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CLASSIFICATION OF CORN PLANT DISEASES USING VARIOUS CONVOLUTIONAL NEURAL NETWORK

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Abstract— *Based on data from the East Java Badan Pusat Statistik (BPS) in 2020, corn production in 2019 decreased by 622,403 tons. The decrease in production was caused by a disease that attacked corn plants identified from the corn leaves' physical appearance. This study aims to obtain an architectural model with good performance between AlexNet, LeNet, and MobileNet in detecting diseases of maize plants. The dataset used in this study came from Kaggle, with 4188 images divided into four disease classes: Common Rust, Gray Leaf Spot, Blight, and Healthy. Agricultural experts from Bantul have confirmed the appearance of each class of corn plant diseases. The preprocessing process is carried out to prepare the data so that the amount of data for each class is balanced. The image data used in this study totaled 4000 images which were divided into training data and testing data with a ratio of 80:20. Based on the experimental results, it was found that the MobileNet architecture has better performance than AlexNet and LeNet with an accuracy value of 83.37%, average precision of 0.8337, and g-mean of 0.8298. These results have been validated by agricultural experts in Bantul Regency and corn farmers experienced in corn farming.*

Keywords: *Corn Plant Disease, AlexNet, LeNet, MobileNet, CNN.*

Intisari—*Berdasarkan data Badan Pusat Statistik (BPS) Jawa Timur pada tahun 2020, produksi tanaman jagung pada tahun 2019 mengalami penurunan sebesar 622.403 ton. Penurunan produksi disebabkan penyakit yang menyerang tanaman jagung yang diidentifikasi dari penampakan fisik pada daun jagung. Tujuan dari penelitian ini adalah mendapatkan model arsitektur dengan kinerja yang baik antara AlexNet, LeNet, dan MobileNet dalam mendeteksi penyakit tanaman jagung. Dataset yang digunakan pada penelitian ini berasal dari Kaggle dengan jumlah data 4188 gambar yang terbagi menjadi empat kelas penyakit yakni Common Rust, Gray Leaf Spot, Blight, dan Healthy. Penampakan tiap kelas penyakit tanaman jagung sudah dikonfirmasikan dengan ahli pertanian dari Bantul, Daerah Istimewa Yogyakarta. Proses preprocessing dilakukan untuk mempersiapkan data agar jumlah data tiap kelas seimbang. Data gambar yang digunakan pada penelitian ini berjumlah 4000 gambar yang dibagi menjadi data latih dan data uji dengan perbandingan 80:20. Berdasarkan hasil percobaan diperoleh bahwa arsitektur MobileNet memiliki kinerja yang lebih baik daripada AlexNet dan LeNet dengan nilai akurasi 83,37%, average precision 0,8337, dan g-mean 0,8298. Hasil tersebut telah divalidasi oleh ahli pertanian di Kabupaten Bantul dan petani jagung yang berpengalaman pada pertanian jagung.*

Kata Kunci: *Penyakit Tanaman Jagung, AlexNet, LeNet, MobileNet, CNN.*

INTRODUCTION

Corn plays an important role as one of the main crops in meeting the carbohydrate needs of the Indonesian population. Corn is a source of food that contains carbohydrates. Corn ranks third in the world after wheat and rice and second in Indonesia after rice as the most significant food crop [1]. Corn has a high economic value and a wide range of benefits because it can be processed into food, industrial raw materials, and a source of animal feed [2]. One of the popular food preparations made from corn is corn rice.

According to data from the East Java Badan Pusat Statistik (BPS), in 2020, corn productivity in the region decreased by 622,403 tons compared to 2018 [2]. Disturbances in the growth process caused the decline in corn production due to disease attacks on corn plants. If this disease is not detected and not treated immediately, it will damage the plant and cause the corn plant's death [3]. Early recognition of the disease in maize can be identified by observing the affected parts of the plant, especially the leaves, which show symptoms such as discoloration and spots that appear [4].

Along with the development of technology and science, a computer can make identifying diseases in corn plants easier. Using computers to detect plant diseases has entirely accurate results [5]. Utilization of computers in the detection of plant diseases uses one of the areas of Deep Learning artificial intelligence. Deep Learning is the use of an artificial neural network architecture that has a large number of processing layers [6]. One of the Deep Learning methods commonly used for image classification of plant diseases is the Convolutional Neural Network (CNN).

Convolutional Neural Networks have the advantage of better classification results than other algorithms. CNN's high accuracy makes it popular for image recognition compared to other Deep Learning models [7]. The CNN architecture comprises a convolutional layer, a pooling layer, and a fully connected layer. The convolutional layer is the central part of CNN's computational process [6].

Research [8] used the CNN model with DenseNet architecture in classifying diseases on corn leaves. A dataset of 12,332 images divided into four disease classes with a resolution of 250 x 250 pixels was used in this study. Researchers divided the data into 90% training and 10% validation data. Preprocessing is done by augmenting the training data and then training the model. Optimization of the DenseNet architecture in this study obtained an accuracy value of 98.06% with an average training time of 3 minutes per epoch. In another study, [9] proposed a pre-training model from DenseNet and EfficientNetB0 using 15,408 image data in 4 different classes. The dataset is divided into 80% training and 20% test data. The proposed DenseNet and EfficientNetB0 models received accuracy values of 97.91% and 96.26%.

Research [10] proposes a CNN model with AlexNet architecture to classify corn leaf diseases. The research dataset comes from Kaggle with a total of 4198, divided into four classes: Blight, Healthy, Gray Leaf Spot, and Common Rust. This research was preprocessed by changing the image resolution to 256 x 256 pixels. Evaluation of the AlexNet model in this study obtained 88.68% accuracy and 0.284 loss in training data, 90.19% accuracy and 0.2635 loss in test data, and 85.68% accuracy and 0.3649 loss in validation data. In research [11] using the AlexNet architecture to detect diseases in tomato plants. The dataset comes from Kaggle, with 18,435 images as training data and 4,585 images as test data. This study uses an input image size of 64 x 64 pixels with an RGB scale. The evaluation of this research model has an accuracy of 96%, precision of 96%, recall of 95%, and f-measure of 97%.

Research [12] proposed the CNN MobileNet V2 architecture to detect diseases on tomato plant leaves. The dataset used in this study consists of 4,671 images from Kaggle and then rescaled to a size of 224x224 pixels. The best evaluation results of this study were obtained when the data was split with a 4:1 ratio between training data and test data. The accuracy value obtained is 95%, and the loss value is 0.1402. In research [13] using the MobileNet architecture to detect disease in rice leaves. The dataset comes from the UCI repository, which is processed to be 224 x 224 pixels. The accuracy value in this research model is 92%.

Research [14] proposes a LeNet architectural model compared to other algorithm models such as GA-SVM, ANN, and SVM in detecting diseases of maize plants. The dataset used in this study comes from PlantVillage, with 3,852 images. The input data size is 64 x 64 pixels. The proposed LeNet model gets the highest accuracy score with a score of 97.89% compared to the accuracy of GA-SVM at 92.82%, ANN at 94.4%, and SVM at 89.6%. In research [15] using the LeNet architecture to detect diseases in tea plant leaves. The dataset used comes from the plant village consisting of blister blight, red scab, red leaf spot, and leaf blight classes. This study uses input data measuring 227 x 227 pixels and has an accuracy evaluation result of 90.23% and an MCA of 90.16%.

Research [16] used the VGG16 architectural model to predict disease in corn and tomato plants. This study uses a Plant Village dataset with 5,300 images divided into 14 classes. Input images of 224 x 224 pixels are used in training the VGG16 model. The efficiency of this VGG16 model ranges from 70% to 85% in each class.

Based on the problems above to help solve these problems, in this study, the CNN AlexNet, LeNet, and MobileNet architectures were used to classify corn plant diseases. This research will produce architectural models of AlexNet, LeNet, and MobileNet, which can assist corn farmers in detecting diseased maize plants. This study aims to compare the performance of the AlexNet, LeNet, and MobileNet models against the classification of maize plant diseases using the same dataset and preprocessing process. There are two contributions to this research. First, the developed model can be a solution for detecting maize plant diseases, especially with image datasets. Second, the results of the comparison of model performance in this study can be used as a reference for further research in developing image-based plant disease classification models.

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MATERIALS AND METHODS

Dataset

This research uses a public dataset from Kaggle with additions from corn fields in Bantul, the Special Region of Yogyakarta. The dataset contains 4188 images divided into four disease classes with a different number of images in each class. To ensure that there is no mistake in the image of each disease of the corn plant. Agricultural experts from Bantul, Special Region of Yogyakarta, have confirmed the appearance of each class of corn plant diseases. The table below is an overview of the condition of the dataset, which includes classes and the number of images for each class.

Table 1. The condition of the dataset

Code	Class	Amount of images	Image
C1	Common Rust	1306	
C2	Gray Leaf Spot	574	
C3	Blight	1146	
C4	Healthy	1162	

Research Flow

The dataset is adjusted for the number of images for each class. Also, it applies data augmentation to the minority class so that the number of images for each class is balanced. After that, the image size is changed so that the size of each image used is the same. Then, the dataset is divided into training data for the modeling process and test data for the classification model testing process. Then the training data is classified with Convolutional Neural Network architectures LeNet, AlexNet, and MobileNet. The final step is to evaluate each architecture's results to ensure the classification results performance. The research flow can be seen in the flowchart below.

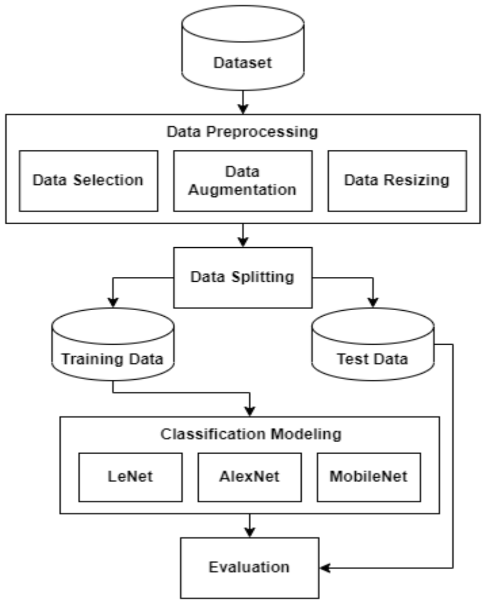

Figure 1. Research flowchart

Data Selection

All classes in the dataset have different amounts. Data selection is used to select some of the images to be used so that each class has the same number of images. In the common rust, blight, and healthy classes, 1000 images were selected for use in the following process.

Data Augmentation

Data augmentation is one stage of data preprocessing. Data augmentation increases the variety of data in classes with fewer data than the majority class so that each class's data is balanced [17]. To vary the minority class data, in this process, the image is flipped with a probability of 0.5 and rotated between -25 to 25 degrees. Data augmentation was carried out in the gray leaf spot class to increase the number of images from 574 to 1000.

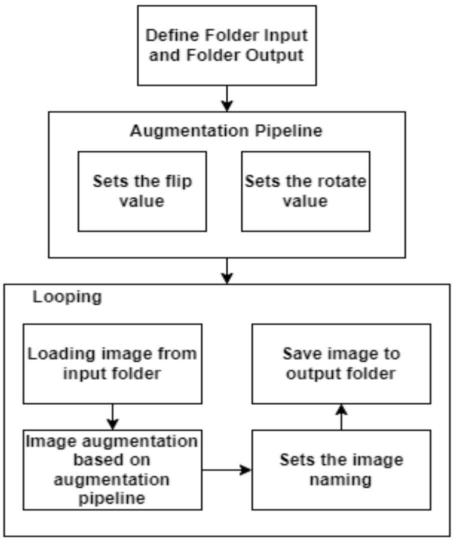

Figure 2. Data Augmentation Flowchart

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Data Resizing

Image resizing is done so that the image resolution is the same size. Unequal image sizes can affect the performance of the model being trained [18]. The image resolution is changed to 100 x 100 pixels for all classes used in training.

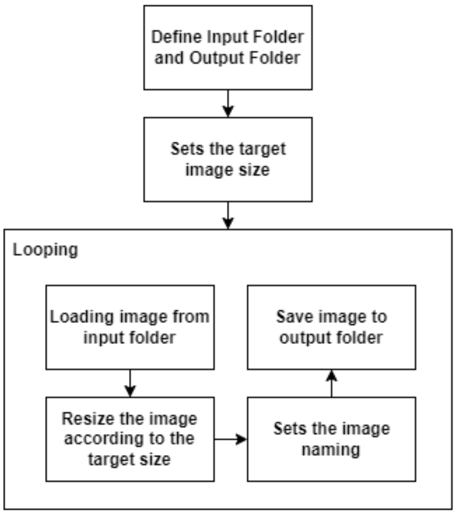

Figure 3. Data Resizing Flowchart

Data Splitting

The next step of this research is to divide the dataset into training and test data. The training data distribution is 80%, and test data is 20% of the total existing data. Training data is used in the modeling process, and test data is used to test the model.

AlexNet

AlexNet is one of the CNN architectures often used to classify images. The AlexNet architecture has good computing capabilities for mapping data complexity compared to other architectures [10], [19], [20]. AlexNet comprises five convolutional layers, a pooling layer, three fully connected layers, and a dropout on the first two fully connected to reduce overfitting.

Table 2. AlexNet Architecture Configuration

Layer	Filters	Kernel Size	Stride	Activation
Convolution	96	11x11	4	Relu
Max Pooling	-	3x3	2	-
Convolution	256	5x5	1	Relu
Max Pooling	-	3x3	2	-
Convolution	384	3x3	1	Relu
Convolution	384	3x3	1	Relu
Convolution	256	3x3	1	Relu
Max Pooling	-	3x3	2	-
FC	4096	-	-	Relu
FC	4096	-	-	Relu
FC	4	-	-	Softmax

LeNet

LeNet is an architecture by Yann LeCun that played an essential role in the early appearance of CNN in recognizing handwriting [21], [22]. The arrangement of layers in LeNet is less complex than the structure of artificial neural networks at this time. The LeNet structure consists of 2 convolutional layers, two pooling layers, and three fully connected layers.

Table 3. LeNet Architecture Configuration

Layer	Filters	Kernel Size	Stride	Activation
Convolution	6	5 x 5	1	Relu
Max Pooling	-	2 x 2	1	-
Convolution	16	5 x 5	1	Relu
Max Pooling	-	2 x 2	1	-
FC	120	-	-	Relu
FC	84	-	-	Relu
FC	4	-	-	Softmax

MobileNet

MobileNet uses depthwise separable convolution as the central part of its architecture. The depthwise separable convolution layer provides a light computing process, so MobileNet is very suitable for use on devices with low specifications and mobile devices [23], [24].

Table 4. Depthwise Convolution Configuration

Layer	Filters	Kernel Size	Stride	Activation
Depthwise Convolution	*filters*	3 x 3	*strides*	Relu
Batch Normalization	-	-	-	-
Convolution	*filters*	1 x 1	1	Relu
Batch Normalization	-	-	-	-

Table 5. MobileNet Architecture Configuration

Layer	Filters	Kernel Size	Stride	Activation
Convolution	32	3 x 3	2 x 2	Relu
Depthwise separable convolution	64	-	1 x 1	-
Depthwise separable convolution	128	-	2 x 2	-
Depthwise separable convolution	128	-	1 x 1	-
Depthwise separable convolution	256	-	2 x 2	-
Depthwise separable convolution	256	-	1 x 1	-
Depthwise separable convolution	512	-	2 x 2	-
Depthwise separable convolution	512	-	1 x 1	-
Depthwise separable convolution	1024	-	2 x 2	-
Depthwise separable convolution	1024	-	1 x 1	-
Global average pooling	1024	-	-	-
Dense	4	-	-	Softmax

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Evaluation

This study uses a confusion matrix to measure the performance of the classification model. The confusion matrix describes the predicted and true values shown in the table.

Table 6. Confusion Matrix

		Predicted Labels			
		Common Rust	Gray Leaf Spot	Blight	Healthy
True Labels	Common Rust	TCR	FGLS	FB	FH
	Gray Leaf Spot	FCR	TGLS	FB	FH
	Blight	FCR	FGLS	TB	FH
	Healthy	FCR	FGLS	FB	TH

True Common Rust (TCR) is the number of classes of common rust that are classified as common rust, False Common Rust (FCR) is the number of classes other than common rust that are classified as common rust, True Gray Leaf Spot (TGLS) is the number of classes of gray leaf spot that are classified as a gray leaf spot, False Gray Leaf Spot (FGLS) is the number of classes other than gray leaf spots that are classified as gray leaf spots, True Blight (TB) is the number of blight classes that are classified as blight, False Blight (FB) is the number of classes other than blight classified as blight, True Healthy (TH) is the number of healthy classes which are classified as healthy, False Healthy (FH) is the number of classes other than healthy which are classified as healthy. Based on the confusion matrix, the classification performance evaluation parameters in accuracy (1), precision (2),(3),(4),(5), and geometric mean (6) can be calculated using a formula below.

$$Accuracy = \frac{(TCR+TGLS+TB+TH)}{(TCR+TGLS+TB+TH+\sum FCR+\sum FGLS+\sum FB+\sum FH)} \ldots\ldots\ldots.(1)$$

$$Common\ Rust\ Precision = \frac{TCR}{(TCR+FCR+FCR+FCR)} \ldots\ldots\ldots\ldots\ldots(2)$$

$$Healthy\ Precision = \frac{TH}{(TH+FH+FH+FH)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

$$Blight\ Precision = \frac{TB}{(TB+FB+FB+FB)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

$$Gray\ Leaf\ Spot\ Precision = \frac{TGLS}{(TGLS+FGLS+FGLS+FGLS)} \ldots\ldots\ldots\ldots(5)$$

$$G-mean = \sqrt[4]{recallCR * recallGLS * recallB * recallH} \ldots (6)$$

RESULTS AND DISCUSSION

The initial step of this research is the process of selecting data from the default dataset. Data selection aims to take the same amount of data for each class so that each class's data is more balanced than before. The table below displays the amount of data after selecting data.

Table 7. Data Selection Result

Code	Class	Amount of images
C1	Common Rust	1000
C2	Gray Leaf Spot	574
C3	Blight	1000
C4	Healthy	1000

Furthermore, data augmentation was carried out in the Gray Leaf Spot class, which totaled 574 images. The augmentation process is carried out by rotating the image with a range of -25 to 25 degrees and flipping the image with a probability of 0.5. This process generates 426 new images, so the Gray Leaf Spot class has 1000 images. The table below displays the amount of data after data augmentation.

Table 8. Data Augmentation Result

Code	Class	Amount of images
C1	Common Rust	1000
C2	Gray Leaf Spot	1000
C3	Blight	1000
C4	Healthy	1000

After doing data augmentation in the gray leaf spot class, common rust, blight, and healthy have 1000 images in each class.

After all four classes have the same amount of data, image resizing is performed so that all images in each class have the same size. The same image size simplifies the process of convolution and pooling during training. All data used in this study is resized to 100 x 100 pixels.

The next step is dividing the dataset into training and test data. In this study, 80% of the data was used as training data for the CNN model, and 20% of the data was used to test the CNN model. The table below shows the amount of data for the training process and data for testing.

Table 9. Data Splitting Result

Code	Class	Train Data	Test Data
C1	Common Rust	800	200
C2	Gray Leaf Spot	800	200
C3	Blight	800	200
C4	Healthy	800	200

Common rust, gray leaf spot, blight, and healthy classes have the same number of training data and test data, namely 800 images of training data and 200 images of test data.

AlexNet

The first model in this study is to classify the dataset using the AlexNet architecture. The AlexNet model's evaluation results are presented in the confusion matrix below.

Table 10. AlexNet Confusion Matrix

True Labels		Predicted Labels: Common Rust	Gray Leaf Spot	Blight	Healthy
	Common Rust	185	1	3	10
	Gray Leaf Spot	2	112	65	20
	Blight	1	17	147	31
	Healthy	1	7	35	163

In the common rust class, 185 correct data out of 189 are classified as common rust. In the gray leaf spot class, 112 correct data out of 137 are classified as gray leaf spot. In the blight class, 147 correct data out of 250 are classified as blight. In the healthy class, 163 correct data out of 224 are classified as healthy.

Based on the confusion matrix above, the AlexNet model has an accuracy value of 0.7587, an average precision value of 0.7779, and a g-mean of 0.7464

LeNet

The second model is classified using the LeNet architecture. The evaluation results of the LeNet model are presented in the confusion matrix below.

Table 11. LeNet Confusion Matrix

True Labels		Predicted Labels: Common Rust	Gray Leaf Spot	Blight	Healthy
	Com mon	189	5	5	4
	Gray Leaf	8	143	50	6
	Blight	5	35	140	10
	Healt hy	4	7	14	175

In the common rust class, 189 correct data out of 206 are classified as common rust. In the gray leaf spot class, 143 correct data out of 190 are classified as gray leaf spots. In the blight class, 140 correct data out of 209 are classified as blight. In the healthy class, 175 correct data out of 195 are classified as healthy.

Based on the confusion matrix above, the LeNet model has an accuracy value of 0.8087, an average precision value of 0.8093, and a g-mean of 0.8024.

MobileNet

The third model is classified using the MobileNet architecture. The results of the evaluation of the MobileNet model are presented in the confusion matrix below.

Table 12. MobileNet Confusion Matrix

True Labels		Predicted Labels: Common Rust	Gray Leaf Spot	Blight	Healthy
	Common Rust	190	2	1	2
	Gray Leaf Spot	7	148	50	5
	Blight	5	30	152	18
	Healthy	1	6	6	177

In the common rust class, there are 190 correct data out of 203 data classified as common rust. In the gray leaf spot class, 148 correct data out of 186 data are classified as gray leaf spots. In the blight class, 152 correct data out of 209 are classified as blight. In the healthy class, 177 correct data out of 202 are classified as healthy.

Based on the confusion matrix above, the MobileNet model has an accuracy value of 0.8337, an average precision value of 0.8337, and a g-mean of 0.8298.

Models Performance Comparison

Comparisons were made to determine the performance of each classification model that had been tested. Model performance comparison involving agricultural experts and corn farmers from Bantul Regency to validate the classification results. The table below compares the three CNN

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architectural models regarding the accuracy, average precision, and g-mean.

Table 13. The Evaluation Comparison

Evaluation	Model		
	AlexNet	LeNet	MobileNet
Accuracy	0,7587	0,8087	0,8337
Precision Average	0,7779	0,8093	0,8337
G-Mean	0,7464	0,8024	0,8298

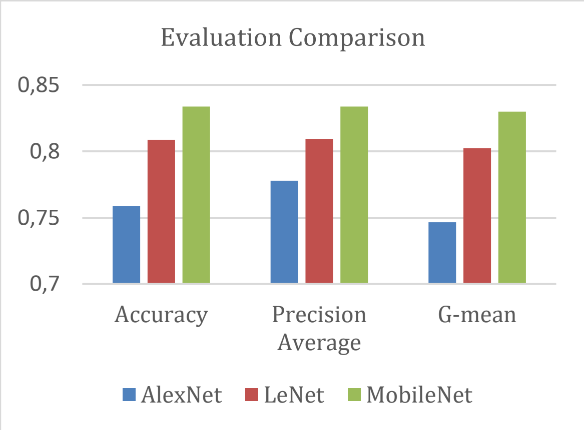

Figure 4. Evaluation Comparison Chart

CONCLUSION

Implementing the CNN AlexNet, LeNet, and MobileNet architectures for detecting corn plant diseases can produce good model performance. The performance of the three models above can be further improved by increasing the size of the input image and the amount of image data used. In general, the model with the MobileNet architecture has the best performance on the dataset used. In the problem of classifying corn plant diseases, the MobileNet architecture has a more complex layer configuration than AlexNet and LeNet. MobileNet has the best performance; this can be seen from the accuracy value of 83.37%, average precision of 0.8337, and g-mean of 0.8298 on MobileNet, which is better than AlexNet and LeNet. The limitation of this research is that the amount of data used is only 4000 images, and it only uses the AlexNet, LeNet, and MobileNet architectures. A suggestion for future research is to compare the performance of other CNN architectures such as VGGNet, DenseNet, ResNet, or EfficientNet using a similar dataset with more images.

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