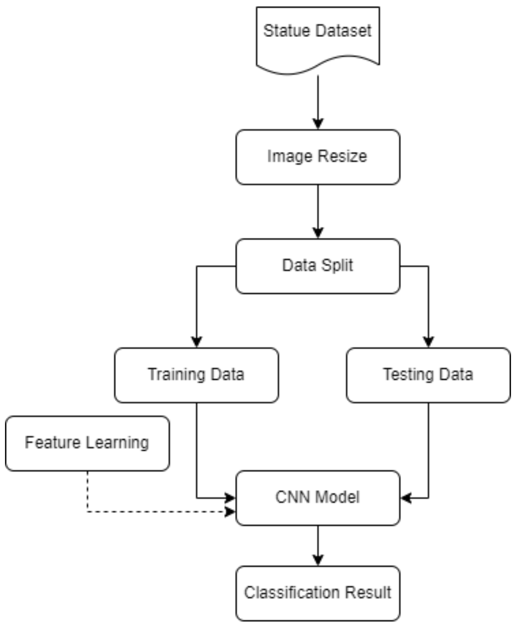

Figure 1. Research Methods

Developed by LeCun, CNN (Convolutional Neural Network) is primarily employed to analyze data organized in a grid-like format. It refers to neural networks that utilize convolutions instead of conventional multiplications. Generally, a convolutional network comprises three main stages. The CNN approach is used explicitly for recognizing trajectories, taking input as a path observed from various perspectives [7], [22]

The initial phase in the CNN architecture is the convolution stage, which involves using a kernel of a specific size. Determining the kernels utilized depends on the desired number of generated features. Subsequently, the output undergoes an activation function, typically employing the ReLU (Rectifier Linear Unit) activation function. Following the activation function, the data proceeds through a pooling process. This series of operations is iterated multiple times until a sufficient number of feature maps are obtained, allowing for the transition to a fully connected neural network. The final output is then derived from this fully connected network, representing the output class.

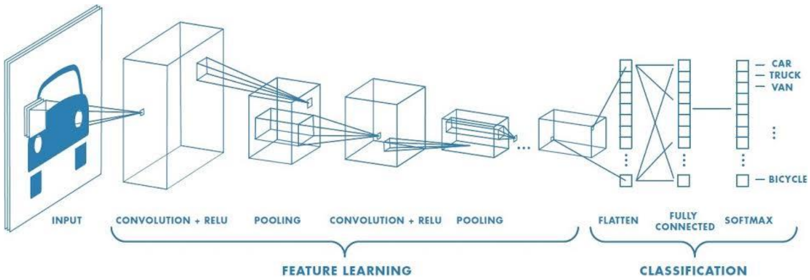

Figure 2. CNN Architecture

The dataset utilized in this research consists of image data sourced from independent collections gathered from multiple artisans and sculpture vendors in Bali, namely, Nirmala Regek Stone Carving, Jun Arta Stone Carving, Griya Utama Stone Carving located in Sukawati, Gianyar and Art Corner Studio located in Darmasaba, Abiansemal. The images taken were 150 images divided into five types of statues: Brahma, Vishnu, Shiva, Saraswati, and Ganesha. So, each character has 30 samples. The samples obtained are then divided into two samples with training and test sample data, divided into three percentages in each sample. The uniqueness of the dataset used is the dataset of God statue images taken directly from the statue artisans so that this image is authentic and can show the variety of God Statues in Bali**.** The following number of samples used can be seen in Table 1.

Table 1. Sculptures Datasets

No	Types of Sculptures	First Test		Second Test		Third Test	
		Training 75%	Testing 25%	Training 50%	Testing 50 %	Training 40 %	Testing 60%
1	Brahma	23	7	15	15	12	18
2	Wisnu	23	7	15	15	12	18
3	Siwa	23	7	15	15	12	18
4	Saraswati	23	7	15	15	12	18
5	Ganesha	23	7	15	15	12	18

3. Result and Discussion

3.1. Training Process

The training process is carried out under several different conditions, namely by using 75% data (115 sample data training), 50% (75 sample data training), and 40% (60 sample data training). Then, learning options were applied to the parameters used in training, including Max Epoch, Mini Bacth, and Initial Learn Rate. Max Epoch represents the maximum number of iterations used in training. Mini batch is the number of images taken by the recognition process. The initial Learn Rate is a value that ensures steps reach the minimum point.

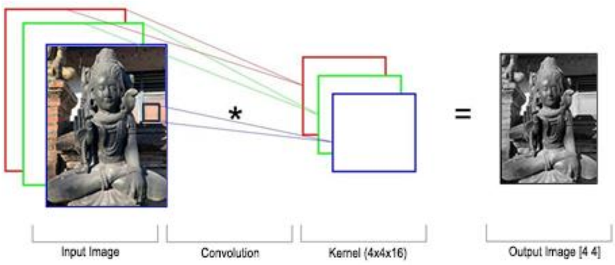

Figure 3. Convolutional Process

Figure 3 shows the first convolution process using a 4x4 kernel with 16 filters and one stride. The number of filters on this convoy is 16 pixels with kernel dimensions (4x4), which means that the photos produced from the convolution result in this time will have as many as 16 map features.

Next is the fully connected layer. This process aims to transform the data dimension to classify the data linearly. In the fully connected process, a 4-dimensional array is changed into two dimensions, where the value of H W C is made in one array; the second is N. This process aims to transform the data dimension to classify the data linearly.

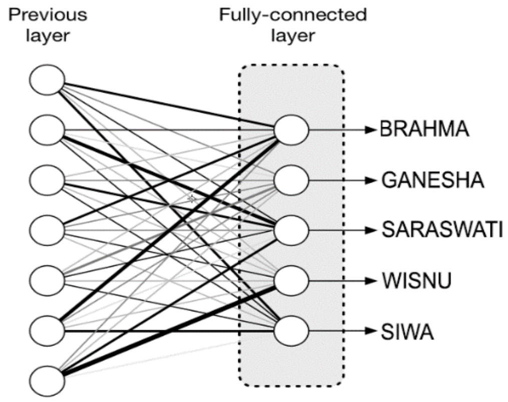

Figure 4. Fully Connected Layer

The last layer is the result of the results after the previous 19-layer processes, where the system will release the output of the results of the classification of statues, whether the image is included in the image of the statue of Lord Brahma, Lord Ganesha, Goddess Saraswati, Lord Shiva or Lord Vishnu.

3.2. Training Result

The training outcomes are obtained upon completing the Feature Learning process within the Convolutional Neural Network (CNN) algorithm. This training process is carried out three times according to the percentage of 75%, 50%, and 40%.

Table 2. Training results using 75%

Epoch	Iteration	Time Elapsed	Mini Batch Accuracy	Mini Batch Loss	Base Learning Rate
1	1	1 sec	25%	2.2479	0.0010
8	50	18 sec	100%	0.0220	0.0010
15	100	35 sec	100%	0.0026	0.0010
16	112	40 sec	100%	0.0018	0.0010

The data used in 75% of this training data is 115 sculpture images with a learning rate of 0.001. The highest accuracy results in this training are reaching 100% with epoch 16, maximum iteration 112, and mini-batch loss 0.0026 with a training time of 40 seconds.

Table 3. Training results using 50%

Epoch	Iteration	Time Elapsed	Mini Batch Accuracy	Mini Batch Loss	Base Learning Rate
1	1	1 sec	12.50%	2.5212	0.0010
13	50	18 sec	100%	0.0091	0.0010
16	64	23sec	100%	0.0063	0.0010

The results of the 50% training data experiment using a learning rate of 0.001 were 100% with a maximum iteration of 64 and a mini-batch loss of 0.0063 with a training time of 23 seconds.

Table 4. Training results using 40%

Epoch	Iteration	Time Elapsed	Mini Batch Accuracy	Mini Batch Loss	Base Learning Rate
1	1	2 sec	31.25%	2.3204	0.0010
16	48	19sec	100%	0.0033	0.0010

The last training process uses 40% of training data; the total number of images used is as many as 60. The results of the training process this time also showed that it was excellent. With a maximum iteration result of 48 and a mini-batch loss of 0.0033 with a training time of 23 seconds, it can achieve a maximum training accuracy of 100%.

3.3. Test Classification Results

The testing process here is the test result of the training process based on the parameters made in Figure 5. The test results are divided into three according to the percentage of predetermined test methods, namely 25%, 50%, and 60%. In the first test, using 25% testing data, seven images were used for each statute classification, and all 21 images were used.

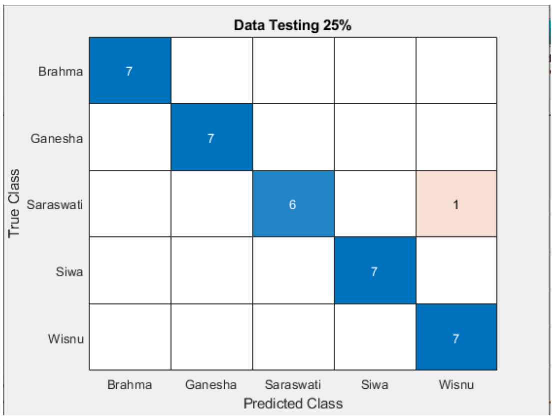

Figure 5. Test Classification Results with 25% Data Testing

The test results using 25% of this data have the highest accuracy compared to other tests, reaching 97.14%. One of the images of the statue of Goddess Saraswati, which is predicted to be a statue of Lord Vishnu, is misclassified.

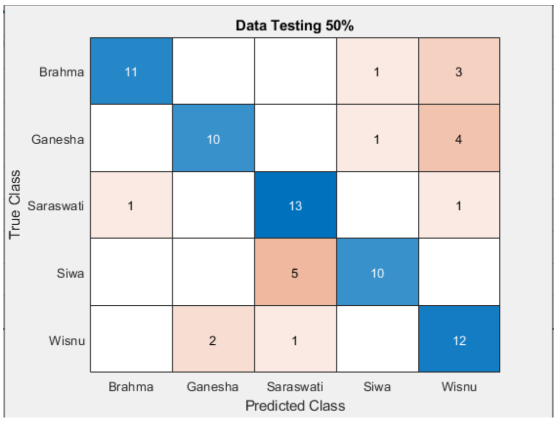

Figure 6. Test Classification Results with 50% Data Testing

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The second test used the same number of images during the training process, using 75 images. For each classification, there are 15 images to test. In this test, the accuracy results obtained were 74.67%. The highest correct prediction is on the statue of Goddess Saraswati, which has two errors, predicted as Lord Brahma and Lord Vishnu. The highest prediction error is found in the statues of Lord Brahma and Lord Shiva, with each error reaching five images.

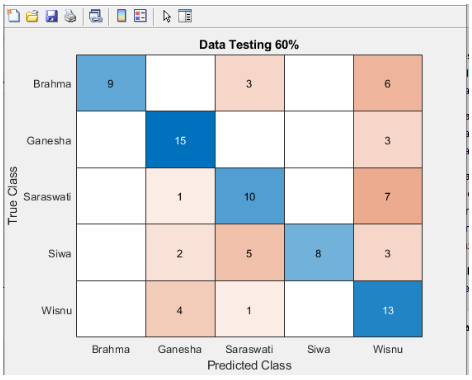

Figure 7. Test Classification Results with 60% Data Testing

The last test was to use the most images in the testing data, which reached 90 images. Each type of sculpture has 18 images to test. This last test had an accuracy rate of only 61.11%, with the best statue calibration prediction being Lord Ganesha, with 15 precise images from a total of 18 images tested as well as the statue of Lord Shiva with the lowest prediction accuracy in this test which only eight images are correct.

3.4. Testing the level of accuracy against the effect of layers

Layer Testing aims to determine the effect of the layer on the sample data used in the classification, which will affect the final accuracy. Where the layer settings to be used are:

a. Convolutional layer with batch normalization without ReLU activation
b. Convolutional layer with ReLU activation without batch normalization.
c. Convolutional layer with batch normalization and ReLU activation.

Testing will be carried out in each experiment, using 75% training data, 25% testing data, 50% training data, 50% testing data, and 40% training data, 60% testing data. Testing the level of accuracy of the layer used still requires using the max pooling layer to find the maximum value.

Table 5. Testing results

Layer Testing	Accuracy Rate		
	Training 75% Testing 25%	Training 50% Testing 50%	Training 40% Testing 60%
A	94,29%	70,67%	61,11%
B	68,57%	38,67%	20,00%
C	97,14%	74,67%	61,11%

Table 5 shows test A, namely, the convolutional layer with batch normalization without the ReLU layer, produces an accuracy rate of 94.29% using 75% training data and 25% testing, while using 50% training data and 50% testing, the accuracy obtained is 70.67%, and by using 40% training data and testing 60%, the accuracy obtained is 61.11%. Trying this layer, as can be seen in the image, using the first sample image of Lord Brahma with the array used [8 4] can produce a reasonably clear output because the batch normalization layer overcomes the problem of missing gradient and can cause the activation gradient in successive layers to decrease or increase in size so that the resulting image looks equally dark light. This makes the testing accuracy using this layer method excellent.

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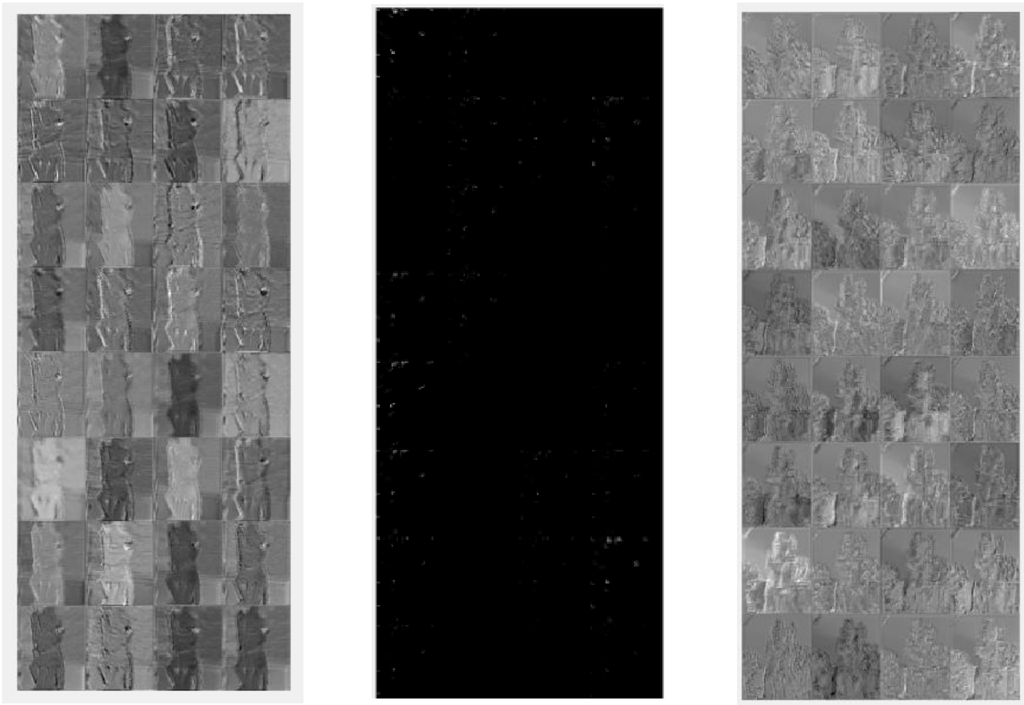

Figure 8. Images result using different layer settings

3.5. Testing the level of accuracy on the effect of its activation level

The activation function serves as a mathematical equation dictating the output of a neural network. This function is applied to each neuron within the network, determining activation based on the relevance of each neuron's input for model prediction. Additionally, the activation function normalizes the output of all neurons to a range typically between 1 and 0 or between -1 and 1. This activation analysis determines the most effective activation function for classifying God Statues in Bali.

In testing the activation function, the activation function used is ReLU. The ReLU activation layer tested uses 1 ReLU layer, 2 ReLU layers, 3 ReLU layers, and 4 ReLU layers. The effect of the number of ReLU on the level of accuracy that can be achieved can be Seen in the following table:

Table 6. Testing results using ReLU

Layer Testing	Accuracy Rate		
	Training75% Testing 25%	Training 50% Testing 50%	Training 40% Testing 60%
1 Reread	85,71%	69,33%	64,44%
2 Reread	85,71%	72,00%	63,33%
3 Proofread	94,29%	72,00%	63,33%
4 Reread	97,14%	74,67%	61,11%

The activation function is a mathematical equation responsible for determining the output of a neural network. This function is applied to each neuron in the network, deciding whether it should be activated based on the relevance of its input for model prediction. Additionally, the activation function normalizes the output of all neurons, typically ranging between 1 and 0 or between -1 and 1. This activation test is carried out to determine which activation is best used in classifying statues of Gods and Goddesses in Bali. In testing the activation function, the activation function used is ReLU. The ReLU activation layer tried to use 1 Rectifier Linear Unit layer, 2 Rectifier Linear Unit layers, 3 Rectifier Linear Unit layers, and 4 Rectifier Linear Unit layers. The effect of the number of ReLU on the level of accuracy that can be achieved can be seen in the following table. It is challenging to recognize the statues tested. Still, CNN can classify statues quite well.

 

Figure 9. Images result based on 1 ReLU layer and 2 ReLU layers

Figure 9 shows activation testing in the calcification of God Statues in Bali. The activation function used is ReLu. The ReLu activation layer was tested using 1 ReLu layer and 2 Relu layers. The influence of the number of ReLu on the level of accuracy is measured by training and testing data. The accuracy results with 1 ReLu layer are 85.71%, 69.33%, and 64.44%. The accuracy results with 2 ReLu layers are 85.71%, 72.00%, and 63.33%. The percentage of training and testing data varies according to Table 6. Test results for the accuracy level of the activation layer.

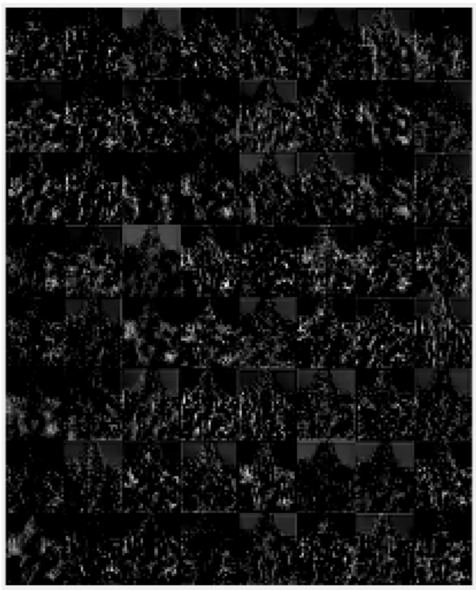 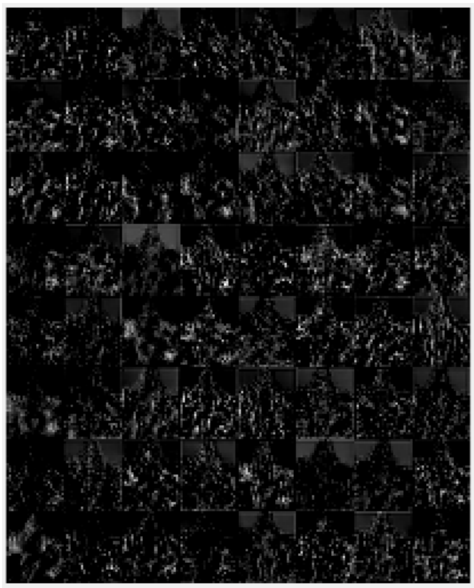

Figure 10. Images result based on 3 ReLU layer and 4 ReLU layers

Figure 10 shows activation testing in the calcification of God Statues in Bali. The activation function used is ReLu. The ReLu activation layer was tested using 3 ReLu layers and 4 Relu layers. The influence of the number of ReLu on the level of accuracy is measured by training and testing data. The accuracy results with 3 ReLu layers are 94.29%, 72.00%, and 63.33%. The accuracy results with 4 ReLu layers are 97.14%, 74.67%, and 61.11%. The percentage of training and testing data varies according to Table 6 test results for the accuracy level of the activation layer.

After conducting a thorough analysis of the results using the ReLu activation layer, it was observed that testing the ReLu activation layer with 4 ReLu activation layers leads to the highest level of accuracy compared to testing the ReLu activation layer with 1, 2, and 3 activation layers. Among the 4 ReLu activation layers, the level of accuracy that can be achieved in testing is 97.14%, using 75% data for training and 25% for testing. Therefore, the CNN model developed has high accuracy in testing on the God Statue dataset in Bali.

From the results obtained by our model, we tried to compare it with other CNN models, namely Alexnet and Resnet, where, based on test results using 70% - 30% data, the results showed that our CNN model had the best accuracy for managing Balinese statue image data with detailed accuracy. The accuracy test results can be seen in the following image:

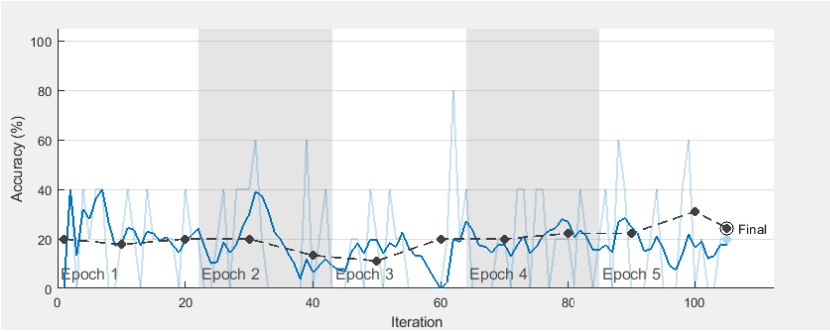

Figure 11. AlexNet Accuracy Test

As shown in Figure 11, we used rand alongside the AlexNet Model for CNN to split the data into 70% and 30%. After testing, we achieved an accuracy rate of 24.22% by using the AlexNet model architecture. The specifics of this test include 21 epochs, 105 maximum iterations, and multiple iterations.

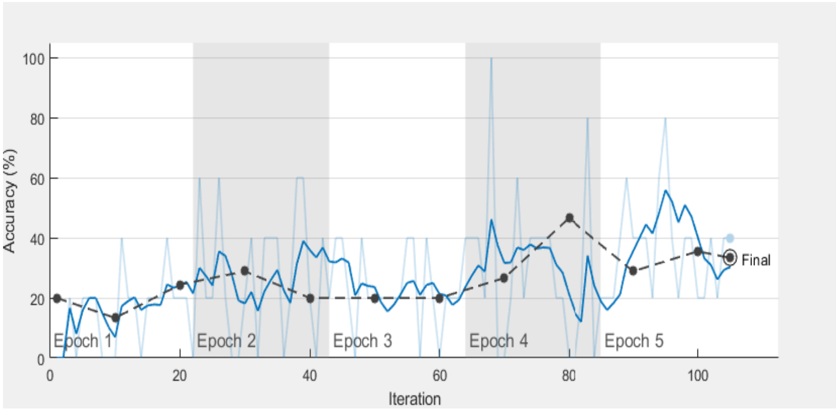

Figure 12. ResNet Accuracy Test

As shown in Figure 12, we used ResNet architecture alongside the ResNet Model for CNN and split the data into 70% and 30%. After testing, we achieved an accuracy rate of 33,33%. The specifics of this test include 21 epochs, 105 maximum iterations, and multiple iterations.

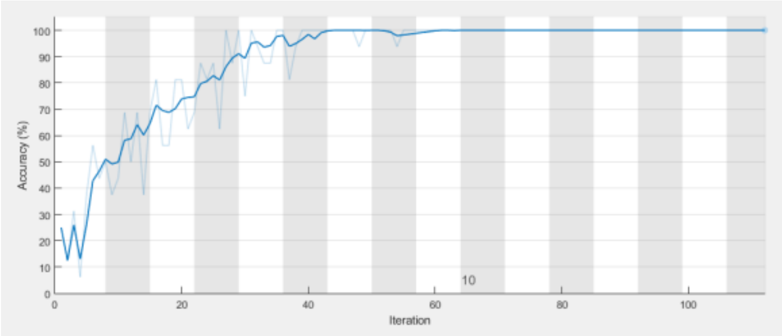

Figure 13. Our CNN Model Accuracy Test

Table 7. CNN Model Comparison

CNN Model	Highest Accuracy
Alexnet	24,44%
Resnet	33,33%
Our Model	97,14%

The experiment's results compared the performance of three different model architectures: AlexNet, ResNet, and CNN models. Our CNN model performed the best, achieving a testing accuracy of 97.41%, as shown in Figure 13. AlexNet reached only 24.44%, and ResNet reached 33.33%. The results showed that our CNN model could learn more complex features and accurately classify the God Statues in Bali, which have unique shapes and designs.

4. Conclusion

The proposed Convolutional Neural Network model can classify God Statues, a unique dataset taken directly from statue artisans, making the images authentic and showing the diversity of God Statues in Bali. The model we propose has a high activation result of 97.14% using convolutional layers with batch normalization and ReLU layers and the learning rate parameter option, namely using a value of 0.001 and 4 ReLu activation layers. Training results are obtained after completing the Feature Learning process on the Convolutional Neural Network (CNN) algorithm. This training process was carried out three times. 75% of the training data results are epoch 16, maximum iteration 112, and mini-batch loss 0.0026. At 50%, complete iterations are 64, and mini-batch loss is 0.0063. At 40%, the final iteration result is 48, and the mini-batch loss is 0.0033. The accuracy results resulting from the testing process using 25% of the test data is the test with the highest level of accuracy, reaching 97.14%; test data with 50% produces an accuracy value of 74.67%, and using 60% test data produces an accuracy value of 61.11%. Based on our experimental results, we compared our CNN model with two other models, AlexNet and ResNet. Using a data split of 70% - 30%, we found that our CNN model had the highest accuracy in managing statue image data. Specifically, our model achieves 97.14% accuracy, while Alexnet and Resnet achieve 24.44% and 33.33%, respectively.

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