Predicting Soldering Failure in Die-Cast Products Using a Surrogate Model Based on Geometrical Features

Tomoya Yamazaki[1,2], Koh Hirokawa[3], Akira Murakami[4], Misato Baba[5], and Chisako Muramatsu[6]

[1]Shiga University, s7021103@st.shiga-u.ac.jp
[2]Toyota Motor Corporation, tomoya_yamazaki_aa@mail.toyota.co.jp
[3]Toyota Motor Corporation, koh_hirokawa@mail.toyota.co.jp
[4]TOYOTA SYSTEMS CORPORATION, a-murakami@toyotasystems.com
[5]IVIS Inc, misato.baba@ivis.co.jp
[6] Shiga University, chisako-muramatsu@biwako.shiga-u.ac.jp

Corresponding author: Tomoya Yamazaki, s7021103@st.shiga-u.ac.jp

Abstract. Die casting is a widely used technology in industrial production, particularly in the automotive industry, for its ability to mass-produce complex shapes quickly. A significant challenge in the process is predicting and minimizing defects such as "soldering failure." This paper presents the development of a surrogate model that predicts soldering failure in die-cast products based on their geometrical features. By comparing the performance of the surrogate model to a conventional rule-based method, we find a significant improvement in accuracy. The surrogate model is constructed using 3D shape data of die-cast products and corresponding information on the occurrence of soldering defects, employing a machine-learning algorithm to create the model. Our results indicate that the surrogate model based on geometrical features effectively predicts the soldering phenomenon between the die and molten metal in the die-casting process. This research has potential applications in defect prediction for various die-casting processes and automatic shape optimization using VAE latent space.

Keywords: Die casting, Surrogate model, VAE, Neural network, Computer-aided design, soldering failure, geometrical features, automotive industry, machine learning, defect prediction, 3D shape data
DOI: https://doi.org/10.14733/cadaps.2024.581-590

1 INTRODUCTION

Die casting is widely used in industrial production because it mass-produces products with complex shapes at high speed. Especially in the automotive industry, die casting has attracted renewed attention in recent years from the viewpoint of vehicle weight reduction and reduction of the number of parts in products, e.g. [1]. To ensure high competitiveness as an industrial product, it is necessary to supply products that correctly reflect market trends on time, and for this purpose, it is crucial to shorten the lead time for product development.

Usually, the product development process in the automotive industry follows the flow below.

Product design ⇒ **die design** ⇒ **Productivity simulation**
⇒ **Process design** ⇒ **Functional evaluation** ⇒ **Mass production**

If a high-quality design that considers the process design up to the product design stage is realized, it can reduce the number of redoing and shorten the product development lead time. However, at the product design stage, only the product shape is determined, so it is basically judged whether or not it meets the product shape standards set by rule-based settings. However, it is only sometimes possible to make good pre-predictions for products with complex shapes, and this has become a factor causing rework.

2 LITERATURE REVIEW

One way to solve this problem is to predict the product's productivity using simulation before actually producing the product and rectify issues beforehand. Indeed, simulation technology is widely adopted and has become a standard technique in industrial product development processes [2]. Efforts are also ongoing to enhance accuracy, for instance, in casting simulation, traditionally focusing on fluid analysis of molten metal, but now also incorporating calculations for ambient air compression behaviors to examine the back pressure influences and improve accuracy regarding splashing behaviors at the spout [3]. Additionally, research is being carried out to reduce computation time using quantum computers to speed up the examination cycle [4]. However, even if these technologies are put into practical use, preparing model information of the mold for manufacturing is necessary to execute a simulation. Including revisions, it takes several days to complete a simulation once. Therefore, even if improvements in simulation accuracy and time reduction are realized, only part of the problem of long preliminary examination time utilizing simulation is solved, leaving the challenge of easy defect prediction in the early stages of product development unresolved.

Given these limitations with simulation technology advancements, an alternative approach is actively pursued, which involves analyzing and utilizing big data obtained from defect occurrence information of actually produced products in the past and accumulated simulation results to convert pattern recognition into added value for current and future productivity predictions [5]. Among these efforts, the technique known as surrogate modeling, which employs machine learning or other methods to predict using patterns obtained from known data instead of executing detailed simulations, is gaining traction as it enables the reduction of computation costs and pre-required information. For instance, Amir Pouya proposed a model capable of predicting the cross-sectional temperature distribution of the welding pool by learning laser welding processing parameters using a neural network [6]. Additionally, Andres and others reported the effectiveness of a predictive model utilizing SVM as a means to estimate the cross-sectional shape of aircraft blades at a low computation cost [7]. Therefore, surrogate models, performing necessary predictions with reduced, original information based on known data, are likely to solve the problem of accurately predicting product quality from product shape in the early development stages. However, many of the cases reported so far simplify the problem by reducing three-dimensional phenomena to two dimensions, and it needs to be clarified whether it can be directly applied to phenomena where complex three-dimensional shapes are the subject of prediction. Also, there are very few reports on the effectiveness of surrogate models for defect occurrence in the casting process based on the geometric information of the product. If the possibility of realization is shown, it significantly impacts the industrial product development process. Hence, in this study, we accurately extracted the geometric information of the 3D model of die-cast products using VAE [8] shape feature technology and constructed a surrogate model that replaces the execution of detailed simulation by learning the features as input to the neural network. We evaluated the technical feasibility by comparing the prediction accuracy with the conventional rule-based prediction.

3 TARGET FAILURE

In the die-casting process, aluminum remains stuck to the die surface after the product is taken out, as shown in Fig. 1, and this phenomenon is called "soldering”. This is a defect that has a significant impact on productivity and is a high-priority issue.

Figure 1: Die soldering Image of actual die-casting process.

As reported by Han et al. [9], the mechanism of die-casting die soldering is the formation of intermetallic compounds by the diffusion reaction between the Fe component of the die and the Al component of the molten cast metal, and the degree of soldering can be defined as a function of temperature and time from the Arrhenius equation, e.g., equation (2.1), where k is the rate constant, This the absolute temperature, A is the pre-exponential factor, E is the activation energy for the reaction, and R is the universal gas constant. From this equation, the extent of the reaction varies exponentially with absolute temperature. Here, the results of a simple simulation of the temperature change of the die surface, which is touching molten metal during the die-casting process, are shown in Figure 2. As can be seen from the results, the drastic temperature change of the die due to contact with molten metal is limited to a few mm on the surface. Therefore, the phenomenon of die/molten metal soldering in the die-casting process can be estimated to some extent by the balance between the thickness of the product, which determines the amount of heat, and the heat capacity of the die surface, which determines how much the die temperature rises due to the heat input from the product. Based on the above, we assume that the die soldering phenomenon is appropriate for the task of creating a surrogate model based on shape characteristics and selecting it as the target defect.

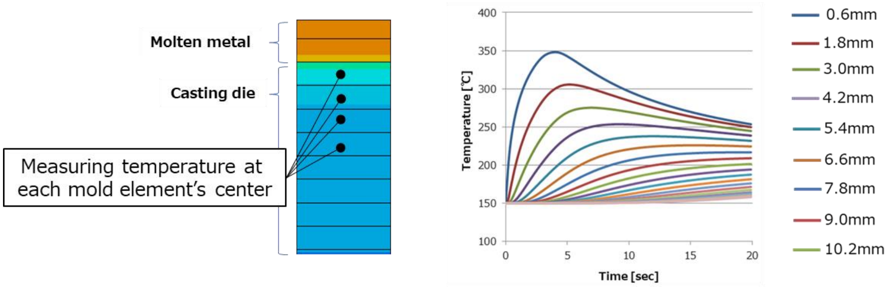

Figure 2: (a) Setup of brief simulation, and (b) simulation result of die temperature change over time at each depth from die surface.

$$k = Aexp\left(-\frac{E_a}{RT}\right) \quad (2.1)$$

4 TARGET DATA

4.1 Simulation of the Prediction Target

In this study, the target for prediction is the "integrated soldering reaction time," which is a risk index for soldering occurrence predicted by detailed simulation using TopCAST, a casting simulation software sold by Toyota Systems, Inc. The integrated soldering reaction time is a numerical value calculated by experimentally weighting the thermal diffusion on the die surface as a function of "temperature" and "time," which can accurately predict actual soldering defects. Although various methods are used to represent the 3D model geometry in fluid simulation, TopCAST uses the voxel-based VOF method.

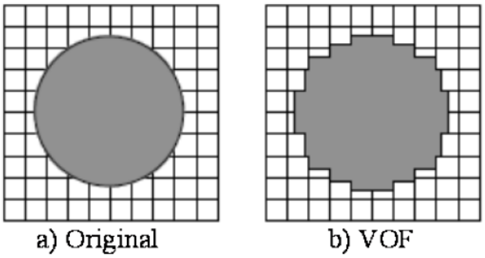

Figure 3: Image of differences between (a) Original shape and (b) VOF shape

4.2 Parts to be Analyzed

This study analyzed 113 kinds of transaxle parts produced by Toyota Motor Corporation by die casting in the past. Figure 4 shows an image of the product shape.

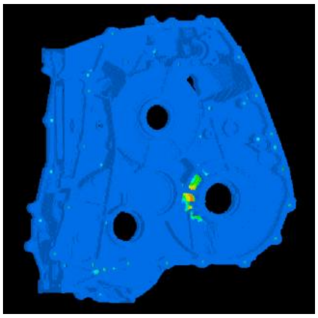

Figure 4: Image of product shape

5 RULE BASED JUDGEMENT MODEL

As a rule-based prediction method, in this study, we used the SAT (Shape Analysis Tool) function implemented as a standard function of TopCAST. This function indicates the risk of soldering by calculating the volume ratio of the die and the molten metal inside the sphere (measuring ball in Figure 5) with the appropriate diameter, e.g., equation (4.1).

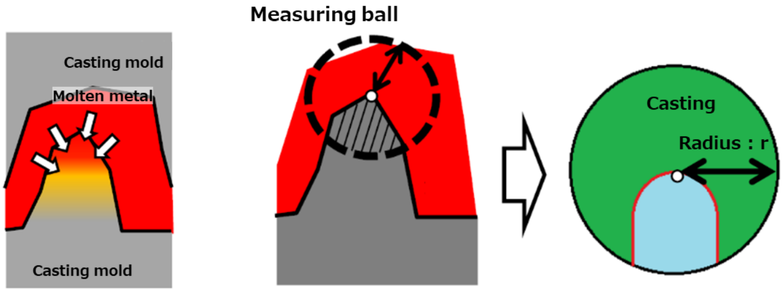

Figure 5: Concept of rule-based prediction.

$$R = {V_{casting}}/{V_{total}} \tag{4.1}$$

6 CREATION OF A SURROGATE MODEL

The procedure for constructing the surrogate model is as follows. First, cut out a cube centered on each surface cell of the target 3D model shape. Next, train VAE using each cubic shape created at each point on the surface. Then, we can get the encoder, which can translate the cubic shape feature to the vector. Finally, the neural network will be trained with the feature vector as input and the simulation result on the cube center as output. The flow of estimation is shown in Figure 6.
In this study, 20 of the 113 parts were used to train the VAE, and then 73 of the remaining 93 components were used to train the NN. Further details regarding the VAE and neural network structure will be described in the following sections.

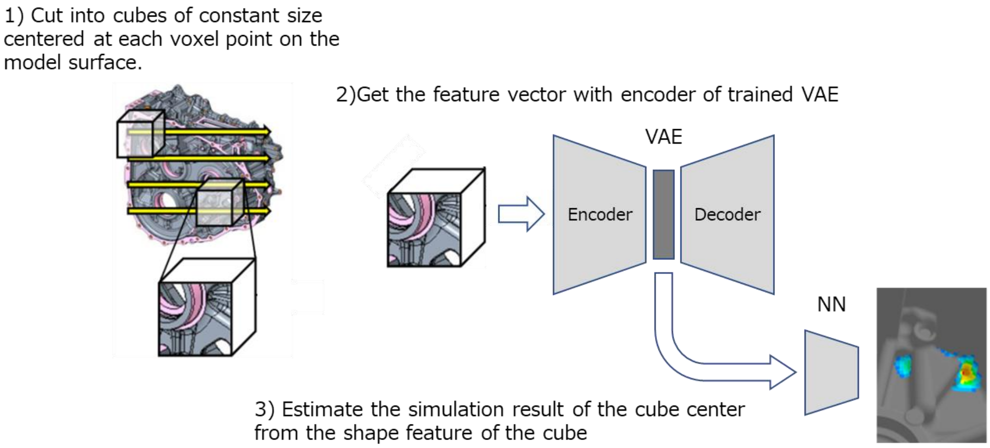

Figure 6: Image constructing surrogate model.

6.1 Evaluation Method of Surrogate Model

When the correct and predicted data were plotted on the 3D model geometry, the clumps of regions with values above a threshold were each defined as soldering regions, and the degree to which the regions in the correct data and the regions in the predicted data matched over the entire part was evaluated.

In this study, the F1 score was used as the evaluation index, and the threshold value at which the F1 score is the maximum was obtained for both the surrogate model and the rule-based model.

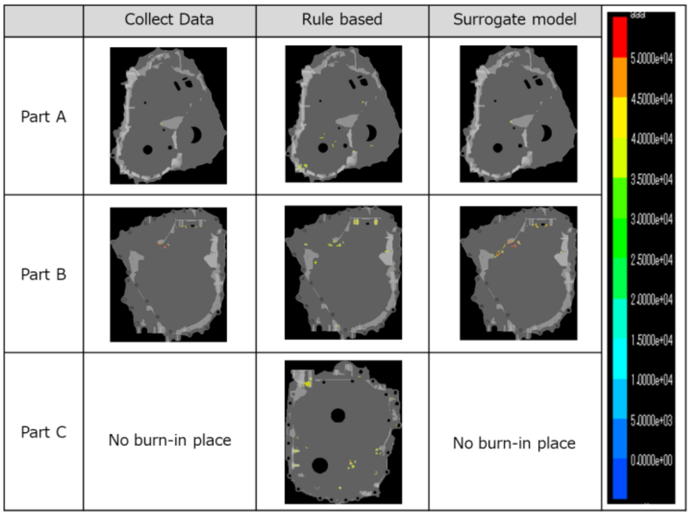

Figure 7: Example of evaluation results.

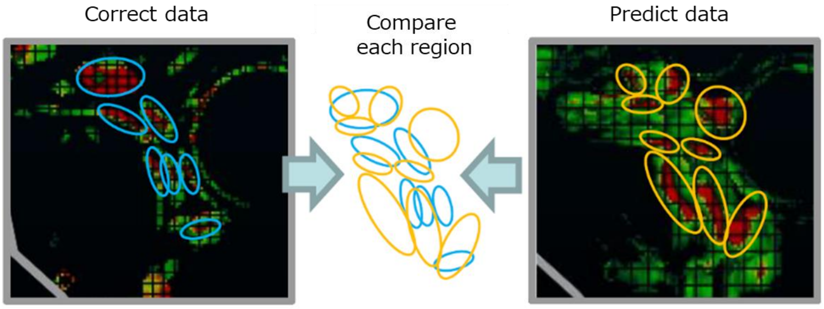

Figure 8: Image of evaluation method.

6.2 Voxel-Based Variational Autoencoder and Neural Network

A Variational Autoencoder (VAE) is constructed in the present study, drawing inspiration from a model that demonstrates high accuracy in object classification tasks [9]. A VAE is an autoencoder, a neural network trained to replicate its input data at the output layer. The 'variational' part adds a probabilistic layer, making it a probabilistic graphical model. The VAE compresses data into a lower-dimensional space and then reconstructs it into its original space. During this process, the VAE learns to capture the essential characteristics of the data in the lower-dimensional space, producing a feature vector. Initially, a simple VAE structure was adopted, as in the referenced literature. Upon constructing the model and conducting a significance test on the difference in F1 scores between it and a rule-based model, we could not achieve a statistically significant result at the 99% confidence level. It is worth noting that in this study, we used the bootstrap method [10] to test the difference in accuracy between models, create sub-samples for each product shape when resampling bootstrap samples, and conduct tests on the differences. The reason why the adopted model did not yield results meeting the 99% confidence interval may be because the shapes targeted in this study are more complex than the 3D shapes targeted in the referenced literature. Based on this consideration, we concluded that there was a need to tune the VAE structure to capture more complex shape features in our application. Therefore, the final VAE structure adopted in this study included additional convolutional and pooling layers compared to the referenced literature. It was confirmed that optimizing the VAE structure by increasing the number of convolutional and pooling layers improved accuracy. The final VAE structure adopted in this study is illustrated in Figure 9. After training the VAE, the feature vectors extracted from the latent space serve as the input for another neural network designed for regression prediction. This neural network is a Multilayer Perceptron with four layers and dropout. It consists of an input layer with 100 nodes, two hidden layers with 50 and 10 nodes, and an output layer with a single node. Each hidden layer is followed by a batch normalization layer with an epsilon of 2e-5 and a dropout layer with a dropout rate 0.25. The activation function used between the layers is the leaky ReLU function with a negative slope of 0.2, and the output layer uses the softplus function. Details of the learning process will be described in the following chapter.

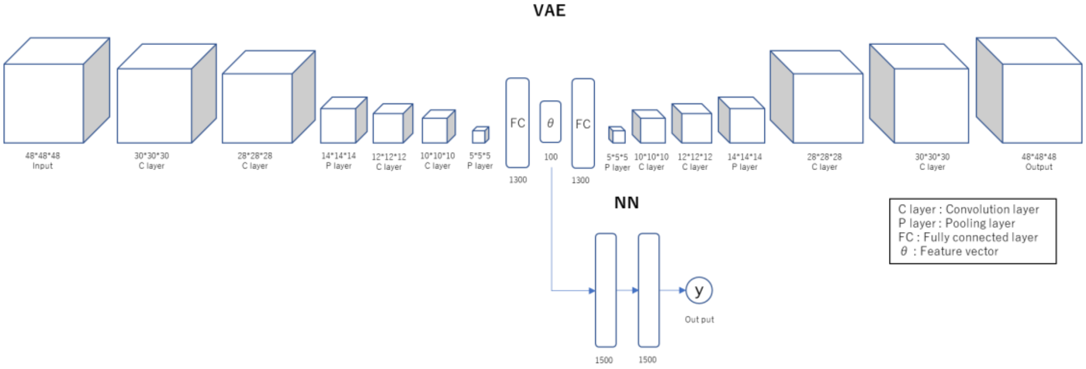

Figure 9: Architecture of VAE and Neural Network.

6.3 Model Training

For the VAE, the training was conducted with a batch size of 10 and for one epoch with a learning rate of 0.001. The optimizer used was AdaGrad, and the loss function parameters included a reconstruction error calculation sampling number of 1 and a KL divergence term coefficient of 1. For the Neural Network, the training was conducted with a batch size of 32 for one epoch and a learning rate of 0.001. These parameters ensured the appropriate progression of learning for each network. Figure 7 shows the training curve of (a) VAE and (b) Neural Network, and we can see that both of them were trained appropriately. The results confirm that learning progressed appropriately in each network.

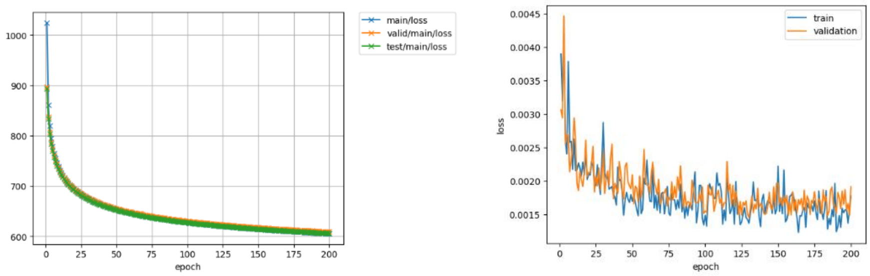

Figure 10: Train curve of a) VAE and b) Neural network.

7 EVALUATION RESULT

We evaluated the performance of two predictive models, the Surrogate model and the Rule-based model, for predicting the occurrence of defects. The performance of the models was assessed using the F1 score, which is the harmonic mean of precision and recall. The Rule-based model had True Positives (TP) of 6, False Negatives (FN) of 16, and False Positives (FP) of 38, resulting in an F1 score of approximately 0.19. On the other hand, the Surrogate model had a TP of 12, FN of 10, and FP of 12, leading to an F1 score of approximately 0.53. We conducted the bootstrap mentioned above test to validate whether there was a statistically significant difference in these results. Figure 11 shows the transition of F1 scores as the decision threshold was varied for both the Surrogate model and the Rule-based model, represented by a line graph and the bootstrap distribution of the differences represented by a histogram. The results indicated a statistically significant difference between the Surrogate and Rule-based models at a 99% confidence level.

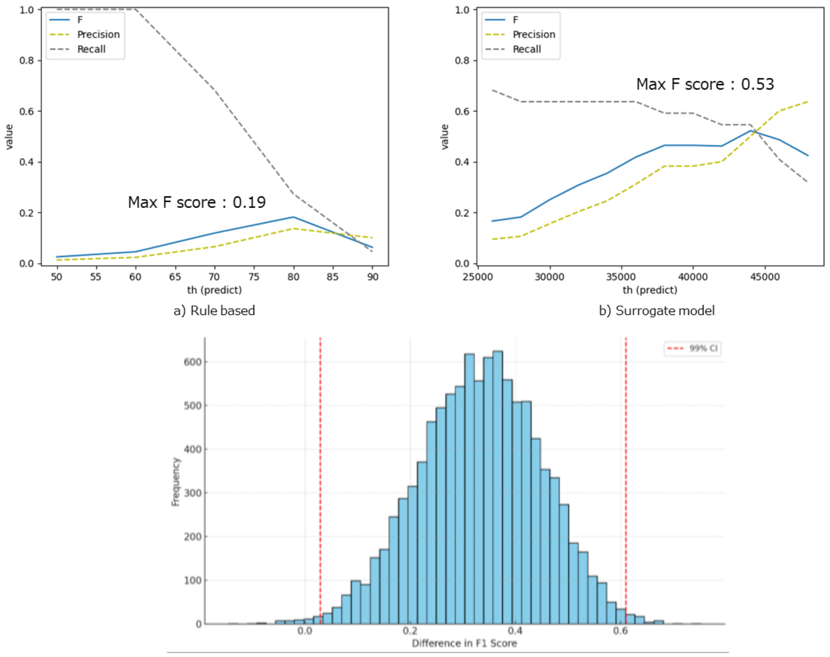

Figure 11: Transition of F1 score of a) rule-based prediction and b) surrogate model prediction when the threshold was changed and c) Bootstrap distribution of F1 score difference.

8 CONSIDERATION

As indicated in the results, the surrogate model constructed using VAE and NN demonstrated a statistically significant higher F1 score than the conventional rule-based model prediction, with a particular tendency to reduce the false positive rate. Figure 12 depicts (a) an example of the false positive region predicted by the rule-based model and (b) the actual die model. In the area enclosed by the yellow line, no soldering was predicted by CAE and surrogate model prediction. In contrast, the rule-based model identified it as a concern for soldering. As seen in Figure 12(b), there is a hole in the concerned area, and in this hole, a separated die, as shown in Figure 13, will be inserted during the actual manufacturing process. This separated die, equipped with an additional cooling circuit inside, possesses a high cooling capacity and is applied to areas where the risk of soldering is deemed high based on simulation results. However, it does not apply to all parts and is only used for parts that can be divided due to the die structure. Most of the learning data utilized in this research were the results of simulations conducted after such design efforts were made. Therefore, in the surrogate model, the risk of soldering was not only recognized as a physical phenomenon, but pattern recognition also included whether measures like additional cooling were implementable due to the mold shape. It is presumed that this background led to the observed difference in accuracy between the actual surrogate model and the rule-based model.

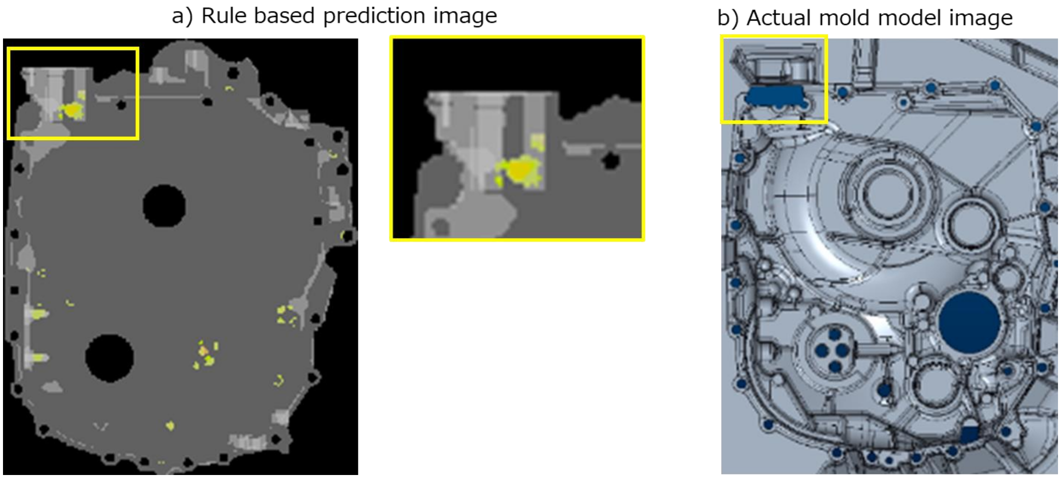

Figure 12: Example of (a) rule-based prediction and (b) actual die model.

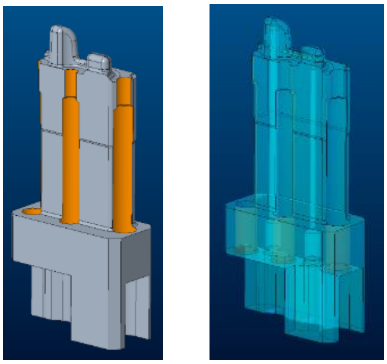

Figure 13: Separated die model which has internal cooling circuit.

9 CONCLUSION

The defect prediction performance of the surrogate model was confirmed to be superior to that of the rule-based model, as indicated by a higher F1 score. This difference in performance was statistically significant, as demonstrated by the bootstrap method. Based on these results, the surrogate model constructed using VAE and NN can effectively predict product quality based on product shape, thereby potentially reducing product development lead times.

However, it is essential to note that the data used in this study consisted of models and simulation results of 113 types of automobile transaxle cases. Collecting detailed product development-related data of this scale is difficult, which could be a limitation in applying this approach in other contexts or for smaller-scale projects. Additionally, while this study focused on predicting the occurrence of soldering defects, there are different die-casting defects, such as cracking and wrinkling, which were not examined in this study. It is still being determined whether the surrogate model could be effectively applied to predict these other types of defects, and this is an essential area for further research and verification.

Overall, this study demonstrates the potential of using a surrogate model constructed using VAE and NN for predicting defects in die-casting but also highlights the challenges in collecting the necessary data and the need for further research to assess the model's applicability to other types of defects.

Tomoya Yamazaki, http://orcid.org/0009-0008-1771-7418

REFERENCES

[1] Czerwinski, F.: Current Trends in Automotive Lightweighting Strategies and Materials, Materials, 14)21), 6631. https://doi.org/10.3390/ma14216631
[2] Morgan, J. M.; Liker, J. K.: The Toyota Product Development System. Productivity Press, New York, 2006.
[3] Matsushita, S.; Aoki, T.: Gas-liquid two-phase flows simulation based on weakly compressible scheme with interface-adapted AMR method, Journal of Computational Physics, 445, 2021, 110605. https://doi.org/10.1016/j.jcp.2021.110605
[4] Gaitan, F.: Finding Solutions of the Navier-Stokes Equations through Quantum Computing—Recent Progress, a Generalization, and Next Steps Forward, Advanced Quantum Technologies, 4(10), 2021, 2100055. https://doi.org/10.1002/qute.202100055
[5] Fei, T.; Jiangfeng, C.; Qinglin, Q.; Meng, Z.; He, Z.; Fangyuan, S.: Digital twin-driven product design, manufacturing and service with big data, Int. J. Adv. Manufacturing Technology, 94, 2018, 3563–3576. https://doi.org/10.1007/s00170-017-0233-1
[6] Hemmasian, A. P.; Ogoke, F.; Akbari, P.; Malen, J.; Beuth, J.; Barati Farimani, A.: Surrogate Modeling of Melt Pool Temperature Field using Deep Learning, Additive Manufacturing Letters, 5, 2023. https://doi.org/10.1016/j.addlet.2023.100123
[7] Paulete-Periáñez, C.; Andrés-Pérez, E.; Lozano, C.: Surrogate modelling for aerodynamic coefficients prediction in aeronautical configurations. Proceedings of the 8th European Conference for Aeronautics and Space Sciences (EUCASS). https://doi.org/10.13009/EUCASS2019-870
[8] Brock, A.; Lim, T.; Ritchie, J. M.; Weston, N.: Generative and Discriminative Voxel Modeling with Convolutional Neural Networks. arXiv preprint arXiv, 2016, 1608.04236.
[9] Han, Q.: Mechanism of Die Soldering During Aluminum Die Casting, China Foundry, 12(2), 2015, 136-143.
[10] Roger, L.: An Introduction to the Boostrap, 2021.
[11] Wu, Z.; Khosla, A.; Yu, F.; Zhang, L.; Tang, X.; Xiao, J.: 3d shapenets: A deep representation for volumetric shapes, In CVPR 2015.
[12] Kingma, D. P.; Welling, M.: Auto-encoding variational bayes, In ICLR 2014
[13] Saxe, A. M.; McClelland, J. L.; Ganguli, S.: Exact solutions to the nonlinear dynamics of learning in deep linear neural networks, In ICLR 2014.