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RAIN PREDICTION USING CONVOLUTIONAL NEURAL NETWORK (CNN) METHOD BASED ON DIGITAL IMAGE

Alya Syifa Ihsani¹, Anggunmeka Luhur Prasasti², Wendi Harjupa³ Umar Ali Ahmad⁴, Reza Rendian Septiawan⁵

^{1,2,3,4,5} Computer Engineering, Electrical Engineering Faculty, Telkom University
 ³ Research Center of Atmospheric Science and Technology, Research Organization of Aeronautics and Space, National Research and Innovation Agency

Abstract. Hydrometeorological disasters such as floods and landslides are natural disasters caused by heavy rain. These natural disasters often occur in Indonesia, not only causing material losses, but natural disasters also often take lives. To reduce the impact of natural disasters, it is necessary to predict rain which is one of the factors in natural disasters and any other needs. Rain prediction was developed using numerical models cannot predict rain accurately. Because of this reason, the rain prediction system was developed using the Convolution Neural Network (CNN) method in this research. One thousand of cloud images from Garut sky were used for the training process. It consists of two categories, cloudy images and rain images, to build predictive models. The simulation process is carried out by inputting a cloud image through several processes such as preprocessing, feature extraction, and learning process, so this system can predict the rain in the next hour. The accuracy of this system can reach up to 98% obtained from the results of tests carried out such as 80:20 data partition, 0.001 learning rate, and 50 epoch. The model that has been built can strengthen the existing rain models and provide more accurate information about the occurrence of hydrometeorological disasters.

Keywords: cloud image, convolutional neural network (CNN), hydrometeorological disasters, image processing, rain prediction.

1 Introduction

1.1 Background

Rain is a condensation process of water vapor that rises to the atmosphere and turns into water droplets that fall to the earth [1]. Irregular rain patterns are caused by damage to the system in the hydrological cycle. This condition causes hydrometeorological natural disasters such as floods and landslides. These natural disasters often occur in Indonesia and cause environmental damage, material losses but can take lives [2].

In this research, a system that can predict rain using a Convolutional Neural Network (CNN) algorithm based on digital images reduces the impact of these natural disasters.

Convolutional Neural Network (CNN) is a method that can be used on images. This method can extract essential features from an image. CNN has been widely used to create a system that can recognize, classify and detect objects [3].

Previously there have been studies using the CNN method to classify or detect an object. As an example of designing an Arabic language recognition application, this study aims to help Hajj and Umrah pilgrims translate Arabic using smartphones [4]. Expression classification for user experience testing video games. This study aims to determine user satisfaction in playing the gameplay, which will be very helpful for their product developers. The system has successfully classified various facial expressions such as angry, afraid, sad, happy, neutral, disgusted, and surprised in real-time [5]. Classification of Batik Motif Images is designed to recognize various types and information of batik by classifying batik from its motif [6].Handwritten Javanese Character Recognition, preserving Javanese script so that it can be used for daily communication, divided into 20 character classes to build software which can display automatic handwritten Javanese [7]. Hiragana and katakana handwriting transliteration system makes it easier for someone to learn Japanese [8].

In this study, the CNN method is used for a rain prediction system that will process a thousand cloud images consisting of two categories, namely, cloudy images and rain images, obtained from a camera that points to the sky in the city of Garut, which is owned by Space and Atmospheric Observation and Technology Test Center (BUTPAA). The data is used for the learning process using the CNN method and produces a prediction model. So this system can predict the occurrence of rain in the next hour.

2 Materials and methods

2.1 Data

This study uses a dataset in the form of cloud images taken from a real-time camera that points to the sky in Garut city by the Space and Atmospheric Observation and Technology Test Center (BUTPAA).

2.1.1 Cloud Image Dataset

We are using image data of 1000 images from two categories of cloudy and rainy with a size of 1080 x 1920 pixels. The difference between the two categories can be seen if the cloudy image is blue, bright and the clouds form separately. the image of the rain is gray, tends to be dark, and the clouds are lumpy. **Figure 1** is a sample of cloudy and rain image.



Figure 1. Cloud and Rain Image Data Sample

2.1 Pre-processing

The data size of 1920 x 1080 pixels is cropped and equated to 1180 x 690 pixels. Cropping is used to make the image uniform, and this process reduces the dimensions of the outermost area of the image to remove unnecessary objects. [9] so that only cloud images can be seen. This process is used to avoid noise during the learning process. **Figure 2** is an example of an image that has the original image, and **Figure 3** has a cropped size.



Figure 3. image size 1180 x 690

After changing the image size, the following process is contrast manipulation images using a computer [10] such as sharpen the image quality so that the colors in the image data will look clearer and brighter [11]. **Figure 4** and **Figure 5** are a comparison between the original image and image quality enhancement:



Figure 4. original quality image



Figure 5. image sharpening results

2.3 Training and Validation data

From the amount of image data obtained, it is divided into two parts randomly consisting of:

- Training data: data used to train image data using Convolutional Neural Network and produce a CNN model.
- Validation data: data that is used to avoid overfitting and is used to test the CNN model's performance.

Data are separated and grouped into different directories and names. as in **Figure 6** is an illustration of the grouping of image data



Figure 6. Illustration of image data grouping

2.4 Research Design

This rain prediction system starts by inputting cloud image data into cloudy and rain images in png format. The first process is preprocessing, and the image size is changed to the same size. Second, they improve the image by sharpening the image quality so that the colors in the image data will look clearer and brighter. After that, the image data is divided into two parts, training data, and validation data. An augmentation process processes the training data to add images of different variations based on existing images. This training data is used for the training process using the Convolutional Neural Network (CNN) algorithm to obtain a specific input image feature and produce a CNN model. Next, the model will be tested and product recall, precision, and accuracy. The model that has been tested is used for the prediction process using new data and produces an output in the form of information on the occurrence of rain in the future. **Figure 7** shows an overview of the rain prediction system design:



Figure 7. Rain prediction system design

2.5 Convolutional Neural Network Architecture

Convolutional Neural Network (CNN) is one type of Neural Network architecture that can provide information processed from a connected neuron. [12]. Convolutional Neural Network (CNN), the development of the Multi-Layer Perceptron (MLP), has a unique convolution and merging layer to study an object [13]. CNN has a high network depth and is widely applied to image data so that it belongs to the type of Deep Neural Network [14], is the development of the concept essential machine learning that uses layers that more [15]. The first method to study multiple hierarchical layers successfully [16]. CNN is divided into two main categories, namely learning features that will extract images and classification with softmax as the output [17] .Figure 8 shows two main parts to the Convolutional Neural Network (CNN) architecture. The image also shows several processes for processing image data. For example, convolutional layer, pooling layer, and fully-connected layer. Convolution is a process to extract essential features in the input image [18]. The pooling layer serves to reduce the image that aims to increase the position invariance of the features. Can present data to be smaller, easier to process, and easy to control overfitting. The pooling process commonly used is max pooling [19]. This research uses three convolution layers and two Neural Network layers as shown in Table 1.



Figure 8. Convolutional Neural Network Architecture used in the system

Layer (type)	Output	Shape	Param #
conv2d_1 (Conv2D)	(None,	100, 150, 64)	4864
max_pooling2d_1 (MaxPooling2	(None,	25, 37, 64)	0
conv2d_2 (Conv2D)	(None,	25, 37, 128)	204928
max_pooling2d_2 (MaxPooling2	(None,	6, 9, 128)	0
conv2d_3 (Conv2D)	(None,	6, 9, 256)	819456
max_pooling2d_3 (MaxPooling2	(None,	1, 2, 256)	0
flatten_1 (Flatten)	(None,	512)	0
dropout_1 (Dropout)	(None,	512)	0
dense_1 (Dense)	(None,	512)	262656
dense_2 (Dense)	(None,	1024)	525312
dense_3 (Dense)	(None,	2)	2050
Total params: 1,819,266 Trainable params: 1,819,266 Non-trainable params: 0			

	Table 1. La	ver of CN	NN used in	the system
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2.5.1 Feature Learning

In the feature learning section, there are three convolution layers, and zero paddings are applied to add a value of 0 to all parts of the image input. Zero paddings are used to manipulate the output size in the convolution layer so that it does not decrease drastically and prevent a lot of information from being lost during the feature learning process.

The convolution layer has many layers, starting from 64, 128, and 256 layers. Kernel size 5x5 and stride or one-time kernel migration. This kernel is used for the feature ecstasy process of the image, which will move from the first value to the end and obtain a new pixel size. Next, enter the normalization process using the ReLU activation function. If there is a negative pixel value, it will be normalized to 0. Using a max-pooling size of 4x4, the pooling layer reduces the pixel value and produces a new pixel size. The output of the process is called a feature map. This stage continues according to the number of convolution layers used. To calculate the dimensions of the feature map, we use equation 1.

$$output = \frac{n+2p-k}{s} + 1 \tag{1}$$

n is the length or height of the input image, **2p** zero paddings, **k** is the length or height of the kernel, and **s** is the displacement of the kernel or stride.

2.5.2 Classification

The classification section begins by converting a 2D feature map into a 1D vector, and this process is flattened. There is a neural network layer with layers 512 and 1024 connected by lines called weights using fully connected. A fully connected process use to transform data dimensions so that they can be classified linearly. [20]

This process produces output in the form of predictions of rain using the softmax activation function. Softmax can generate a label from the probability calculation process. From the resulting label, it is converted into a vector with a value between 0 and 1, and when added up, it will have a value of one [21]. Equation 2 is the Softmax Classifier.

$$f_j(z) = \frac{e^z j}{\sum_k e^z k} \tag{2}$$

The function f_j is the result of every jth element in the class output vector. The z function is a hypothesis given by the training model to be classified by the Softmax function.

3 Results and Discussion

In this study, the test scenario was carried out to determine the model's performance generated from the learning process using the CNN algorithm. The scenarios used are data partition, learning rate and epoch. This test uses a confusion matrix to find out the three values of accuracy, precision and recall.

3.1 Confusion Matrix

Confusion Matrix is a method used to evaluate the algorithm's performance in classifying images from different classes [22]. **Table 2** is a way to find out the values in the confusion matrix.

Table 2. Confusion matrix

Prediction

		Positive	Negative
Actual	Positive	TP	FN
Attual	Negative	FP	TN

The following variables serve to evaluate the classification algorithm.

- TP (True Positive) : positive data that is predicted correctly
- TN (True Negative) : correctly predicted negative data
- FP (False Positive) : negative data predicted as positive data
- FN (False Negative) : positive data predicted as negative data

3.2 Accuracy

Accuracy Parameters that can measure how accurate the model is in classifying new data correctly. To find out the accuracy is calculated using equation 3.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$
(3)

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3.3 Precision

Precision is a parameter that can measure the accuracy of the requested data with the prediction results provided by the model. To find out the precision is calculated using the equation 4.

$$Precision = \frac{TP}{TP + FP} \times 100 \tag{4}$$

3.4 Recall

Recall parameter that calculates the success of the model in predicting the entire object correctly. To find out the recall is calculated using the equation 5.

$$Recall = \frac{TP}{TP + FN} \times 100$$
⁽⁵⁾

3.5 Data Partition Testing Scenario

This test has different data comparisons of 90:10, 80:20, 70:30, 60:40 and 50:50. From this test, the highest accuracy is obtained at 98% on the 80:20 data partition. Estimated time during training 15 minutes 46 seconds. Table 3 show the scenario results of data partition testing.

Table 3. Scenario Results of Data Partition Testing

	Epochs 50, Adam's optimization ($lr = 0.001$)				
Data Partition	n Precision	Recall	Accuracy	Time	
50:50	83 %	99 %	89 %	11 min 2 s	
60:40	93 %	96 %	95 %	12 min 39 s	
70:30	97 %	96 %	97 %	13 min 36 s	
80:20	97 %	99 %	98 %	15 min 46 s	
90:10	93 %	100 %	96 %	16 min 48 s	

From the results obtained, the data partition can affect the level of accuracy, the highest accuracy is 98% on the 80:20 data partition. the training data used is more than the validation data, so the system can learn more data variations. After that, there is sufficient validation data to avoid overfitting, and during training the accuracy increases steadily.

3.6 Learning Rate Testing Scenario

This test compared the accuracy results obtained from the learning rate test used 0.01, 0.001, and 0.0001. The highest accuracy is 98%. The estimated training time is 14 min 35 seconds. **Table 4** shows the learning rate scenario result.

80:20 data partition, epoch 50, Adam optimization				
Learning Rate	Precision	Recall	Accuracy	Time
0.01	24 %	23 %	24.5 %	15 min 46 s
0.001	98 %	99 %	98.5 %	14 min 35 s
0.0001	97 %	99 %	98 %	16 min 42 s

Table 4. Learning Rate Scenario Results

From the results obtained, the learning rate can affect accuracy, where the learning rate is the number of steps taken in the training process. The size of the learning rate used can affect the speed during the training process. It can be seen that the 0.01 learning rate produces the lowest accuracy because the step when training is too extensive, so the system cannot learn the object correctly. While the highest accuracy is obtained at a learning rate of 0.001 with an accuracy of 98.5%, this is due to the small training steps to learn more specific objects.

3.7 Epoch Testing Scenario

This test compares the accuracy results obtained from the 10, 20, 30, 40, and 50. The highest accuracy was obtained at 98%, epoch of 50. The estimated time during training was 15 min 46 seconds. The epoch result can be seen in **Table 5**.

80:20 da	80:20 data partition, Adam optimization, learning rate 0.001				
Epoch	Precision	Recall	Accuracy	Time	
10	92 %	97 %	93 %	3 min 10 s	
20	99 %	92 %	95.5 %	6 min 10 s	
30	98 %	93 %	95.5 %	9 min 31s	
40	88 %	99 %	90.5 %	12 min 31 s	
50	97 %	96 %	98 %	15 min 46 s	

Table 5. Epoch Scenario Results

From the results obtained, epoch can affect the level of accuracy, epoch is the process of learning training data in one round. From this test, the highest accuracy is 98% at epoch 50. From this test, many epochs can increase accuracy and when training is not overfitting.

3.8 Evaluation Result

After evaluating using the architecture that has been designed, the 80:20 data partition, which is 800 images for training data and 200 for validation data, the learning rate of 0.001, and 50 epochs produce 98% accuracy. **Figure 9** is a graph resulting from the test.



Figure 9 graph of accuracy and loss evaluation results

3.9 Model Convolutional Neural Network (CNN)

After the evaluation process and getting the most optimal in an accuracy of 98%. The model is saved using the "*model.save(model_name*" function. The saved model can be used for the prediction process. **Figure 10** shows the convolution neutral network model.



Figure 10. Convolutional Neural Network Model

3.10 Graphical User Interface (GUI)

In this study, a Graphical user interface (GUI) was designed to display a rain prediction system visually. There is a feature to input a new image, pressing the choose file button. After that, the image size is changed, and the image quality is sharpened. the system will predict using the CNN model that has been tested and obtain the best accuracy, and we can find out rain information in the next hour. **Figure 11** is the Graphical user interface (GUI) of this rain prediction system.

	RAIN PRE	DICTION USING CONV METHOD BASED C	OLUTIONAL NEURAL NETWORK NN DIGITAL IMAGE	
ORIGINAL IMAGE IMAGE SHARPENING PROCESS	INPUT IMAGE	Choose File No file chosen SUBMIT IMAGE		
THE SYSTEM PREDICTS THE NEXT HOUR : ITS RAIN		ORIGINAL IMAGE	IMAGE SHARPENING PROCESS	
THE SYSTEM PREDICTS THE NEXT HOUR :				
ITS RAIN	THE SYSTEM PREDICTS THE NEXT HOUR :			

Figure 11. GUI of the rain prediction system

3.11 Cloud prediction simulation

Table 6 shoes the prediction simulation using cloud images in different conditions which are inputted using the GUI.

No	Sample Images	System Prediction In The Next Hour	Validation
1		Predict No Rain	Correct
2		Predict Rain	Correct

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3	Predict No Rain	Correct
4	Predict Rain	Correct
5	Predict No Rain	Correct

Sample image of cloud number 1, the clouds are grey, and the sky is clear. This cloud condition does not cause rain. Sample image of cloud number 2, the cloud is grey, dark, and the cloud's shape is lumpy. This cloud condition causes rain. Sample image of cloud number 3, the cloud is white, the sky is clear, and the cloud is separate. The cloud condition does not cause rain. Sample image number 4, the clouds are grey, and the shape of the shadows is lumpy, but the clouds do not look dark because they are illuminated by the sun, even though these cloud conditions cause rain. Sample image of cloud number 5, the cloud is white, the sky is clear, and the cloud forms are separated. This cloud condition does not cause rain. Of all the cloud image samples used, the system can correctly predict the rain conditions in the next hour.

4 Conclusions

The performance of this CNN model is good which is used to process image data, based on the test results to determine the most optimal accuracy of the CNN model and the combination of parameters such as data partition 80:20, learning rate 0.001 and epoch 50 get accuracy up to 98%. So from this research it can be concluded that the system with the CNN model and the combination of parameters that have been tested can recognize and classify various cloud image conditions and the system can predict rain in the next hour.

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