Image Classification for Datasets Composed of Depth Prediction and Edge Extraction Images from Overhead by Convolutional Neural Network

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***Abstract*—In this study, we classify images by using Convolutional Neural Network. We aim at differentiating humans or cars taken from overhead with a camera far from an object. Datasets are composed of depth prediction images and edge extraction images. We investigate the prediction of the depth of some objects, such a human and cars, in overhead images with Fully Convolutional Residual Networks (FCRN). We investigate each train and test accuracy of image classification with the datasets.**

I. Introduction

Image recognition by deep learning is used in various fields. Autonomous vehicles use image recognition by deep learning when they avoid dangers. Therefore, it is important to use image recognition by deep learning on various machines. In recent years, drones have been applied in various fields such as delivery, rescue and security. Therefore, the drones need to fly safely. Then, we thought the image recognition by deep learning would be important for drones to fly safely because it is necessary to grasp the dangers of landing early. We used YOLOv3 [1]∼[3] to recognize objects in images from the drones' view. This is a general object detection algorithm, and is suitable for avoiding dangers because it can recognized objects quickly. However, YOLOv3 cannot recognize people in images taken from overhead like drones' view with a camera far from people. It is difficult for YOLOv3 to recognize a person whose body part is hidden in order to learn the shape of a person.

In this study, we investigate the depth prediction of objects such as people and cars in images taken from overhead using fully convolutional residual network (FCRN) [4]. This system can predict the depth of an image taken with a monocular camera so it is less expensive than any other system. The convolutional neural network (CNN) can acquire more data than the 2D image because the depth prediction images generated from the FCRN contains 3D data. Edge extraction images are generated using OpenCV in order to extract edge of a person or a car. However, the depth prediction images and the edge extraction images have less information about RGB than the RGB image. In order to solve this problem, blend images in which RGB images, depth prediction images, and edge extraction images were blended at a ratio of 1 : 1 are added to the datasets. It aims to classify datasets composed of RGB images taken with a monocular camera, depth prediction images, edge extraction images, and blended images, and to classify humans or other objects by using CNN.

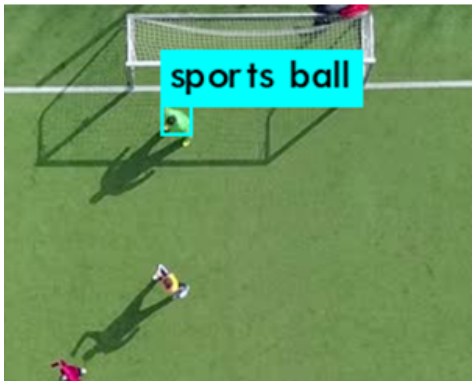


Fig. 1: Object detection by YOLOv3.

II. Convolutional Neural Network

In recent years, neural networks have been applied in various fields. In particular, the convolutional neural network (CNN) has produced many results in the image field. In image recognition, results that exceed human ability are also seen. In this study, learning data is created by labeling images of the same type, and images are classified from the features extraction by CNN. In this way, we try to make learning datasets specialized for images taken from overhead.

CNN has convolution layers, pooling layers, and fully connected layers. In a convolution layer, matrix calculation is performed using some filters, and feature quantities of the same number as the number of filters are extraction. Next, in a pooling layer, the feature map obtained in the convolution layer is reduced while leaving important information. In this study, the maximum value is obtained by max pooling, and the amount of calculation can be reduced. Finally, in a fully connected layer, a label is connected to each feature amount, and a label with high probability can be selected.

Such network having some layers is called deep learning, and many layers enables accurate image classification. In this study, we use the CNN which has two convolution layers, two pooling layers, and two fully connected layers in fig. 2.

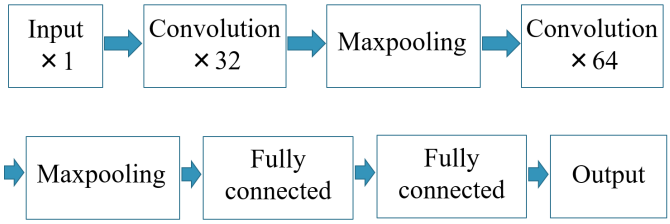


Fig. 2: Stracture of CNN.

III. Residual Network

It is possible to improve accuracy by deepening the network layer in image classification. However, it is known that in deeper networks, the accuracy decreases. A residual network uses a residual function to improve this problem. The residual function express a residual between from an output to an input by using a neural network and map it. The residual network can obtain an output close to the input due to this. In this way, gradient disappearance and gradient divergence are prevented by mapping the residuals.

The depth prediction image is generated by FCRN using this residual network.

IV. Proposed Method

We propose to classify human and car in images from overhead using CNN. First, a depth prediction image is created from an RGB image using FCRN. At this time, existing learning data learned in advance is used. The darker the color, the closer the distance, and CNN can obtain the feature value for the depth. Also, because the outline is easy to understand, it is possible to improve recognition by shape. Furthermore, an edge extraction image is created by using canny edge detection of OpenCV. Edge extraction makes the outline clearer than the depth prediction image. Then, a blend image is created by blending the RGB image and the depth prediction image, the RGB image and the edge extraction image at a ratio of 1 : 1 (Figs. 3, 4) or other ratios.

Six datasets are composed of these images. The first dataset is composed of 200 RGB images. The second dataset is composed of 100 RGB images and 100 depth prediction images. The third dataset is composed of 100 RGB images and 100 edge extraction images. The fourth dataset is composed of 100 RGB images and 100 images blended with RGB images and depth prediction images. The fifth dataset is composed of 100 RGB images and 100 images obtained by blending the RGB image and the edge extraction image. The sixth dataset is composed of 100 images blended with RGB images and depth prediction images, and 100 images blended with RGB images and edge extraction images (Table I).

Next, we classify human and car in images by using a CNN with two convolution layers, two pooling layers, and two fully connected layers.

Finally, the learning accuracy and test accuracy of each dataset are compared. When CNN learns, training images and test images are compressed to 32 ×32 pixels. The learning rate of this CNN is 0.000009. Each learning is from 600 to 700 steps, and the training is conducted until the training accuracy converges to about 1.00.

TABLE I: Datasets.

	RGB images	Depth prediction	Edge extraction	Blend (RGB:Depth)	Blend (RGB:Edge)
1	200	0	0	0	0
2	100	100	0	0	0
3	100	0	100	0	0
4	100	0	0	100	0
5	100	0	0	0	100
6	0	0	0	100	100

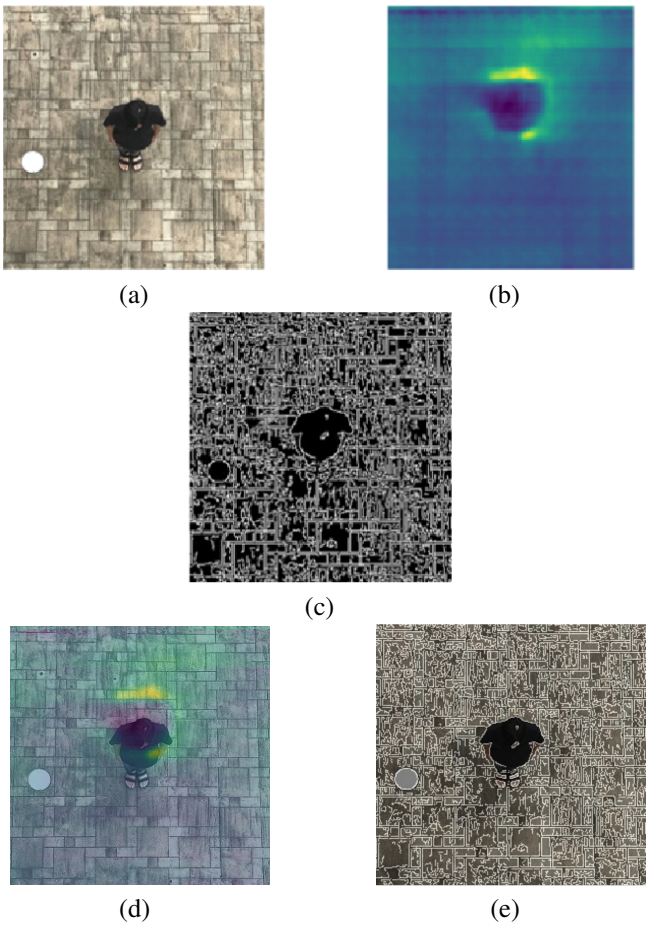
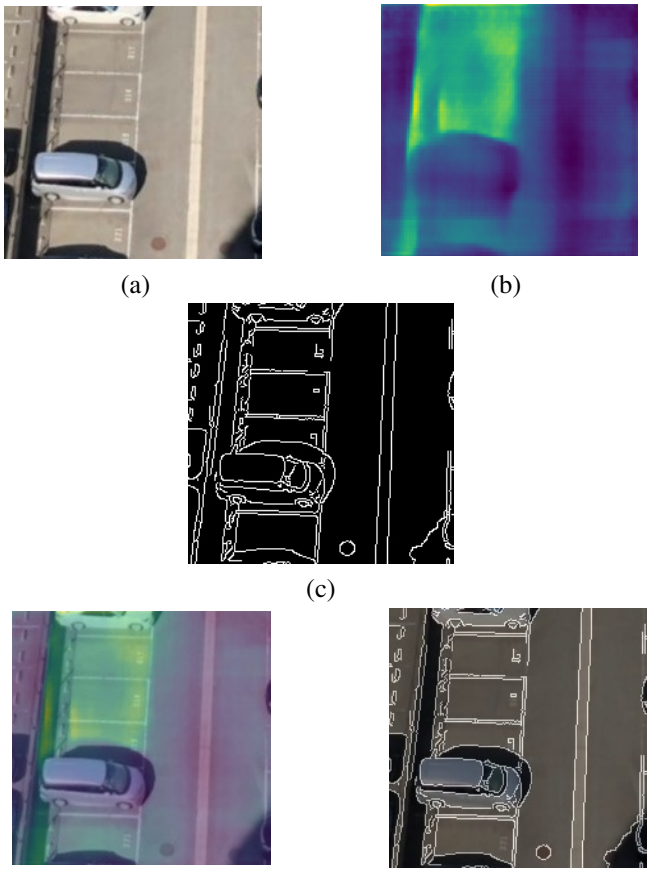


Fig. 3: Human images from overhead.
(a) RGB image. (b) Depth prediction image.
(c) Edge extraction image.
(d) Blended image with RGB image and Depth prediction image.
(e) Blended image with RGB image and Edge extraction image.



(a) (b) (c) (d) (e)

Fig. 4: Car images from overhead.
(a) RGB image. (b) Depth prediction image.
(c) Edge extraction image.
(d) Blended image with RGB image and Depth prediction image.
(e) Blended image with RGB image and Edge extraction image.

V. Simulation results

The test accuracy when the object and the camera are close to each other is investigated for comparison in Table Ⅱ. The dataset at this time uses 200 RGB images. The test accuracy is 0.97, but when the distance between the camera and the object is large as shown in Table Ⅲ, it is 0.50. In other words, CNN cannot classify people and cars in images taken from far overhead.

However, because the test accuracy in Table Ⅳ is higher than that in Table Ⅲ, it is considered that CNN learning the depth prediction image is effective in classifying images taken from overhead.

Further, when the CNN learns the blended image, the test accuracy of Tables Ⅵ , Ⅶ and Ⅷ is higher than that of Table Ⅲ. From these results, it can be said that the combination with RGB information is important.

Table Ⅸ shows the test accuracies when the CNN learns 100 RGB images and 100 blended images with RGB and depth prediction images with other ratios from 1 : 9 to 9 : 1. From this result, when the blend ratio of RGB images and depth prediction images is 6 : 4, the test accuracy is the highest. Similarly, in Table X, the blend ratio of the RGB image and the edge extraction image is changed. From Table X, when the blend ratio of RGB images and Edge extraction images is 6 : 4, the test accuracy is the highest. It can be said that a little more RGB information is easier to recognize objects.

Figure 4 shows the learning accuracy and the steps of learnings. From fig. 4, it can be said that the accuracy of 32 ×32 pixel image trained by CNN is faster than 28×28 pixels in all situations.

TABLE II: Test accuracy when a camera is close.

Train accuracy	1.00
Test accuracy	0.97

TABLE III: Test accuracy when the CNN learns 200 RGB images.

Train accuracy	1.00
Test accuracy	0.50

TABLE IV: Test accuracy when the CNN learns 100 RGB images and 100 depth prediction images.

Train accuracy	1.00
Test accuracy	0.80

TABLE V: Test accuracy when the CNN learns 100 RGB images and 100 edge extraction images.

Train accuracy	1.00
Test accuracy	0.67

TABLE VI: Test accuracy when the CNN learns 100 RGB images and 100 blended images with RGB and depth prediction images.

Train accuracy	1.00
Test accuracy	0.70

TABLE VII: Test accuracy when the CNN learns 100 RGB images and 100 blended images with RGB and edge extraction images.

Train accuracy	1.00
Test accuracy	0.67

TABLE VIII: Test accuracy when the CNN learns 100 blended images with RGB and depth prediction images and 100 blended images with RGB and edge extraction images.

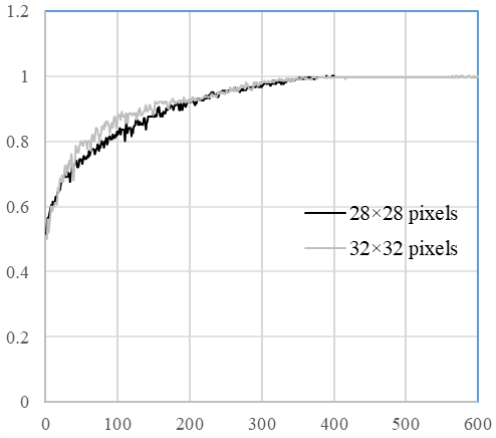
Train accuracy	1.00
Test accuracy	0.73

TABLE IX: Test accuraccies when the CNN learns 100 RGB images and 100 blended images with RGB and depth prediction images with other ratios.

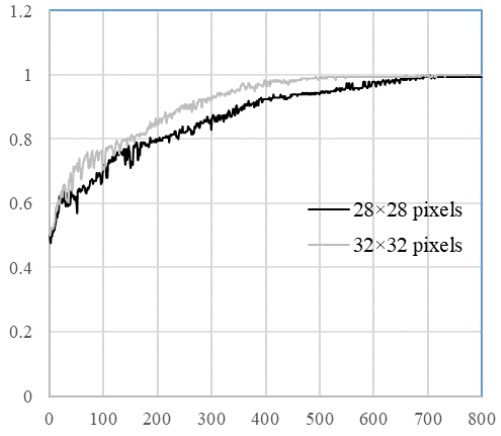
Blend RGB : Depth	Train accuracy	Test accuracy
1 : 9	1.00	0.80
2 : 8	1.00	0.73
3 : 7	1.00	0.70
4 : 6	1.00	0.77
5 : 5	1.00	0.70
6 : 4	1.00	0.83
7 : 3	1.00	0.73
8 : 2	1.00	0.63
9 : 1	1.00	0.70

TABLE X: Test accuraccies when the CNN learns 100 RGB images and 100 blended images with RGB and edge extraction images with other ratios.

Blend RGB : Edge	Train accuracy	Test accuracy
1 : 9	1.00	0.73
2 : 8	1.00	0.70
3 : 7	1.00	0.70
4 : 6	1.00	0.73
5 : 5	1.00	0.67
6 : 4	1.00	0.80
7 : 3	1.00	0.70
8 : 2	1.00	0.70
9 : 1	1.00	0.70



(a)



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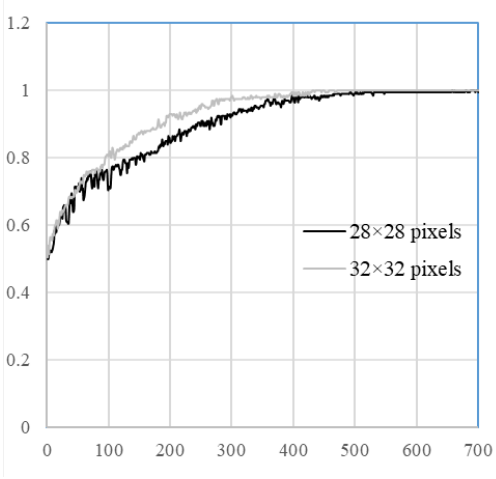

(c)

Fig. 5: Train accuracy and epochs.
(a) Train accuracy and epochs when the CNN learns only RGB images.
(b) Train accuracy and epochs when the CNN learns only depth prediction images.
(c) Train accuracy and epochs when the CNN learns 100 RGB images and 100 depth prediction images.

VI. Conclusions

In this study, depth prediction images, edge extraction images, and blended images were used as learning data in addition to RGB image, and we tried making to improve the accuracy of image recognition by CNN. From these simulation results, it is considered effective to classify images taken by a camera far from the object and predict the depth of the image. The test accuracy of CNN learned with RGB and depth prediction images is higher than with only RGB images. However, the test accuracy is still low, and it is necessary to improve the test accuracy of image classification.

In the future, we will examine new combinations with RGB images and combinations with different image processing. It will also improve the CNN network itself.

References

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