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# CONSTRUCTION OF A SURROGATE MODEL FOR CRASH BOX CORRUPTION

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**Abstract.** *The structural strength evaluation of crash boxes is predicted by machine learning in this study. The training data was obtained from the dynamic elastic plastic analysis of the crash box. The input physical quantities are barrier angle, box thickness, material properties and mass equivalent to vehicle weight. The output physical quantity is the reaction force. Buckling occurs in the analysis and different directions of corruptions are one of the most interesting phenomenon from a point of engineering view. We would like to propose an adaptive method for machine learning in structural evaluation that can be used for a wide range of structural evaluations.*

## 1 INTRODUCTION

In the manufacturing industry, it is important to design better products within a certain period for shortening of product lifecycles. Since a large number of computational simulation cases are required in the initial stage of development. In order to shorten evaluation period, machine learning technologies and 1D-CAE become popular in addition to conventional CAE evaluation[1].

The use of predictive models based on deep learning as a substitute for CAE is one of the evaluation methods. While we have much expectations for high accuracy, the applications to engineering problems are not enough to satisfy the expectations[2]. In the fields of material design and computational fluid dynamics, good results have been reported, because huge amounts of data are eventually generated in those research fields[3]. Therefore, the objective of this study is a construction of framework using machine learning technology to evaluate crash box corruption for a significant reduction of CAE analysis cost.

# 2 CRASH BOX ANALYSIS AND TRAINING DATA DESIGN

## 2.1 Data sets

### 2.1.1 Prediction Target

The learning and prediction were conducted on the dynamic elasto-plastic analysis of a crash box, which is a component fixed to the front and rear of a car. Crash box are attached to the front and rear of the frame and are responsible for protecting the body frame and occupants from front/rear collisions. The crash box are shaped like the parts shown in Figure 2.1.1, which absorb collision energy by collapsing themselves.

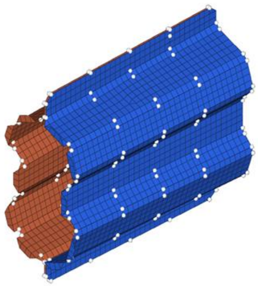

**Fig 2.1.1**: Crash box

### 2.1.2 Fundamental statistical evaluation of training data sets

The training data will be the physical quantities used in the dynamic elasto-plastic analysis of the crash box. The input physical quantities are the barrier angle, box thickness, material properties, and mass equivalent to the vehicle weight. In the analysis, physical phenomena buckling, are occurring depending on the conditions of the plate thickness and barrier angle.

Figure 2.1.2 shows the frequency of the predicted maximum reaction force, which is the output. The larger the value, the fewer the number of data, representing an imbalanced frequency.

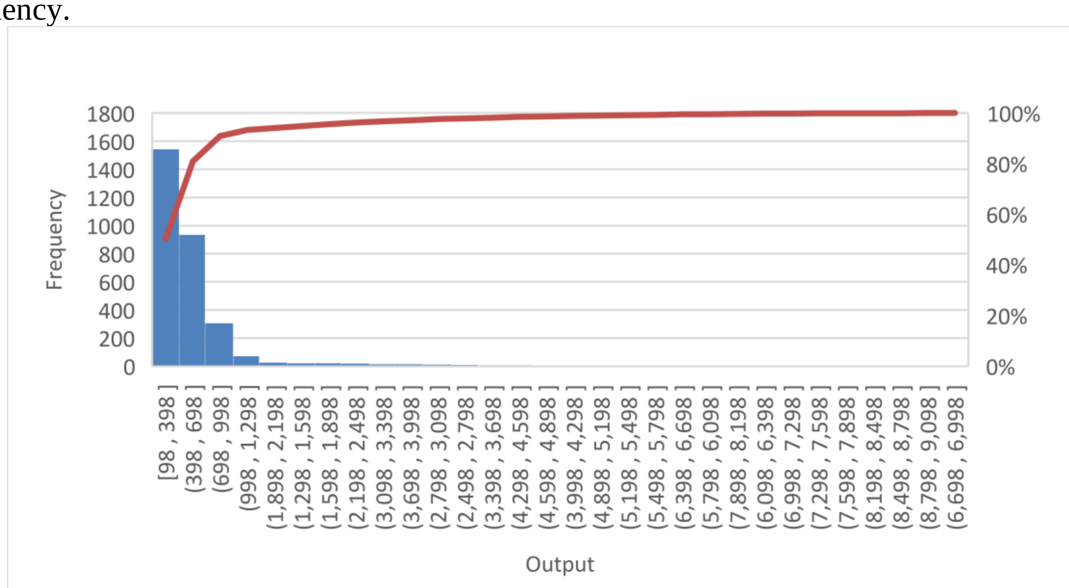

**Fig 2.1.2**: Output Frequency

## 2.2 Convolutional Neural Network

### 2.2.1 Convolutional Neural Networks Overview

Deep learning has been attract attention because of its extremely high performance for image recognition tasks. Neural networks that have been developed specifically for image recognition are convolutional neural networks(hereafter referred to as CNN).

CNN is composed of multiple layers, and there are three types: convolutional, pooling, and Fully connected layer. The image is put into the convolutional layer, and the convolutional and pooling layers are repeated several times, leading to the all-join layer. The all-coupled layer is also repeated several times, and the last all-coupled layer is the output layer. This configuration is shown in Fig. 2.2.1.

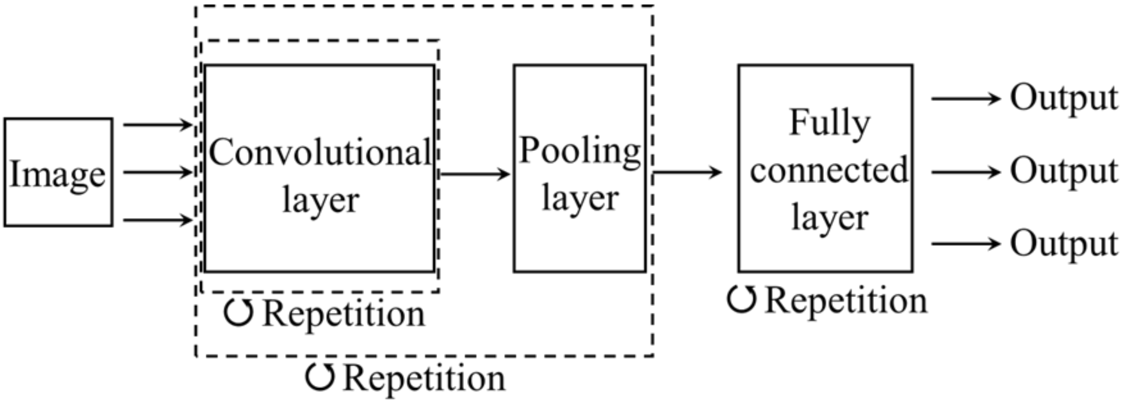


**Fig 2.2.1**: Convolutional neural network

### 2.2.2 CNN-IPD（CNN with Input Parameters Design）

In order to interpolate discrete physical quantities for feature extraction in CNN training, we estimated the distribution of output frequency according to input parameters in advance and expanded the input data as shown in Figure 2.2.2.

| | ① | ② | ③ | ④ | ⑤ | ⑥ | ⑦ | ⑧ | ⑨ | ⑩ | ⑪ | ⑫ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $1/x$ | | | | | | | | | | | | |
| $x^{1/2}$ | | | | | | | | | | | | |
| $x$ | | | | | | | | | | | | |
| $x^2$ | | | | | | | | | | | | |

**Fig 2.2.2**: CNN-IPD

## 2.3 Augmentation of features

### 2.3.1 Area-equivalent features value

Based on the results of multiple regression analysis of the training data and from the viewpoint of material mechanics, features were added that were judged to be highly influential. The results of the multiple regression analysis (Table 2.3). From the results, the partial regression coefficients are larger than those of the other input factors, indicating that the thickness variable has a greater weight. Also, from the viewpoint of material mechanics, areas are highly important in the phenomenon of collision.

**Table 2.3**: The partial regression coefficients

| Name | Weight |
|---|---|
| Box Thickness1 | -267.8 |
| Box Thickness2 | -365.9 |
| Material Properties | -0.334 |
| Barrier Angle | 34.12 |
| Vehicle Weight | 0.461 |

### 2.3.1 Sectional secondary moment and stiffness

The nodal outputs in the analysis are incorporated into the training data for generalization to crash boxes of other shapes. The cross-sectional quadratic moments of the three surfaces of the crash box (front, middle, and rear surfaces) are calculated using the following method. ($I$: sectional secondary moment, $b$: plate thickness, $h$: nodal distance, $E$: Young's modulus, $M$: Bending rigidity)

$$I_1 = b_1\left(\frac{{h_1}^3+{h_2}^3+{h_3}^3\ldots+{h_{17}}^3}{12}\right) \tag{1}$$

$$I_2 = b_2\left(\frac{{h_1}^3+{h_2}^3+{h_3}^3\ldots+{h_{17}}^3}{12}\right) \tag{2}$$

$$I = I_1 + I_2 \tag{3}$$

The bending rigidity is then derived by multiplying by 200 GPa, the Young's modulus of steel.

$$M = EI \tag{4}$$

# 3 PREDICTION RESULTS

## 3.1 Before adding features value

Figure 3.1.1 shows the prediction results and loss function before the addition of the features value. The results of the forecast accuracy validation are also shown in Table 3.1.

Validation loss is $1.37 \times 10^{-4}$ and Train loss is $1.11 \times 10^{-4}$. In Fig.3.1.1 we consider that learning has been achieved. The correlation coefficient between the reference and predicted values is also high at 0.954. However, there are some points deviated from reference values. In particular, the outlier around No. 100 is not well predicted, even though the adjacent points are predicted with high accuracy.

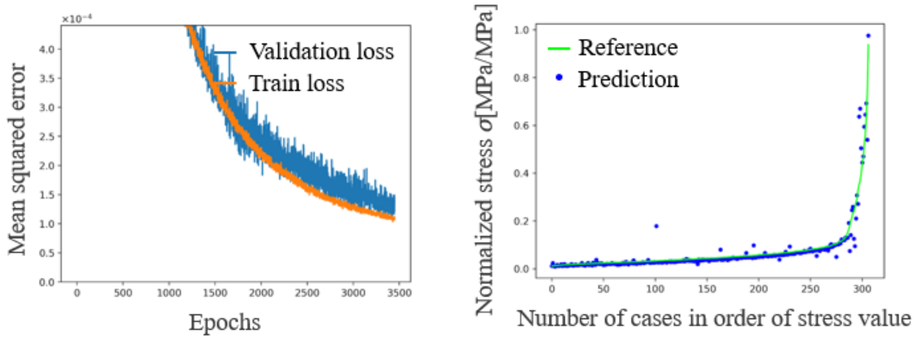


**Fig 3.1.1**: Prediction Results and Loss Functions

**Table 3.1**: The prediction accuracy validation

| Accuracy validation | |
|---|---|
| Maximum error | 32.50% |
| Minimum error | 0.00% |
| Error average | 1.34% |
| Correlation coefficient | 0.954 |
| The outlier | 8 |

## 3.2 After adding features value

Figure 3.2.1 shows the prediction results and loss function after the addition of the features value. The results of the forecast accuracy validation are also shown in Table 3.2.

Validation loss is $6.69 \times 10^{-5}$ and Train loss is $1.74 \times 10^{-4}$, showing an improvement in accuracy compared to before the addition of features value.The results of other prediction accuracy validation, such as correlation coefficients, also show higher accuracy, indicating that accuracy improves with the addition of additional features value.

As for outliers, the number of points exceeding 10% and the maximum error are reduced, but no essential improvement is achieved.

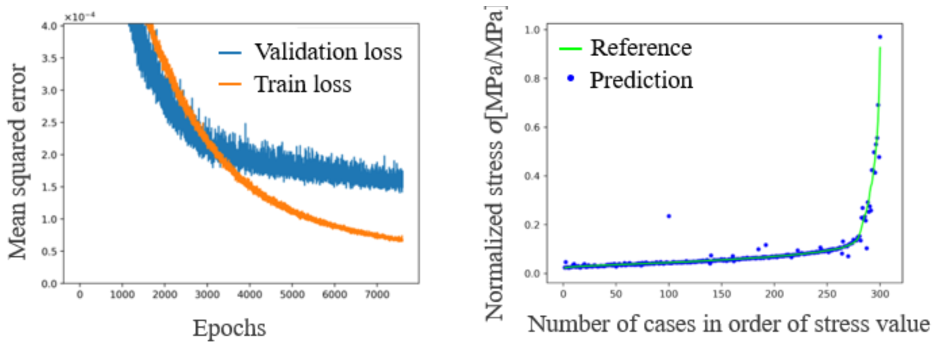


**Fig 3.2.1**: Prediction Results and Loss Functions

**Table 3.2**: The prediction accuracy validation

| Accuracy validation | |
|---|---|
| Maximum error | 29.00% |
| Minimum error | 0.00% |
| Error average | 0.75% |
| Correlation coefficient | 0.970 |
| The outlier | 4 |

## 4 DISCUSSION

We pursued the cause of the outlier because it would be difficult to use the system in the actual field if it is not known. The target is an outlier around No.100, where all but the outlier could be learned with high accuracy.

There is a difference in the physical phenomenon of longitudinal reaction force between the outlier data and the data with the same output as the outlier, as shown in Figure 4.1.

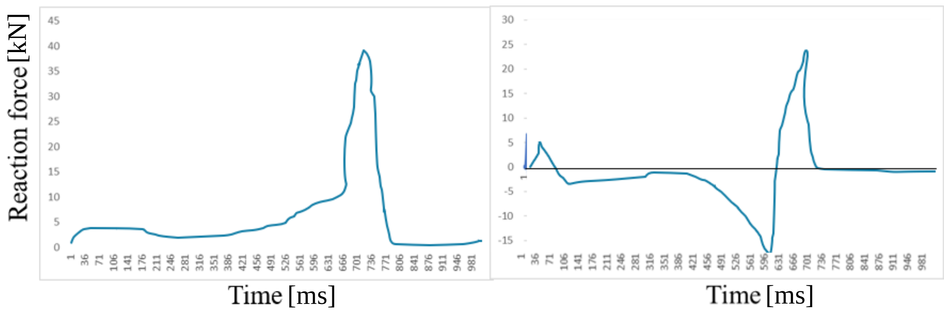


**Fig 4.1**: Comparison of longitudinal reaction forces

The data used for outliers indicates that the reaction force is applied only in the positive direction, while the data included in the training data indicates that the reaction force is also applied in the negative direction.

Based on these results, it is necessary to take countermeasures against this outlier. In addition, since the current outlier does not contain the features necessary for learning, we will propose an effective improvement method for this outlier and verify it with other outliers.

## 5 CONCLUSION

In this study, a surrogate model is constructed to predict the maximum reaction force from the input physical quantities in the dynamic elasto-plastic analysis of a crash box as an alternative model for CAE analysis, and the following results were obtained.

・We extended the regression problem to image-like data and showed that learning with CNN is possible. In learning physical phenomena, it is important to design training data considering physical laws, properties, and the shape of the equations.

・Predictions can be made more accurate by deriving physically meaningful values and adding new features value.

・Need to design training and validation data that take into account possible physical phenomena for large outlier

## REFERENCES

[1] Kentaro Yamamoto, *Approach to reduce the computational cost of crash simulation using machine learning*. Proceedings of the conference on computational engineering and science. (2021) 26: B-05-03.

[2] Kai Ogata, *Construction What Surrogate Model Using Evaluation Safety Performance When Cars Clash Walking People*. Proceedings of the conference on computational engineering and science. (2021) 26: B-05-04.

[3] Yoshitaka Wada, *Application of convolutional neural network to regression problem for physical phenomenon*. Proceedings of the conference on computational engineering and science. (2021) 26: B-05-05.