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Alphabet and number recognition of banknote by using the deep learning

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***Abstract*— The forgery of banknotes has been around for a long time. It is effective to recognize the banknote number as a way to confirm the forgery of the banknote. However, the conventional methods such as OCR are not suitable for recognition of identification numbers. Therefore, an approach using deep learning is tried. In this paper, we verify the recognition accuracy of the unverified alphabet and number, and also change the way to give the training data and confirm whether the recognition accuracy changes. As a result, a recognition rate of 96% or more was confirmed.**

I. INTRODUCTION

The forgery crimes on banknotes have existed for a long time [1]. The forgery prevention technology for banknotes is improved every time a new banknote is issued. However, even now the case regarding counterfeit banknotes is not ending. In Japan too, more than 1000 counterfeit banknotes are found each year. Most counterfeit banknotes often have the same serial number, and there are cases where multiple counterfeit banknotes have been discovered simultaneously overseas. Therefore, we consider it is necessary to recognize and record the banknote serial number in some way. As one of them, OCR (Optical character recognition) technology exists in the recognition of the serial number of the banknote.

OCR is a reading method that uses features to perform pattern matching and outputs recognized characters. This method makes it difficult to recognize characters when there are indistinct parts due to the influence of complicated backgrounds, dirt, and creases. Therefore, conventional methods such as OCR are not suitable for recognition of banknote identification numbers. Hence, methods other than OCR are desired.

In this paper, we try to use the deep learning to read banknote numbers. And we consider the usefulness. We have proposed a method to verify a total of 10 characters of numbers "0" to "9" using deep learning in Ref. [2]. In Ref. [2], the correct answer rate for recognition exceeds 95%. Therefore, we consider that deep learning is suitable for recognizing banknote serial numbers. However, in addition to numbers, alphabets are also used as serial numbers for banknotes. In this research, we try to add 24 alphabets of "A"-"Z" except "I" and "O" which are used as serial numbers of banknotes to the data and make it learn using deep learning. As an experiment, it is divided into cases when only numbers are trained, when only alphabets are trained, and when numbers and alphabets are combined and trained. In this research, we also verify how to give data when learning in deep learning. In this paper, we report the learning results of alphabets and numbers and how to give learning data.

II. BANKNOTE NUMBER READING TECHNOLOGY USING DEEP LEARNING

A. *Data preparation*

In this paper, as in Ref [2], images of “A” to “Z” excluding “I” and “O” used for serial numbers of Japanese banknotes as learning data[3], and image “0” to “9” are newly prepared as learning data. Therefore, there are a total of 34 types of images for learning. These images are JPEG image of 56 x 56 pixel. In this paper, 60 pieces of “2”, 90 pieces of “3” and 100 pieces of other characters are prepared, for a total of 3850 pieces. Also, as with the training data, a total of 34 types of images from "A" to "Z" and "0" to "9" ,except "I" and "O" prepare as test data. These images are also JPEG image of 56 × 56 pixel. A total of 340 sheets of 10 sheets of each are prepared, and the correct answer rate for each character and the overall correct answer rate are observed with the test data. The reason for using JPEG is that a digital camera was used to prepare the data.

In this paper, we focused on how to give learning data, and in the first experiment, we input at once for each type of character. In the next experiment, the image data of “A” to “Z” and “0” to “9” except “I” and “O” are sequentially input one by one.

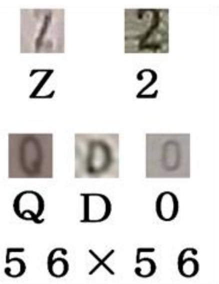

Fig2.1 Images used for training data and test data

B. *Configuration of neural network[4]*

This paper uses a convolutional neural network with 3-tier convolution and pooling. After that, it inputs into the neural network of two layers of all connection layers. The pooling layer uses max pooling. In addition, an activation function and a dropout layer are sandwiched between all the coupled layers. The activation function uses ReLU (Rectified Linear

Unit). The configuration of CNN used in this paper is shown in Fig. 2.2.

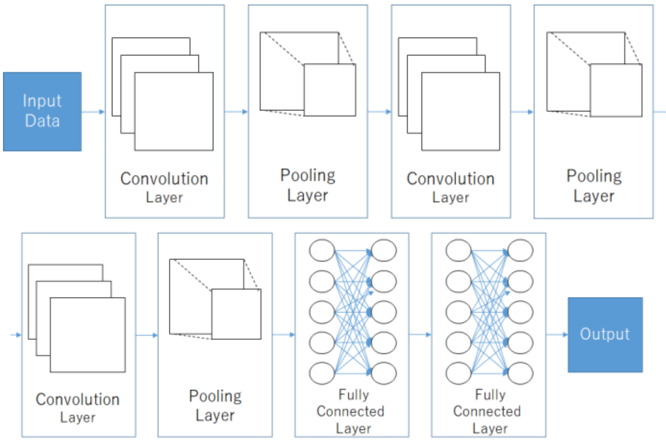

Fig2.2 CNN configuration diagram

This neural network is trained using the gradient descent method .The hyper parameters in this paper are shown in Table 2.2 below. The batch size is 24 for the alphabet only and 34 for the number combined with the alphabet.

The hyper parameters refer to parameters set by the human hand such as batch size and epoch number. Epoch is the number of times of learning. The learning rate is a value that determines the amount of parameter updates. Validation is a test data that is randomly extracted from learning data and treated as test data. It is randomly selected for each epoch to improve learning accuracy.

Table 2.1 Hyper parameters

epoch	60
Learning rate	1E-04
Validation	0.1

Also, in this paper, two learning progress graphs are used. The model accuracy shows the correctness of the model, and val_accuracy shows the correctness of the validation data. Model loss indicates loss of learning, and val_loss indicates loss to validation data. It can be said that these two graphs are more versatile for unknown data as the validation data gets closer to the other graphs.

III. EXPERIMENT

A. *Purpose of experiment*

In this research, we change the data to be input and change the input method, conduct experiments to verify. As with Ref. [2], it is verified whether the correct answer rate when learning combining alphabets and numbers exceeds 95% only for alphabet images only. After that, it is verified whether the correct answer rate changes when the input method is changed. There are two input methods: a method of inputting data in a batch for each folder which is alphabet group including an each character and a method of repeating inputting “A” to “Z” and “0” to “9” in order except “I” and “O” .

B. *Evaluation criteria*

In this paper, two learning progress graphs are used. The model accuracy shows the correctness of the model, and val_accuracy shows the correctness of the validation data. Model loss indicates model loss, and val_loss indicates loss to validation data. It can be said that these two graphs are more versatile for unknown data as the validation data gets closer to the other graphs.

C. *Experimental Result*

Case 1. Input all image data at once

Case 1.1 Learning only with alphabet

At first, learning was performed with a total of 2400 sheets of the alphabet only. The experimental results are shown in Table 3.1.1, and the learning progress graph is shown in Figure 3.1.1.

Table 3.1 Experiment result 1

Character type	A	B	C	D	E	F	G	H	J	K
Correct rate	0/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10
Character type	L	M	N	P	Q	R	S	T	U	V
Correct rate	10/10	10/10	0/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10
Character type	W	X	Y	Z	Overall rate		91.666...%			
Correct rate	10/10	10/10	10/10	10/10						

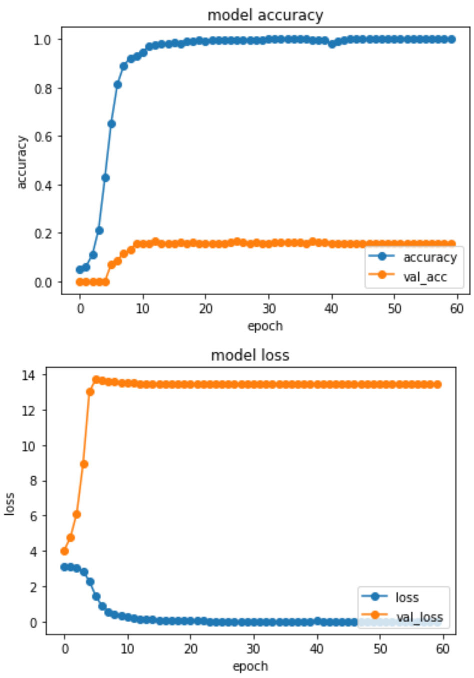

Figure 3.1 Learning progress graph

The overall correct answer rate is about 91.7% and less than 95%. Although the overall rate of correct answers is not low, looking at the rate of correct answers for each character type, the number of correct answers for “A” and “N” is 0. Also, "A" was often recognized as "K" and "N" was often recognized as "M". The learning progress graph shows that the graph of val_acc and the graph of val_loss disengage from the other graph.

From these results, it is considered that the versatility of the learning model created in this experiment is low.

Case 1.2 Learning by combining alphabets and numbers

Next, we conducted learning by combining the alphabet and numbers. The experimental results are shown in Table 3.1.2, and the learning progress graph is shown in Figure 3.1.2.

Table 3.2 Experiment result 2

Character type	0	1	2	3	4	5	6	7	8	9
Correct rate	6/10	0/10	9/10	10/10	9/10	9/10	9/10	9/10	10/10	10/10
Character type	A	B	C	D	E	F	G	H	J	K
Correct rate	0/10	9/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10
Character type	L	M	N	P	Q	R	S	T	U	V
Correct rate	10/10	10/10	0/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10
Character type	W	X	Y	Z	Overall rate		88.235…%			
Correct rate	10/10	10/10	10/10	10/10						

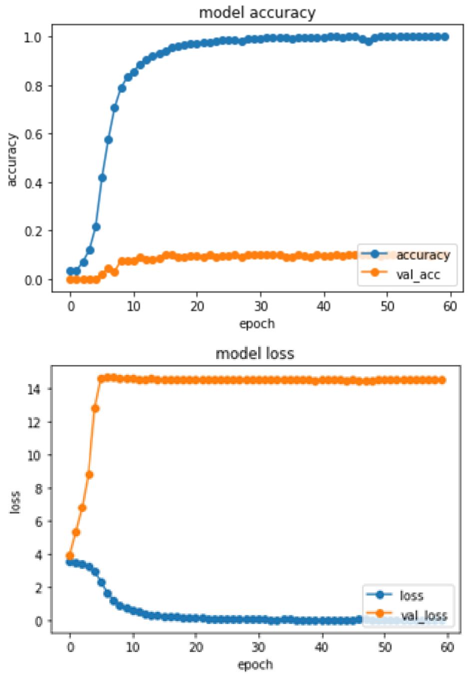

Figure 3.2 Learning progress graph

The overall correct answer rate was lower than that of the alphabet only. Looking at the correct answer rate of the character string, in addition to “A” and “N”, “1” also has incorrect answers. As with the alphabet only, "A" and "N" are misrecognized as "K" and "M". “1” was misrecognized as “J” or “T.” It is considered that the addition of alphabets and the increase of characters with similar features resulted in the recognition of characters that could be recognized so far. It is possible to read that the graphs of val_acc and val_loss diverge from the other graphs, as in 3.1.1.

From these results, it can be said that the versatility of the learning model created in the experiment is low.

Case2. Inputting images in order

Case 2.1 Learning only with alphabet

In this case, one alphabet image is input in order from A to Z, and this is repeated by the number of images. Table 3.2.1 shows the experimental results in which only the alphabet is entered, and Figure 3.2.1 shows the learning progress graph.

Table 3.3 Experiment result 3

Character type	A	B	C	D	E	F	G	H	J	K
Correct rate	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10
Character type	L	M	N	P	Q	R	S	T	U	V
Correct rate	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10
Character type	W	X	Y	Z	Overall rate	100%				
Correct rate	10/10	10/10	10/10	10/10						

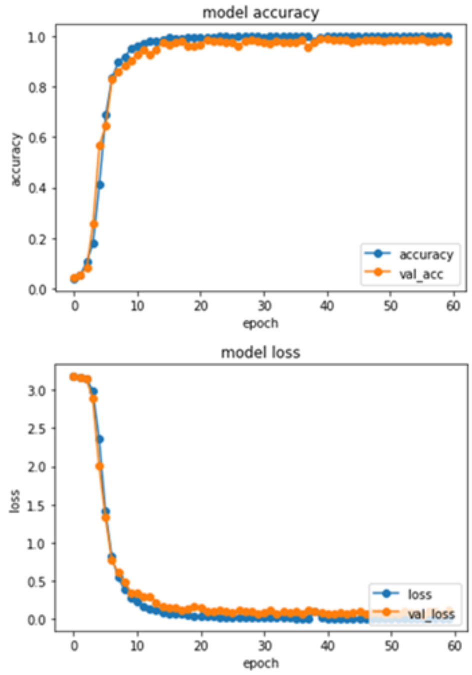

Figure 3.3 Learning progress graph

In the alphabet-only experiment, the correct answer rate reached 100%, and val_acc and val_loss approach the other graph, even when focusing on the learning progress graph.

From this result, it can be said that this learning model has versatility.

Case 2.2 Learning by combining alphabets and numbers

Alphabets and numbers were input sequentially as in case 2.1. The experimental results are shown in Table 3.2.2, and the learning progress graph is shown in Figure 3.2.2.

Table 3.4 Experiment result 4

Character type	0	1	2	3	4	5	6	7	8	9
Correct rate	4/10	9/10	10/10	10/10	8/10	10/10	7/10	8/10	10/10	9/10
Character type	A	B	C	D	E	F	G	H	J	K
Correct rate	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10
Character type	L	M	N	P	Q	R	S	T	U	V
Correct rate	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10
Character type	W	X	Y	Z	Overall rate		95.588%			
Correct rate	10/10	10/10	10/10	10/10						

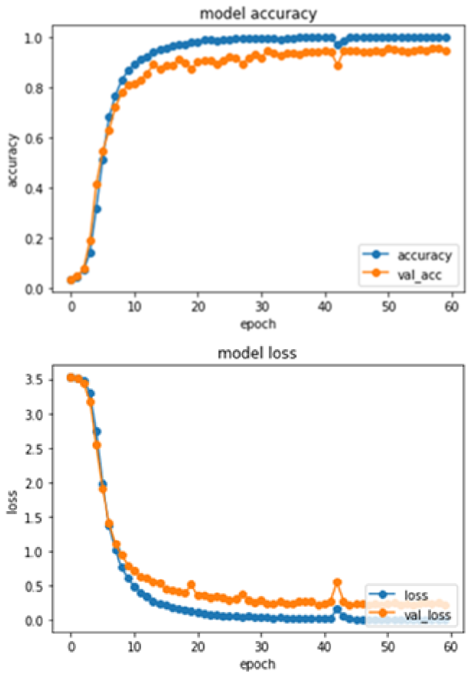

Figure 3.4 Learning progress graph

The overall correct answer rate was about 95.6%, however it exceeded the correct answer rate of 95% of Ref. [2] set for the purpose. In addition, it is 7% better than Case 1.2 of 3.1.2. However, in this experiment, the characters that were correctly answered in Experiment Case 1.2 of Section 3.1.2 are incorrect. Focusing on “0” with a low rate of correct answers, it is recognized as “D.” Also, “6” was misrecognized as “R”, “K”, and “B”. When you look at the learning progress graph, val_acc and val_loss are closer to the other graph than in Figure 3.1.2.However, it can’t be said that it is closer than the learning progress graph in Figure 3.2.1. It is thought that this difference also affects the overall rate of correct answers.

D. Discussion of the experiment

In this experiment, the same learning data, the same test data, and the same learning model are used, but the correct answer rate is different when input in a batch and when input in order. It is thought that generalization ability is lowered by inputting the same type of learning data at once. Therefore, we think that it is better not to input learning data of the same type continuously when inputting learning. In addition, in both experiments, the accuracy decreased when learning was performed by combining numbers and alphabets. It is considered that the cause is that characters with similar features have been misrecognized due to competition.

IV. CONCLUSIONS

In this paper, an experiment was conducted on the recognition of the alphabet that was unverified in the previous research. And character recognition accuracy was verified.

We also confirmed how to provide the image data. As a result, it was found that accuracy and generalization performance cannot be obtained by simultaneously learning alphabets and numbers, and that the accuracy changes depending on how to provide learning data. In this research, high accuracy has been obtained for Japanese banknotes, and in the future, we would like to be able to be widely adapted to banknotes in various countries. Also learning was made for each character, but learning with character strings is also conceivable. However, as neural networks may become complicated, we will consider this as a future task.

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