PREDICTION OF PEDESTRIAN PROTECTION PERFORMANCE USING MACHINE LEARNING

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ABSTRACT

According to WHO's report, there are over 270,000 people who are involved in traffic fatal accidents. This figure accounts for 22% of traffic fatalities in the world in 2013. To reduce those pedestrian accidents, many countries apply the pedestrian protection tests for the regulation and the third-party evaluation. For that reason, a method to design the pedestrian protection performance efficiently is required for many cars sold all over the world by automobile manufacturers. In recent years, there are some cases to assist or automate the development using the artificial intelligence acquired by the machine learning. The authors investigated whether it is possible to predict pedestrian head protection performance without using tests or CAE (Computer Aided Engineering) in this research.

The authors used the bonnet hood structures compatible with pedestrian protection and head injury value obtained from CAE for the training data. As for the hood structure, the data obtained by converting 3D geometry into a 2D image was used as the input data. Head injury value was examined by both classification and regression as output information. For the learning model, LeNet-5 of CNN (Convolutional Neural Network) was used, and the layer structure of the model was modified to be suitable for learning of pedestrian protection.

Using the learned model and validated it with some unknown hood images, the model predicted the pedestrian NCAP (New Car Assessment Program) score with an error less than 5% compared with CAE results. Also the predicted head injury criteria map agreed with accuracy more than 75%. In addition, LeNet-5 showed shorter computation time and higher accuracy when comparing the other algorithms.

Although the model was able to reasonably predict the head injury value in the center area t of hood, the accuracy of the perimeter area tended to be lower. Since the data around the perimeter area used for learning was small amount, it is considered that the accuracy is low. In future study, it is necessary to add such data or to device a method to improve accuracy even with the small amount of data.

INTRODUCTION

According to the traffic accident data, it is well known that pedestrian fatal accident is caused by head injury (See Figure 1). Based on this accident data, the third-party assessment organization define WAD (Wrap Around Distance) and validate pedestrian protection performance using a head impactor (See Figure 2). Because mostly test area is on the bonnet hood, it is important to design hood construction to improve head protection performance. As the hood construction depends on styling, it is one of the difficult parts to divert the structure developed in the past. Therefore, it takes a long time to design so that the structure can satisfy the pedestrian safety and other performance. In order to solve this issue, the authors studied the method to design efficiently using optimization techniques in past study [1]. However, the conventional method is required to define the design variables when the styling is changed. For that reason, we could not establish the design method such as to investigate the structure in a short time by using the response surface like.

On the other hand, research in machine learning has advanced in recent years, and cases of utilization are also being reported in design development of manufacturing industry [2]. Since deep learning especially has property to extract attribute by itself [3], the outcomes have been reported for cases where setting attribute and the prediction were difficult [4]. So the authors decided to research the method to investigate the structure satisfied the pedestrian performance in a short time by deep learning.

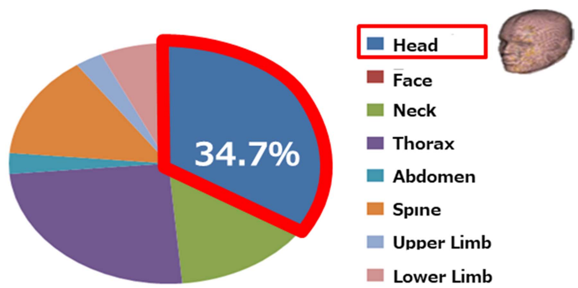


Figure 1. Fatality rate by injury site in pedestrian accident (PCDS 1994-1998)

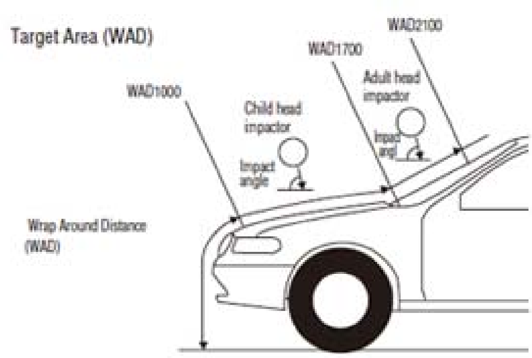


Figure 2. Wrap Around Distance (http://www.nasva.go.jp)

METHODOLOGY

Application process of machine learning

In general, the part design process follows the flow of Figure 3. A target value is set first, then a structure plan that satisfies the target is created and validated by CAE. In many cases, CAE is often performed multiple times with optimization CAE or the like so as to satisfy required characteristics. In this study, we used the surrogate model by machine learning between the structure design and the CAE as Figure 4. By doing this, we estimated the approximate performance of the structure without using CAE, and decided to reduce the number of investigation by CAE.

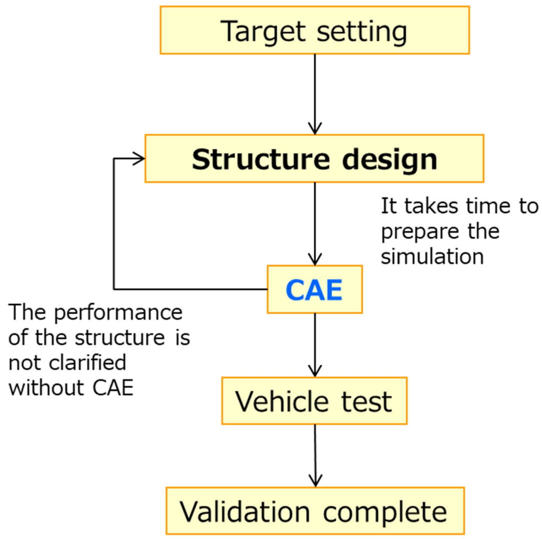


Figure 3. General process of component design

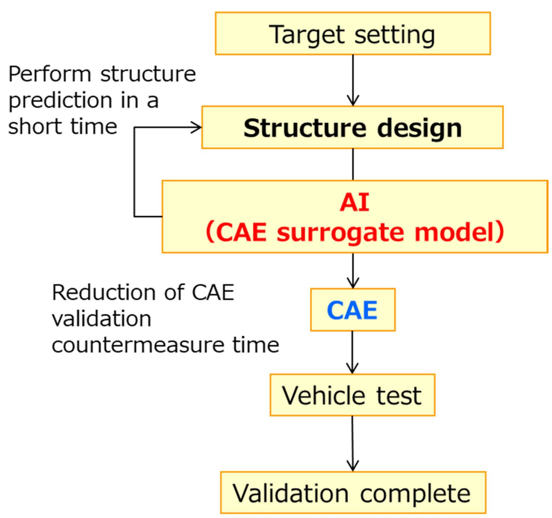


Figure 4. Process using surrogate model

Learning and validation data

The 29 vehicles which were developed for pedestrian protection were used for the learning. The 2D image of each different vehicle's hood data were prepared separately for hood skin, hood frame and others from CAD data. 3D information was represented by displaying the image depth. Furthermore, the difference images of skin and frame were prepared. Finally, a total of 4 images was taken as input data (See Figure 5). As each image was processed with the median filter, the tiny holes and fine shapes were simplified. Also, the input data were divided by 800mm square (48*48 pixel) for each head impactor crash point (See Figure 6). HIC

(Head Injury Criteria) of the CAE result was used for the training data. And the relationship between HIC and hood images near the crash point was learned. In order to validate the learned model, we prepared the 3 vehicles apart from learning data. These vehicles were selected from the category of Mini-van, SUV and Sedan respectively to be able to validate the different hood sizes.

The material and thickness of the hoods used for the learning and the validation were all same property. The ratio of the data used for the learning and validation was 1977: 269. However, 10% of the learning data was also used for checking the degree of learning. TensorFlow [5] was used for the model implementation. The learned model was based on LeNet-5 of CNN [6] but the input image was changed to 4 channels configuration. In addition, the output was set to regression in consideration of convenience. Figure 7 and Table 1 show this model architecture. In the following, this model is written as Modified LeNet-5.

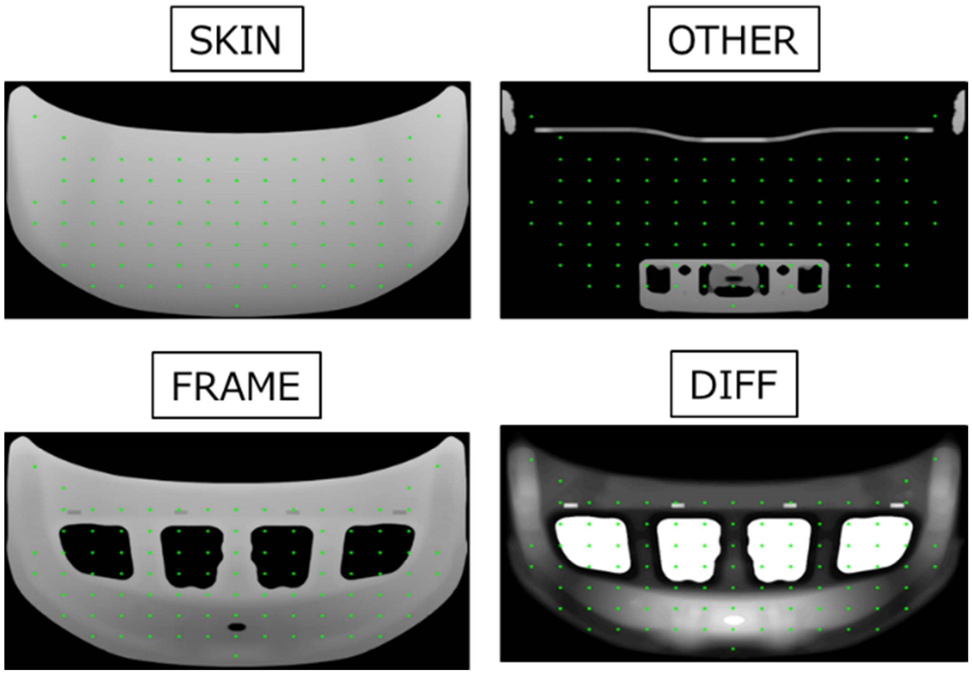


Figure 5. Input data for learning

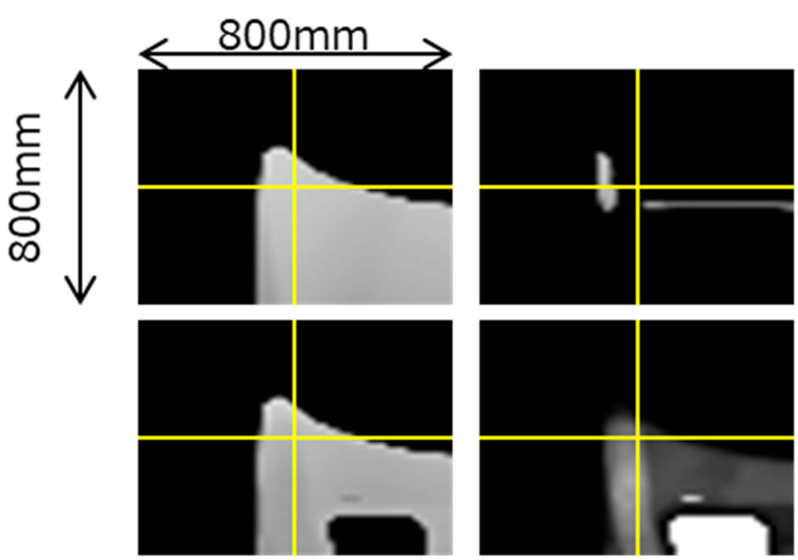


Figure 6. Image data for each crash point

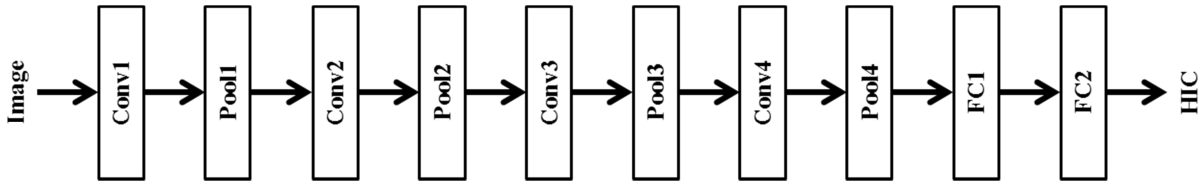


Figure 7. Network Architecture Diagram of our CNN model

Table.1
Network Topology of our CNN model

Network	Input Size	Kernel Size	Stride Size	Channel Size	Output Size	Padding	Activation Function
Conv1	48 x 48	5 x 5	1 x 1	16	44 x 44	VALID	Leaky ReLU
Pool1	44 x 44	2 x 2	2 x 2	16	22 x 22	VALID	-
Conv2	22 x 22	3 x 3	1 x 1	32	20 x 20	VALID	Leaky ReLU
Pool2	20 x 20	2 x 2	2 x 2	32	10 x 10	VALID	-
Conv3	10 x 10	3 x 3	1 x 1	64	8 x 8	VALID	Leaky ReLU
Pool3	8 x 8	2 x 2	2 x 2	64	4 x 4	VALID	-
Conv4	4 x 4	3 x 3	1 x 1	128	2 x 2	VALID	Leaky ReLU
Pool4	2 x 2	2 x 2	2 x 2	128	1 x 1	VALID	-
FC1	128	-	-	-	128	-	ReLU
FC2	128	-	-	-	1	-	-

RESULTS

GPU (NVIDIA Tesla GP100) was used for the learning. The mini batch size was set to 300 and the epoch number was set to 5000. MSE (Mean Square Error) was used for the loss function. The calculation time taken for the learning was 140 seconds. The history of loss function shows Figure 8. It indicates that the learning result was valid. Then we confirmed the pedestrian protection performance by using the learned model. The pedestrian protection performance was validated by a NCAP score and a degree of injury value map coincidence. The validation result of each vehicle shows Figure 9. The model predicted the pedestrian NCAP score with an error less than 5% compared with CAE results. The predicted head injury value map agreed with CAE results with accuracy more than 75%. Furthermore, creating an injury value map of each vehicle by CAE took about 40 hours, but the prediction time from the learned model was about 10 seconds. It was confirmed that the learned model can predict the CAE result with sufficient accuracy in a short time.

Figure 8. History of loss function

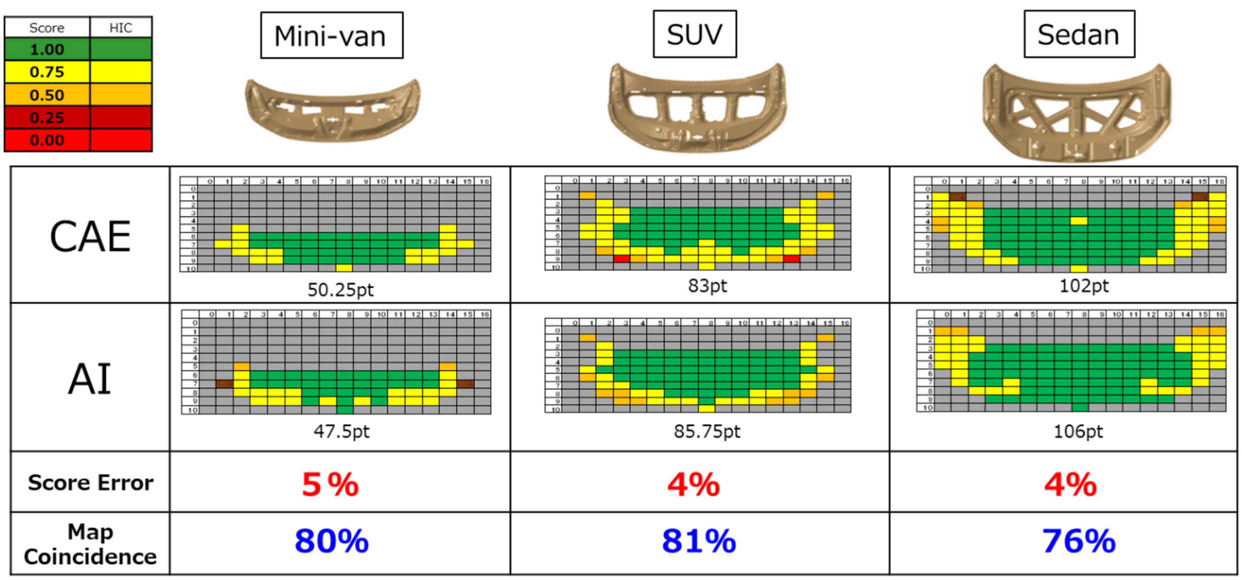


Figure 9. Validation result

DISCUSSION AND LIMITATION

There is room to improve of accuracy in the degree of map coincidence compared with the score error from the validation results. Therefore, the authors decided to further study to improve the accuracy of the map coincidence. Then we implemented the VGG16 [7] and InceptionV3 [8] which are the successor model of LeNet-5 and we compared the results and LeNet-5 result. As for VGG16, the input configuration was changed to 4 channels from the specification for ImageNet. Inception V3 was also set to 4 channels for the input. However, the image size was enlarged to 139*139 pixel due to the model restriction. Since VGG16 and InceptionV3 have a large model capacity, there is a possibility that the calculation does not converge when learning is performed by regression. In this study, the learning was performed by classification for these models considering the calculation stability. The mini batch size was set to 300 and the epoch number was set to 6000. Cross entropy was used for the loss function. The data used for the learning was the same as that used for Modified LeNet-5.

Figure 10 and 11 show the history of loss function for each model. Figure 12 and 13 show the accuracy of each model. Although VGG16 has certain accuracy, InceptionV3 has a low accuracy from these figures. In addition, Table 2 shows the comparison of the map coincidence accuracy for each model. VGG16 accuracy was almost the same as Modified LeNet-5 but this model took more calculation time than Modified LeNet-5. Inception V3 resulted in quite low accuracy. This is considered that the model capacity is too large for this study with a small number of data. As shown in Figure 14, not only the hood but also the fender and the headlight affect the head impactor. Since the data used for the learning is only the hood images, it can be considered that the attribute of these parts could not be extracted. In addition, all data used in this study is at the completion of pedestrian protection development. Therefore, the data on high HIC was taken countermeasure, so there were few data available (See Figure 14). In order to improve the accuracy of the outer area of a hood, it is necessary to enhance such data.

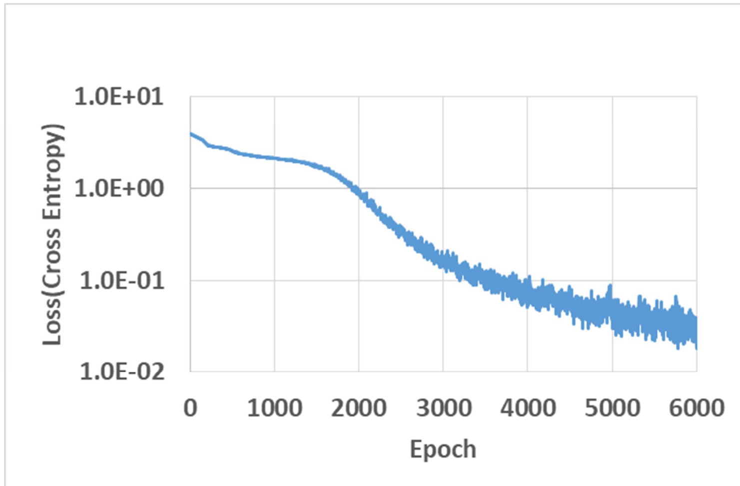


Figure 10. History of VGG16 loss function

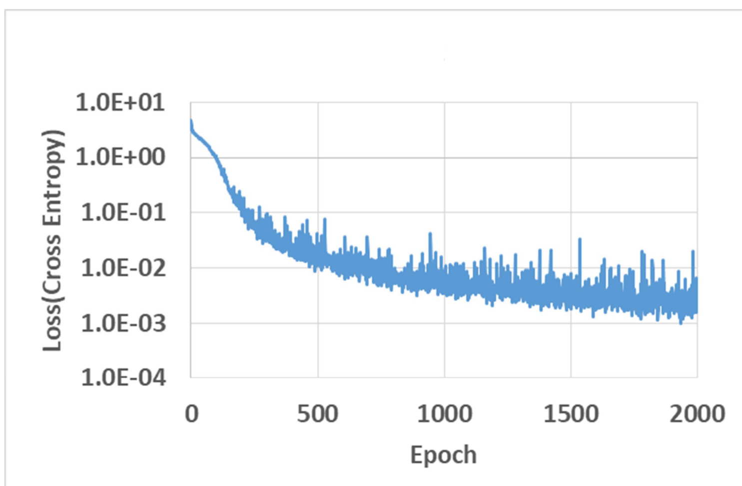


Figure 11. History of InceptionV3 loss function

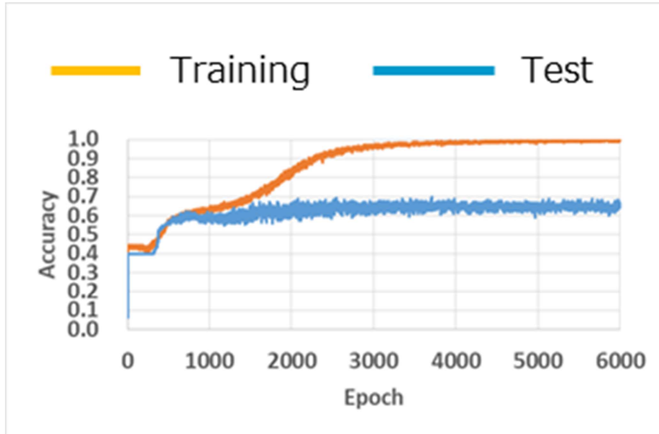


Figure 12. Accuracy of VGG16

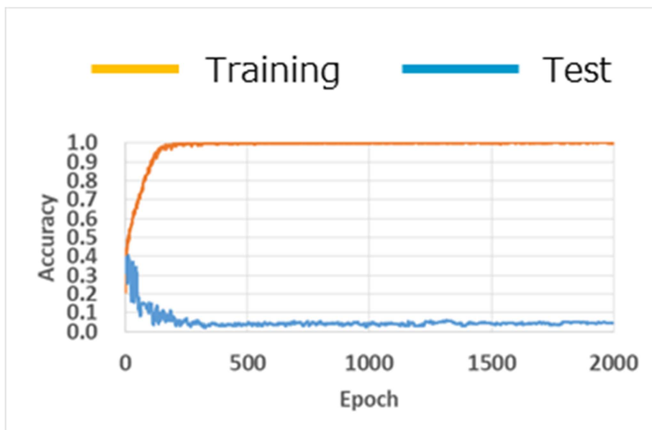


Figure 13. Accuracy of InceptionV3

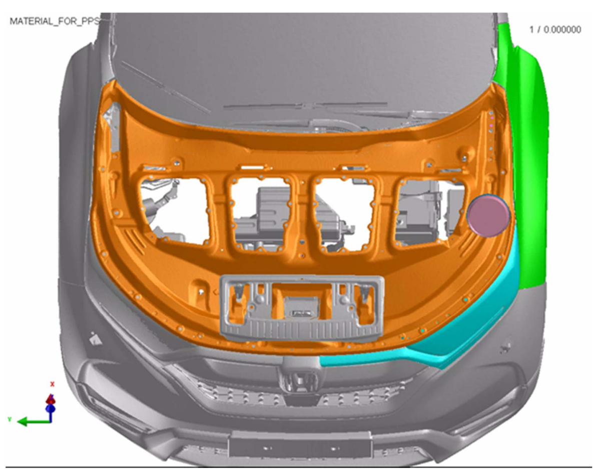
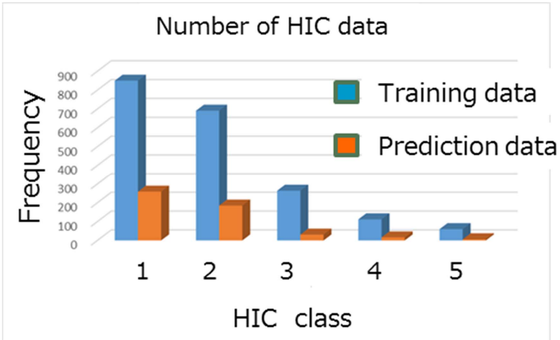


Figure 14. Effect of other parts in outer hood portion



	HIC	Class
Green	HIC < 650	1
Yellow	650 ≦ HIC < 1000	2
Orange	1000 ≦ HIC < 1350	3
Brown	1350 ≦ HIC < 1700	4
Red	1700 ≦ HIC	5

Figure 15. Distribution of data by HIC

Table 2.
Comparison of accuracy of each model

		Modified LeNet-5 (Our method)	**VGG16**	**InceptionV3**
Convergence time		140 sec	1 hour	1.4 hours
Map coincidence	Mini-van	80%	81%	0%
	SUV	81%	64%	0%
	Sedan	76%	72%	2%

CONCLUSIONS

The authors studied whether it is possible to predict pedestrian head protection performance by deep learning without CAE.

Modified LeNet-5 was able to predict the score with an error less than 5% for the CAE result. The predicted color map by Modified LeNet-5 matched at 75% or more compared with CAE result.

The accuracy was mostly equivalent between VGG16 and Modified LeNet-5 but Modified LeNet-5 was more suitable considering the learning time.

The data that can be used for learning and validation was only 31 vehicles (2246 crash points), but the learned model could predict the pedestrian protection performance with sufficient accuracy.

For further improvement of accuracy, it is necessary to add or high HIC data or data obtained by increasing the attribute of the outer of hood area.

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