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Variational Autoencoder Model Based on 3D Convolutional Neural Network for generative design framework of 3D chair

T. Park[a], J. min Park[a], S. A. Murdivien[a], J. Um[a,*]

[a] *Kyung Hee University, 26 Kyungheedae-ro, Dongdaemun-gu, Seoul, South Korea*

ABSTRACT

To actualize an advanced smart factory, personalized products are important to develop immediately during the design stage, particularly when producing novel shapes, which demands experts with many design experiments. This study proposes an automated 3D shape design system that actively evolves into new products quickly during the design stage. The framework consists of a series of 3D-generated using variational autoencoder, classification with 3D convolution neural network, and evaluation models by analyzing new shape similarity to existing shapes through an autoencoder. The main objective of this study is to optimize the generative design process, reduce the need for human intervention, and automate design novelty evaluation, thereby addressing a significant research gap. The proposed framework was applied to create a new chair design procedure wherein new 43 chairs were generated in a single iteration with 989 existing chair shapes. The proposed framework for generative design of 3D chairs introduces a novel, automated approach through a variational autoencoder model and 3D convolutional neural network, addressing a research gap by streamlining the generative design process, reducing the need for human intervention, and providing automated evaluation of design novelty.

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*Corresponding author:
Jumyung Um
jayum@khu.ac.kr

1. Introduction

Due to the crucial competition of recent manufacturing industry, leading companies are receiving pressure of customized products and fast model shift causing shorter product lifecycle than before in order to keep market leaders [1]. The increasing requirements of customers in the market has led to the emergence of various innovative platforms in a short period. The growing demand for individualized products and e-commerce platforms gives customers a way to easily compare various products at the same time. This, in turn, creates a competitive market, and subsequently encourages manufacturers towards generating newer ways to cater to the rising demand. A shorter product lifecycle means a reduction in the product development procedure, and here, each activity is labor-intensive and requires highly experienced and skilled labor. Customized products with high added value and reflecting trends must be developed immediately in the design and production phases [2]. The challenges associated with the current development process can be summarized as follows: The decision-making process is time-consuming because of the difficulty in accumulating subjective knowledge and

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experience. Therefore, an automatic framework of product development using a data-driven approach that can analyze costs and novelties without human intuition is necessary [3].

A representative application of automatic physical design is topology optimization [4], wherein both redesign approaches possess the theoretical structure and algorithm of each domain. Such a knowledge-oriented design tool is utilized in various domains such as topology optimization and is widely used in mechanical design products. For the existing design method, parametric design or topological optimization was developed to supplement the mathematical or mechanical modelling. However, the primary limitation of this method that it cannot create an original design. Many research groups who are invested in concepts related to deep learning have recently focused on developing a learning model for 3D modelling information. The 3D Generative Adversarial Network (3D GAN) [5], PointNet [6], and ShapeNet [7] are examples of deep learning applications for 3D shapes. However, even though this method can create new forms, it does not cater to artificial intelligence, which is necessary for a systematic as well as automatic verification of the same. Thus, an interface that allows experts to intervene in the final form is required.

The method proposed in this paper is different from the traditional design method or expert system-based design method in the automation ratio. The illustration comparing those differences is provided in Figure 1.

Traditional design approaches create new concepts through discussions with the company's development team and interviews with external people such as customers. All the work is done by hand, and it requires the experience and time of many working professionals. On the other hand, design systems based on expert systems also require human decisions at each stage. The design expert system is used to support the optimized design of each component. Parametric design and topology optimization are methods used for detailed design, and there are many initial conditions that experts need to input to create a conceptual design. However, even in this method, the results vary greatly depending on the proficiency of the design team because push, an expert who requires a lot of design experience, is absolutely required. Therefore, in order to overcome this limitation, in this study, we propose a concept generation method that can verify the novelty following creation and classification of a new image based on a design catalogue using an automated deep learning model.

The primary objective of this study is to address the limitations associated with traditional and expert system-based design methods, which necessitate substantial human intervention and decision-making. A more automated approach to generative design,

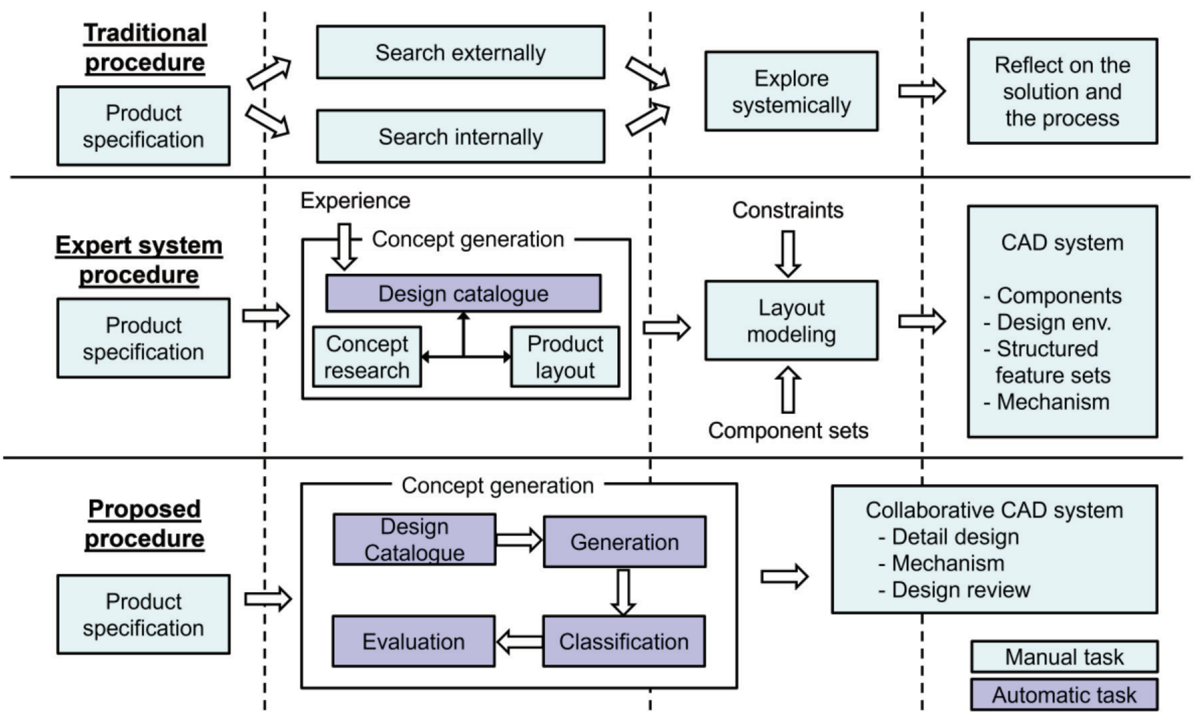


Figure 1. The comparison of the legacy process and the proposed process of product development

utilizing advanced deep learning techniques, is proposed. This approach not only reduces the need for human intervention but also enhances the efficiency and effectiveness of generative design, especially for 3D products. Furthermore, a novel approach is introduced by the proposed framework, employing a Variational Autoencoder (VAE) model within a 3D Convolutional Neural Network (3D CNN) to generate new shapes based on an existing product-form database [8], [9]. This innovative method is believed to significantly improve the efficiency and effectiveness of generative design across various industries.

In this study, an automated 3D shape design system was developed that rapidly evolves into new products during the design stage in an intelligent factory environment. New forms are generated from the current product-form database by the proposed method. Additionally, fresh shapes are created through a VAE that has learned the existing shapes. A 3D CNN model, capable of recognizing product types, is constructed, facilitating the development of an automatic design system that identifies multiple product images in 3D space and derives new recommended shapes.

The proposed framework for generative design of 3D chairs introduces a novel approach by utilizing a VAE model within a 3D CNN. This innovation effectively addresses a research gap in the field by offering a more efficient and automated method for generating 3D products, distinguishing itself from prior works primarily focused on 2D images or lacking deep learning techniques. Furthermore, an automated deep learning model for evaluating the novelty of generated designs is introduced, adding a unique dimension to the quality assessment of generative designs.

The paper is structured as follows: Section 1 describe the background and motivation of this research. In Section 2, previous generative design approaches are compared, and their limitations are discussed. Section 3 outlines the proposed architecture for generating a new design using an existing product database and explains the generative models. Section 4 explains the outcomes of the experiment using a chair product. The performance of the proposed approach is compared with that of conventional models has been discussed in detail in Section 5. Finally, the conclusions are presented in Section 6.

We summarize the key contributions of our work as follows:

(1) We present a novel operation for learning from point clouds to better capture local geometric features of point clouds while still maintaining permutation invariance.
(2) We show the model can learn to semantically group points by dynamic.

The increasing demand for individualized products and e-commerce platforms gives customers a way to easily compare various products at the same time. A shorter product lifecycle means a reduction in the product development procedure. Data-driven approach that can analyze costs and novelties without human intuition is necessary. This study proposes a framework to create a new product model using 3D deep learning models. The proposed method creates a new form based on the current product-form database. The suggested approach may fully automate the design process, from generation process until evaluation process. This represents a meaningful contribution since the proposed method connected the whole process. A new shape is created through a variational autoencoder that has learned the existing shape. The performance of the proposed approach is compared with that of conventional models.

2. Literature review

This section describes the overall technologies of computer-aided product design in terms of automating design change or design evolutions. Early computer system for product design was a simple supporter of drawing tasks but the benefits of computer usage was found in re-calculating each dimension updated by product changes without human works. Parametric design defined the concept of dimensions and constraints in drawing notations. Topology optimization, Various 3D representation data formats, 3D Neural networks, Generative design have accelerated the automation of product design than ever.

2.1. Parametric design

The automation of the design process has been widely studied ever since the Computer-Aided Design (CAD) system was introduced. The automation was found in the emergence of the concept of parametric design, which is a method for generating a new draft drawing by adjusting the dimension value. This design method has been applied in various ways, from the overall structure of a product to the detailed design of specific parts. Myung et al. [10] proposed a knowledge-based design system for the overall structure of a Computer Numerical Control

(CNC) machine tool that is guided by parametric design. Han Li. et al. [11] suggested a method that enables rapid practicing from design to construction through parametric design to reproduce the gears and joints required for machinery maintenance. As shown in previous studies, parametric design has the ability to adjust to specific dimensions of predefined drawings according to user requirements, but it is difficult to obtain creative products mainly because parametric design makes only predefined shapes in advance.

2.2. Generative design and Topology optimization

The more advance of design automation started after finite element method is applied to structure analysis. As computer-based structural mechanics was developed and enabled an automated design method, a generative design based on an optimal design method was introduced [12]. Similar to parametric design, Liu et al. [13] proposed topology optimization, which distributes materials to optimal positions based on constraints such as design area and boundary conditions while simultaneously transforming the product shape. This design method is referred to as generative design, which can find an original design by iteratively changing the constraints and parameters of a design structure optimization method, such as topology optimization [14], [15]. Some research studies on generative design approaches have attempted integration with deep learning. Oh [16] proposed a two-dimensional generative design of tire wheels that augments alternative shapes using topology optimization and explored new feasible shapes using deep learning to create various shapes, considering both aesthetic and structural aspects. Sun et al. [17] applied reinforcement learning to the topology optimization of two-dimensional and three-dimensional environments to derive various design alternatives. However, only a few studies have focused on design methods that automate creative product design.

2.3. 3D Data Type

As far as specialized CAD software, such as finite element method, are increased, 3D representation data formats are suggested by various areas of product development. There has been a continuous change in methods that express expressing 3D-shaped objects as data [18]-[20]. In classical computer science, 3D data-related research has been conducted using multi-view [21], [22]. The data formats should be converted to ensure that these 3D data can be read by computers [23]. There are various methods to express 3D data types, such as B-spline, STL, and STEP. However, point cloud and voxel data formats are mainly used in computer-vision AI [24]-[27]. The point cloud is a data form that can be obtained through scanning using a depth camera or RGB-D camera in real 3D objects, forming a set of points in which objects are defined by coordinates on the X-, Y-, and Z-axes, and can be used as raw data [10]. Voxel, in the form of pixel in 2D images, represents a form of data that indicates if each cube is occupied through 0 and 1 in a lattice-shaped three-dimensional space, and can also represent colors by adding dimensions such as 2D images. Voxnet algorithms convert point cloud data into voxels through the occupancy grid [28]. These are the means to collect product information in terms of different aspects. The way to create new product design is to re-organize features of existing product shapes. The increase of 3D data standards has helped make rich in product data management and was the fundamental of applying deep learning to new design generation.

2.4. Recognition of 3D Data

Since the neural network model for 3D shape data was proposed [21], a lot of innovative learning models was applied to various 3d shapes. Qi et al. [29] presented an algorithm that is suitable for this purpose by receiving data in the form of a point cloud. Using a multilayer perceptron, the features of each point are extracted, and the characteristics of the entire object are learned. In addition, Qi et al. [30] also overcomes permutation innovation and innovation under transformation, thus improving the classification and segmentation performance. Qi et al. [30] and Li et al. [31] applied PointNet to improve the capability of capturing local structures. The 3D CNN enhances the dimensions of the existing 2D data recognition model in the form of a pixel. It recognizes three-dimensional (3D) data in the form of voxels. The existing 2D CNNs move the square filter of the grid and grasp the correlation between adjacent data on the plane. The 3D CNN moves the grid's hedral filter and identifies the correlation between adjacent data in space [32]. As high-dimensional data becomes more prevalent, 3D CNN is gaining increased attention and undergoing rapid development [33].

2.5. 3D Generation

A deep learning model for generation is based on an algorithm that learns the probability distribution, and it uses existing data to create new data with a distribution that is similar to that of existing data. Based on the format of the existing autoencoder model, the VAE learns the model by placing the input and output as same data. However, the latent vector helps estimate P and σ of the probability distribution to learn the probability distribution and generate new data [34], [35]. There are several works since 2016 in applying GAN for 3D shape processing. Some studies tried GAN to generate detailed 3D shapes of objects from 2D images [36], [37], generate realistic image from text [38], [39], also generate 3D objects from probabilistic space by leveraging recent advances in volumetric convolutional networks and generative adversarial nets. However, even though they succeed in the generation process, the selection for the novelty is still being manually selected [40]. Point cloud up-sampling network based on GAN is suggested to learn a rich variety of point distribution [41]. An RL-based generative design framework was applied to enhance the diversity of topology optimized designs in 2-dimension shape of automotive wheel [42]. Meanwhile, even though our model has not passed all the stages of generation, selection, and evaluation properly, our model includes every process, therefore it has higher difficulty.

2.6. Collaborative design in virtual reality

Previous studies have presented a few design methods related to design that generate generation using deep learning. However, the methods for arbitrarily creating shapes using artificial intelligence or finding novel objects that have not been considered before having recently emerged. Therefore, the purpose of this study is to limit the automatic shape 3D generation system architecture that can creatively generate phenomena related to the intended category, rather than the generation of a simple production slender man without any direction. Therefore, in this situation, the following problems must be solved:

(1) Generation: We need a generation model based on deep learning that can automatically produce new designs similar to previous designs.

(2) Classification: It is necessary to build another deep-learning model that can determine whether a new design is available. Some designs created with the generation model are not related to previous designs or have inappropriate shapes.

(3) Evaluation: New designs made by the generation model should be evaluated to determine whether they are creative. Generation models sometimes form shapes that are the same as previous shape.

To address the aforementioned issues, this study presented an architecture for the entire process of constructing, inputting, generating, classifying, and judging data from video 1, and tested it based on a specific case.

3. Methodology

This chapter introduces a deep-learning-based design automation process that can be used in the existing design process steps in order to overcome the limitations of the design automation process discussed in the previous section. A typical product development process involves five main stages: market analysis, conceptual design, detailed design, prototype production, and redesign. The important stage of finding a new product shape corresponds to the concept design stage, that is, concept generation. Conventionally, the concept generation method involves the creation of a functional combination using a morphological chart and then reflecting the aesthetic analysis accordingly. However, because aesthetic elements and functional parts have an indirect connection, it is difficult to create them as explicit rules for computer programming. Therefore, in this study, another deep learning method with the ability to create a new shape is performed after constructing a dataset of final product designs that have already been made with aesthetic and functional elements and learning it through data-based deep learning. Thus, we propose a method for reproducing a new product.

The deep learning model, that is trained based on the existing dataset, created a new chair 3D model for the pseudo-model generation algorithm that is generated by random number generation. Existing design processes use morphological charts to generate new product designs. Thus, the feasibility of a new design is evaluated by the expertise of the design team and the know-how database in the company. However, the limitation is that for the creation method of such a designer, product diversification increases, the load on design work increases, and it is difficult to respond quickly to the market. Therefore, in this study, we propose an algorithm for automatically generating new product models. Product development teams can provide new designs without modelling in CAD work.

In this paper, we propose a deep learning model that creates a chair for a desired trend using a data-driven method. The automatic creation of new product shapes guides product development teams towards new designs without modelling CAD work. The learning process consisted of data collection, generation, classification, and evaluation. First, the existing product chair model was used as the dataset. The deep learning model for model generation consists of voxel-based 3D model generation, chair-shape screening, chair-type classification, and novelty evaluation. Specifically, the variation autoencoder model is used to develop a voxel-based 3D model that leverages existing product training data. The generated data were then subjected to chair similarity and category classification. The 3D convolution neural network determines whether the shapes generated have a chair-like shape, and an autoencoder trained with a legacy dataset tries to reconstruct the generated shapes and calculate the noise to study the novelty as compared to legacy shapes. Through this automated design process, a chair with a related trend shape is created with minimal manual work and without high expertise. The whole procedure is shown in Figure 2. Point Cloud requires a large amount of learning data when utilizing 3D CNN. 3DPointNet, for example, learns the position information of the PC using T-net, which necessitates a large amount of learning data. As a result, both Voxel and PC have limitations in that they require extra learning data.

This process differs with respect to two main aspects. In the concept generation of the existing design method, an alternative is created using a morphological chart that is based on functional elements, and an aesthetic evaluation is then performed to materialize the new design. At this time, to find an alternative that satisfies both functional and aesthetic factors, it is necessary to conduct many discussions and manual work with many people. On the other hand, in the limited method, a trendy chair can be created based on data. If the dataset is tuned according to the desired trend, a new shape similar to or in the same trend can be easily created. Because the learning data are automatically generated through adjustments, less human expertise is required. By comparing the generated data with the chair similarity, it is possible to simultaneously analyze whether a meaningful phenomenon is present and to compare the authenticity with existing images. The proposed method has the ability to create trendy shapes with minimal knowledge.

3.1. VAE for Generation

The variation autoencoder is a neural network model that was developed by Kingma and Welling in 2014 [34]. This model compresses the input into a constrained multivariate latent vector that represents P and σ that indicate the probability distribution information. The model's outputs are the results of restructuring the latent information and creating new data similar to the input data with the base of the latent distribution. The structure of variational autoencoder is depicted in Figure 3. The modification of

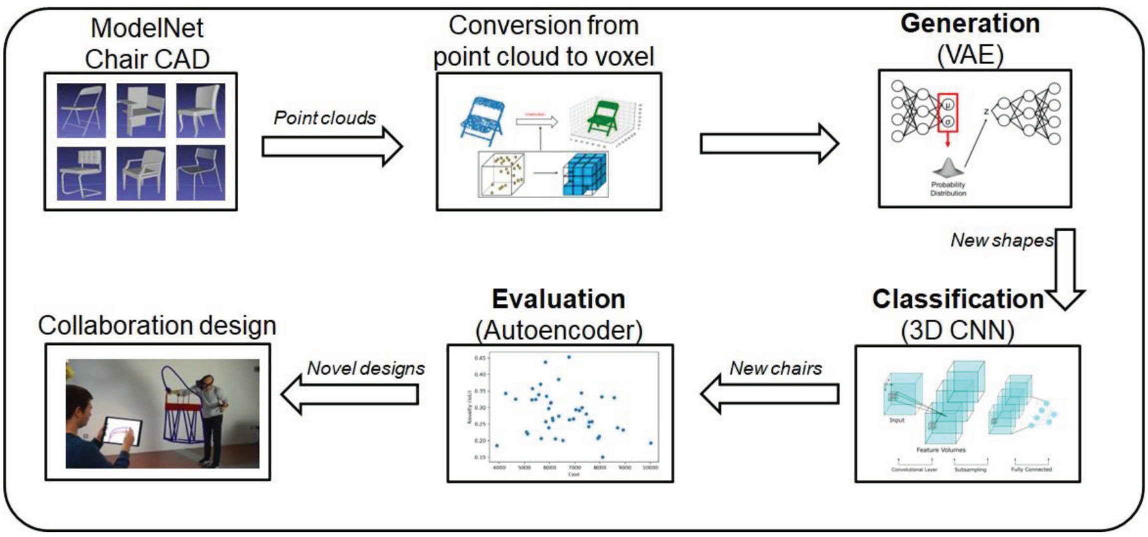


Figure 2. Whole procedure of automated product design procedure

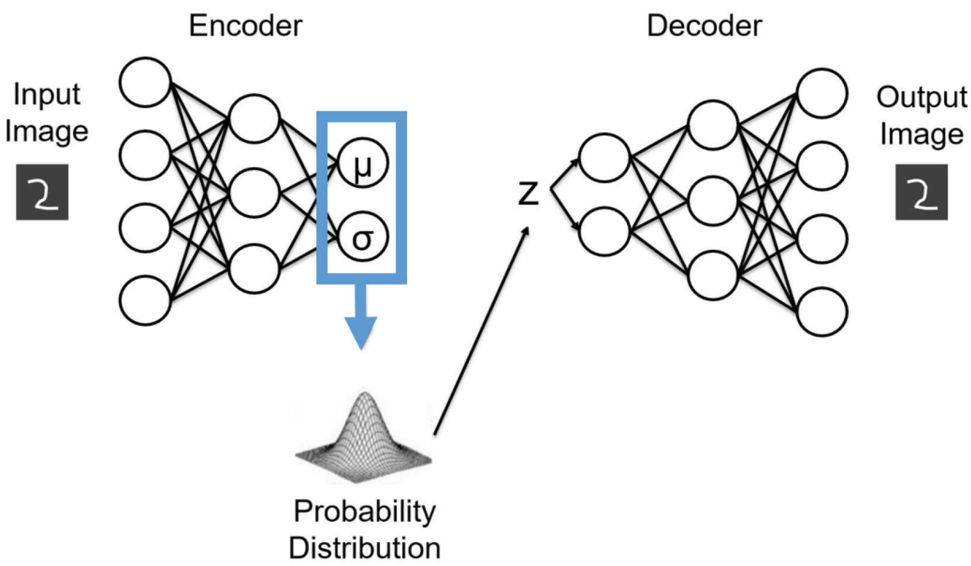


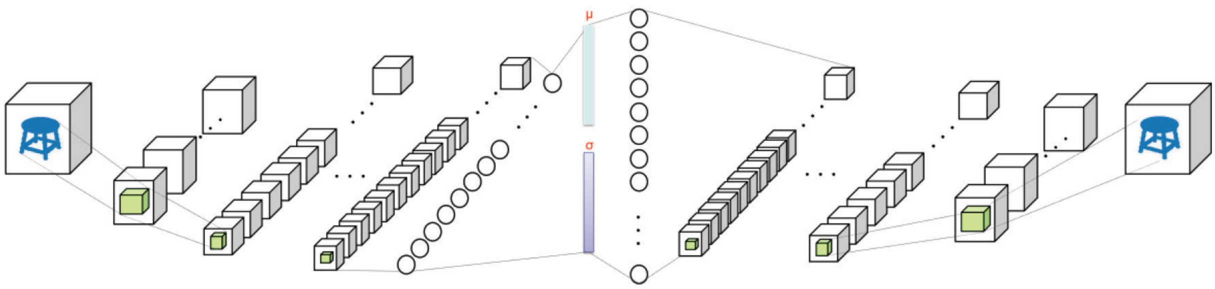
Figure 3. Basic Concept of VAE

the layer structure helps create diverse results. Owing to these characteristics, a variational autoencoder is used in order to generate new shapes by diverting the 3D convolution layers with voxel input data. Through this process, the model can automate the design by creating a new type of product shape by referring to the existing released product shape. The 3D VAE learns the probability distribution based on existing product shape data to create shapes similar to existing shapes [34]. Using the 3D convolutional layer, it verifies the correlation between adjacent voxels of existing data, computes information with P and σ vectors in latent space and updates the weight by feedback between new 3D data generated through Depth Estimation Reference Software (DERS) and the actual data entered [44]. In this process, the late vector approaches the existing data probability distribution, and the decoder part can create 3D data that more similar to the actual data than the late vector.

For the experiment, we used 989 chair datasets in the form of 64 × 64 × 64 voxels. We were inspired by 3D VAE, and the generator was implemented to form the same format as the actual data from a 64-dimensional vector with a uniform distribution between 0 and 1. In the network of the encoder part, the number of kernels was increased to 64, 128, 256, and 512 with each passing layer, the kernel size was set to 4, and the strands were set to 2, 2, 4, and 4, respectively. Subsequently, it was completed by fully connecting the P and σ vectors with 64 dimensions through a flatten process. The decoder part was designed to extract values through sampling from P and am, connect them fully with 512 nodes, and generate 3D transpose convolutional layer data. Each filter number was 256, 128, 6432, 1, the kernel size was set to 4, and the strands were set to 2, 2, 4, 2, and 2. Each layer used the ReLU activation function, and only the last layer was used to determine the presence or absence of grid voxels using a sigmoid function. The structure of the proposed model is shown in Figure 4. Our model is a method of doing all the process of Generation, Selection, Evaluation therefore it has a higher difficulty. It has already been performed as a GAN [41], but the existing model has not passed all three stages, hence it is now being improved. As a result, the complete procedure may be carried out only if a GAN that is distinct from the previous one is created. Successful models are being developed in response to changing situations and networks. In the case of 3D, please refer to the fact that the difficulty of learning is much higher.

3.2. 3D CNN for Classification

Not all data generated through VAEs possess an intact form. Therefore, there is a need for an automation algorithm that plays contributes to the quality control of the actual process. The 3D CNN algorithm is responsible for the binary classification of existing specific product shape data and data that do not automatically adopt the desired data shape and discard the design that fails to do so [45]. In the existing 2D CNN algorithms that recognize pixel-type data, the 3D CNN algorithm, wherein one dimension is added, learns the positional correlation between each voxel, with each three-dimensional filter mov-



Layer	Parameters	Activation	Output
Input			64 x 64 x 64 x 1
Conv3D – 1	4 x 4 x 64 Strides 2	Relu	32 x 32 x 32 x 64
Conv3D -- 2	4 x 4 x 128 Strides 2	Relu	16 x 16 x 16 x 128
Conv3D – 3	4 x 4 x 256 Strides 4	Relu	4 x 4 x 4 x 256
Conv3D – 4	4 x 4 x 512 Strides 4	Relu	1 x 1 x 1 x 512
Flatten	512		512
Dense (Mean)	32		32
Dense (Variance)	32		32
Lamda (z)	32		32

Layer	Parameters	Activation	Output
Input (Latent_space)	32		32
Dense	512	Relu	512
Reshape	1 x 1 x 1 x 512		1 x 1 x 1 x 512
Conv3DTranspose – 1	4 x 4 x 256 Strides 2	Relu	2 x 2 x 2 x 256
Conv3DTranspose – 2	4 x 4 x 128 Strides 4	Relu	8 x 8 x 8 x 128
Conv3DTranspose – 3	4 x 4 x 64 Strides 2	Relu	16 x 16 x 16 x 64
Conv3DTranspose – 4	4 x 4 x 32 Strides 2	Relu	32 x 32 x 32 x 32
Conv3DTranspose – output	4 x 4 x 1 Strides 2	Sigmoid	64 x 64 x 64 x 1

Figure 4. Architecture of VAE

ing in the aspect and height acquisition. After passing through several layers, they learn a wider range of locational correlations, and after passing through the Fully Convolutional Network (FCN) layers, they are finally connected through a sigmoid activation function as a binary classification. This helps separate good and defective products and receives feedback through a cross-entropy function. The conceptual model of 3D CNN is illustrated in Figure 5.

The 3D CNN checks whether the generated chair is defective. Among the numerous data generated through VAEs, efficient data augmentation requires that the generated data be classified according to the purpose and the selected data be re-entered to continuously generate high-quality chair data effectively. To automate this process, a 3D CNN-based deep learning model was constructed to classify the chair shape and data that were not among the data output to voxel. After repeatedly undergoing the classification process, only filtered, (refined chair-shape) data can enter the input of the VAE and gradually produce accurate chair formation. The main reason for classifying data using the 3D CNN structure is that the input of the dataset is voxel. Because the voxel itself floats grid-type data, a 3D CNN can be used mainly because it does change the shape of the data. Although a model to classify the point cloud again by changing data into a point cloud can be easily built, a chair-forming classification model was built by borrowing a 3D CNN structure to create a model with

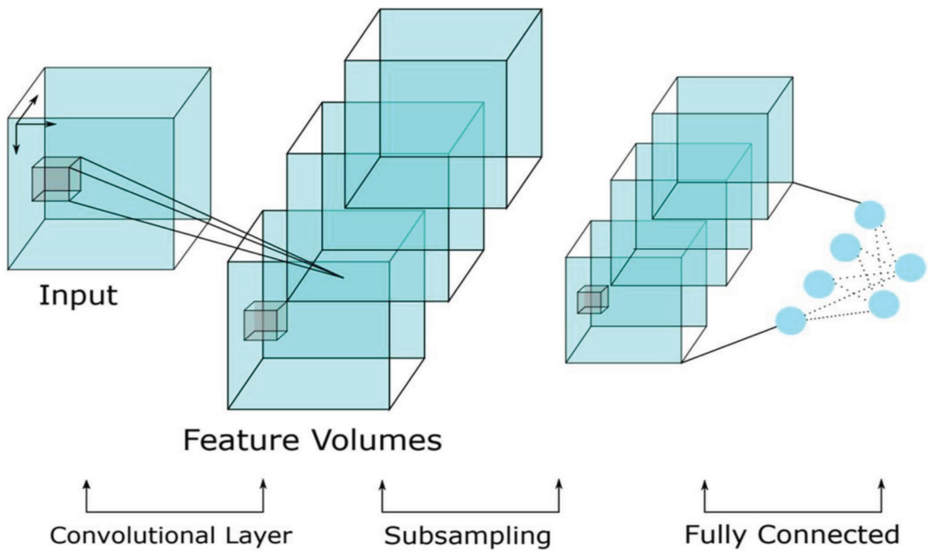


Figure 5. Basic Concept of 3D CNN

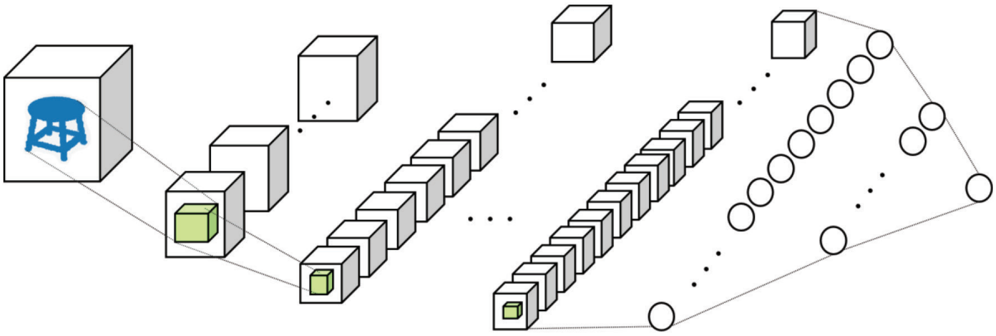
the ability to maintain the shape of the voxel owing to an additional time to change data and increase the size of datasets as shown in Figure 6. The network of the 3D CNN model recycled the encoder portion of the previously utilized 3D VAE model and was completed by gradually reducing the number of nodes to 128 and 16 through the fully connected layer after flattening, and finally placing one node that returns 0 and 1.

3.3. Similarity evaluation

To derive a novel chair model, the differences from the existing chair were compared. The differences are identified based on whether the voxel is filled in the same position between the existing and new shapes [46]. By replacing the space of voxel with a binary, the space occupied by the voxel is treated as 1, and the space that is not treated as 0. The novelty can be determined by calculating the ratio of the combination and intersection of all $64 \times 64 \times 64$ voxels compared to Design's data, which can be used to compare the created data. The overall structure is shown in Figure 7.

3.4. Collaborative design in virtual reality

As the Voxel output is an unfinished form, we use VR collaborative design to quickly create a usable conceptual model. This method derives the final concept more quickly than the expert system design process and the conventional design process. As the overall shape has already been created by AI, the discussion with experts can continue in detail. The



Layer	Parameters	Activation	Output
Input			64 x 64 x 64 x 1
Conv3D – 1	4 x 4 x 64 Strides 2	Relu	32 x 32 x 32 x 64
Conv3D -- 2	4 x 4 x 128 Strides 2	Relu	16 x 16 x 16 x 128
Conv3D – 3	4 x 4 x 256 Strides 4	Relu	4 x 4 x 4 x 256
Conv3D – 4	4 x 4 x 512 Strides 4	Relu	1 x 1 x 1 x 512
Flatten	512		512
Dense	128	Relu	128
Dense	16	Relu	16
Dense	1	Sigmoid	1

Figure 6. Architecture of 3D CNN

Layer	Parameters	Activation	Output
Input			64 x 64 x 64 x 1
Conv3D – 1	4 x 4 x 64 Strides 2	Relu	32 x 32 x 32 x 64
Conv3D -- 2	4 x 4 x 128 Strides 2	Relu	16 x 16 x 16 x 128
Conv3D – 3	4 x 4 x 256 Strides 4	Relu	4 x 4 x 4 x 256
Conv3D – 4	4 x 4 x 512 Strides 4	Relu	1 x 1 x 1 x 512
Flatten	512		512
Dense	50	Relu	50

Layer	Parameters	Activation	Output
Dense	512	Relu	512
Reshape	512		1 x 1 x 1 x 512
Conv3DTranspose – 1	4 x 4 x 256 Strides 2	Relu	2 x 2 x 2 x 256
Conv3DTranspose – 2	4 x 4 x 128 Strides 4	Relu	8 x 8 x 8 x 128
Conv3DTranspose – 3	4 x 4 x 64 Strides 2	Relu	16 x 16 x 16 x 64
Conv3DTranspose – 4	4 x 4 x 32 Strides 2	Relu	32 x 32 x 32 x 32
Conv3DTranspose – output	4 x 4 x 1 Strides 2	Relu	64 x 64 x 64 x 1

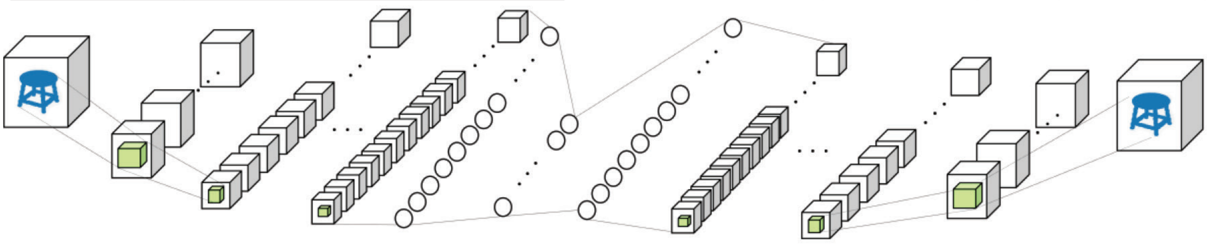


Figure 7. Architecture of autoencoder to evaluate similarity

proposed virtual collaboration design operates as follows. The output of the voxel model should be converted into a form which can be used in a CAD system. In particular, voxel data may not have a partially accurate design because the exact shape of the connection is not described and only a similar chair shape. It is therefore converted into a boundary representation or surface model capable of being used in a CAD system. In this process, the density of the whole form may vary depending on the level at which all voxel cells must be restored. A design team consisting of industrial designers, ergonomic designers and structural designers simultaneously accesses virtual reality and constructs the final concept with the restored CAD data. In this paper, each function outlined above was applied to the design of the chairs.

4. Experiment

4.1. Data

In the experiment, the VAE algorithm learns using 3D data in the form of existing chairs and then creates similar chair shapes through probability distribution. We used the Chair data of Modelnet40 data, which are represented in the form of a 3D voxel that is represented by binary variables on a 3D voxel grid. When each binary tensor points to 1, it means that the voxel is inside the mesh surface, and it is outside the mesh surface when it points to 0. The size of the voxel grid is 64 × 64 × 64, and 989 chairs of Modelnet40 are used (Figure 8) [43].

4.2. Hyperparameter of deep learning model

To train the model we tuned the hyperparameters as follows: (1) VAE for Generation model was trained for 2000 epochs with a batch size of 5, utilizing binary cross-entropy as the loss function, and using the Adam optimizer. Adam, short for Adaptive Moment Estimation, stands as a widely used optimization algorithm in machine learning and deep learning for enhancing the training of neural networks, (2) For 3D CNN for Binary Classification model, we used learning rate of $1\text{x}10^{-3}$, warmup the learning rate until 40 epochs, and keep the batch size at 128, lastly (3) Evaluation by Autoencoder model was trained for 200 epochs with a batch size of 5 using rmsprop as the optimizer and binary cross entropy as loss function.

Figure 8. Representative chair data of ModelNet40

4.3. 3D VAE for Generation

We learned by entering the same ModelNet40 data into the input and output of the 3D VAE model. Consequently, P and σ that were located in the latent part were trained to represent the manifold wherein these data were distributed in an appropriate probability distribution. Thus, the decoder part of the VAE can create unlimited voxel-type chair shapes of various 64,64,64 sizes through random variable input. From Figure 9, it can be seen that there are mixed shapes, with shapes that resemble that of a chair and shapes that do not. It is observed that the shapes are related to the formal chair shape as well as unusual shapes such as wheeled shapes and perforated back pants. This confirms that the model has the ability to learn various characteristics of the existing chair shape and create an imitation.

4.4. 3D CNN For Binary Classification

Several chair shapes created by 3D VAE were classified using 3D CNN, which was trained for binary classification into existing chair shapes. The 3D CNN model was trained with ModelNet40 to identify the chair shape by answering 0 if the input is not a chair or as 1 if the input is a chair. Further, the shapes generated in the VAE were input into the model and

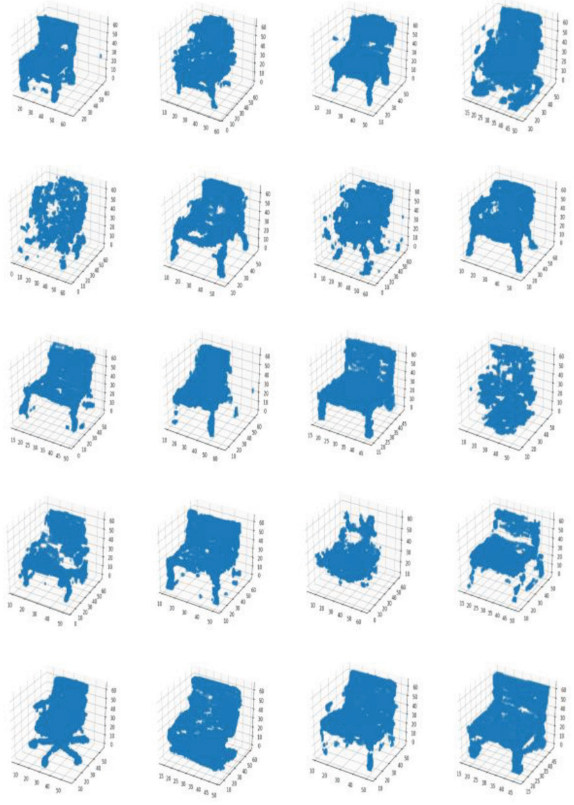


Figure 9. Chair Generated by VAE

indicated. Figure 10 shows the shapes that are classified as a 0. They can be seen that most shapes do

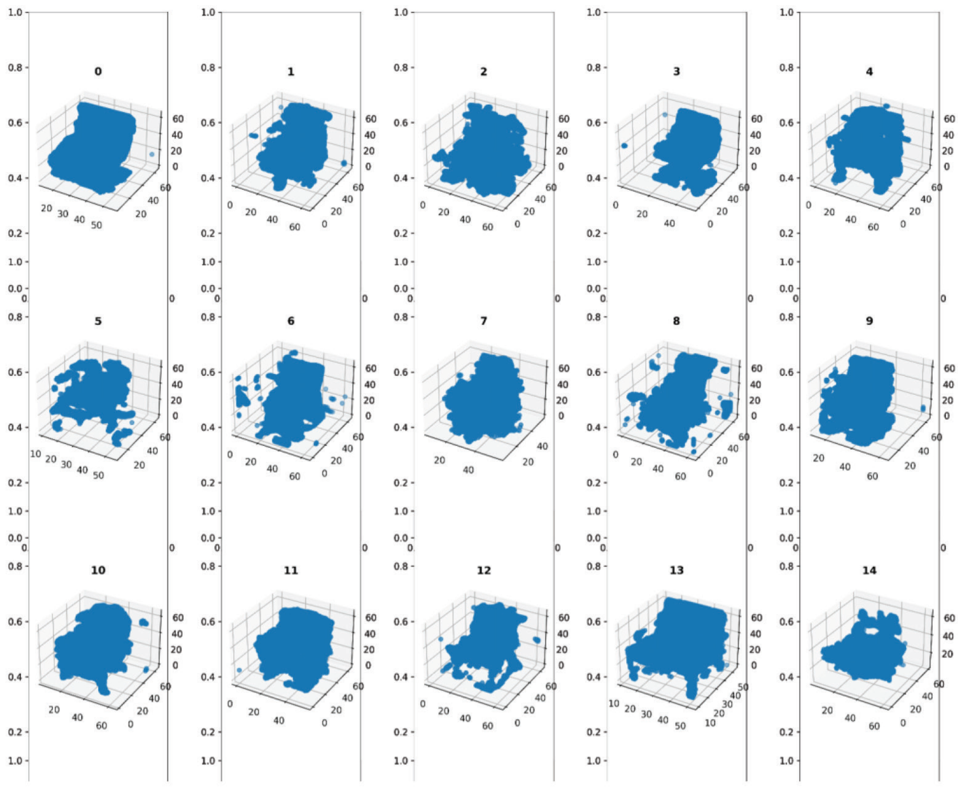


Figure 10. Classified as not chair

not have proper chair shapes. Figure 11 is the collection of the shapes that are classified as 1. Data with relatively intact chair shapes can be observed. Thus, although this model can produce indefinitely, it can also filter out the results of VAEs that are more likely to produce relatively stable data, which enhances the defect management process.

4.5. Evaluation by AutoEncoder

A probability distribution was trained using existing 3D data through 3D VAEs, and similar 3D data was generated from the learned probability distribution. Furthermore, the created data was filtered using a 3D CNN network, rather than focusing on the intended shape.

To determine whether the 3D VAE genuinely generated shapes from the learned probability distribution or simply replicated existing data, an autoencoder model was utilized. ModelNet40 data were input and output to ensure that the input data was duplicated accurately by the autoencoder. Throughout this process, the internal weights of the autoencoder were optimized for the extraction and recognition of features from existing data. Consequently, if input data with characteristics different from the existing dataset were fed into the autoencoder, it might face difficulties in identifying new features, as it was primarily trained on existing shapes. As a result, it might not be capable of reproducing the exact shape of the input data.

The results of the autoencoder verification are presented in Figure 12 (Similar to existing designs) and Figure 13 (Different from existing designs). Therefore, the evaluation of novelty can be carried out by introducing the 3D VAE-generated data into the autoencoder trained with existing 3D data and comparing it with the restored data.

The different chairs generated are depicted in the graph between novelty and cost as shown in Figure 14 As the shapes of the input data and restored data are different from each other, data with different characteristics from the existing data may be evaluated.

The Intersection of Union (IoU) index was used to quantify this factor [46]. The formulation is shown in Figure 15 The number of voxels from the total voxels was determined by dividing the number of intersections by the number of voxels occupied by the two datasets. The lower the IoU value, the more likely it is that the restored data were generated.

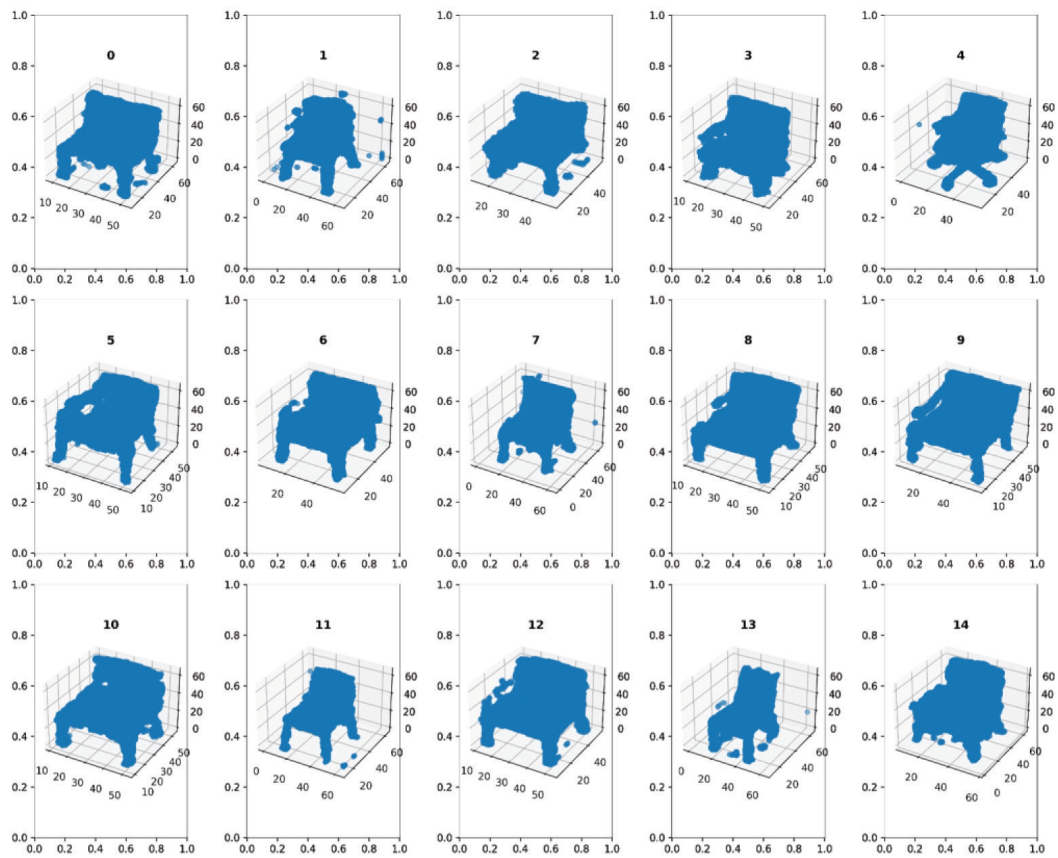


Figure 11. Classified as chair

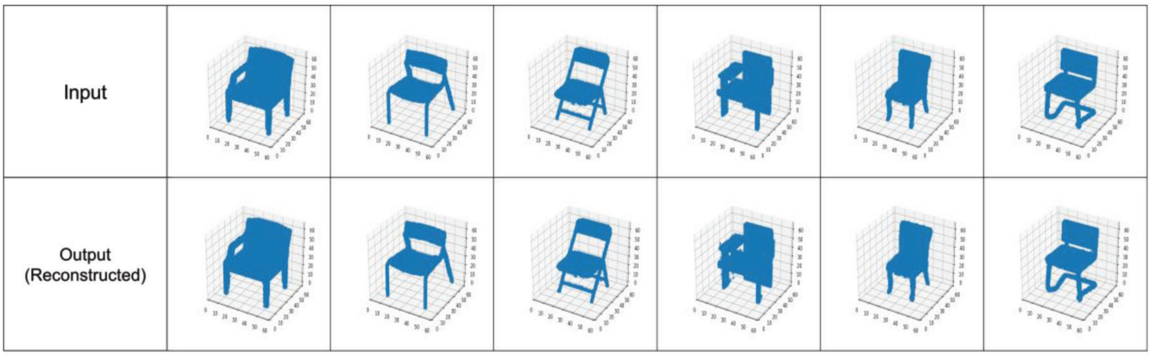


Figure 12. The results of reconstructed images that are similar to previous designs

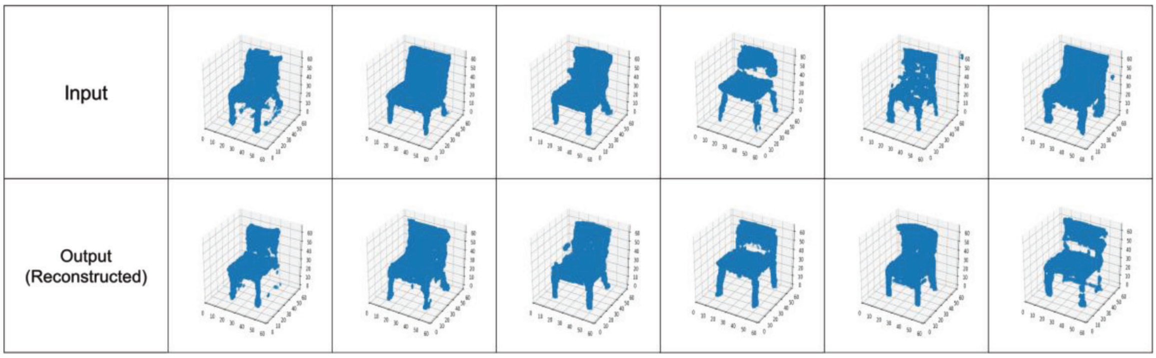


Figure 13. The results of reconstructed images that are different to previous designs

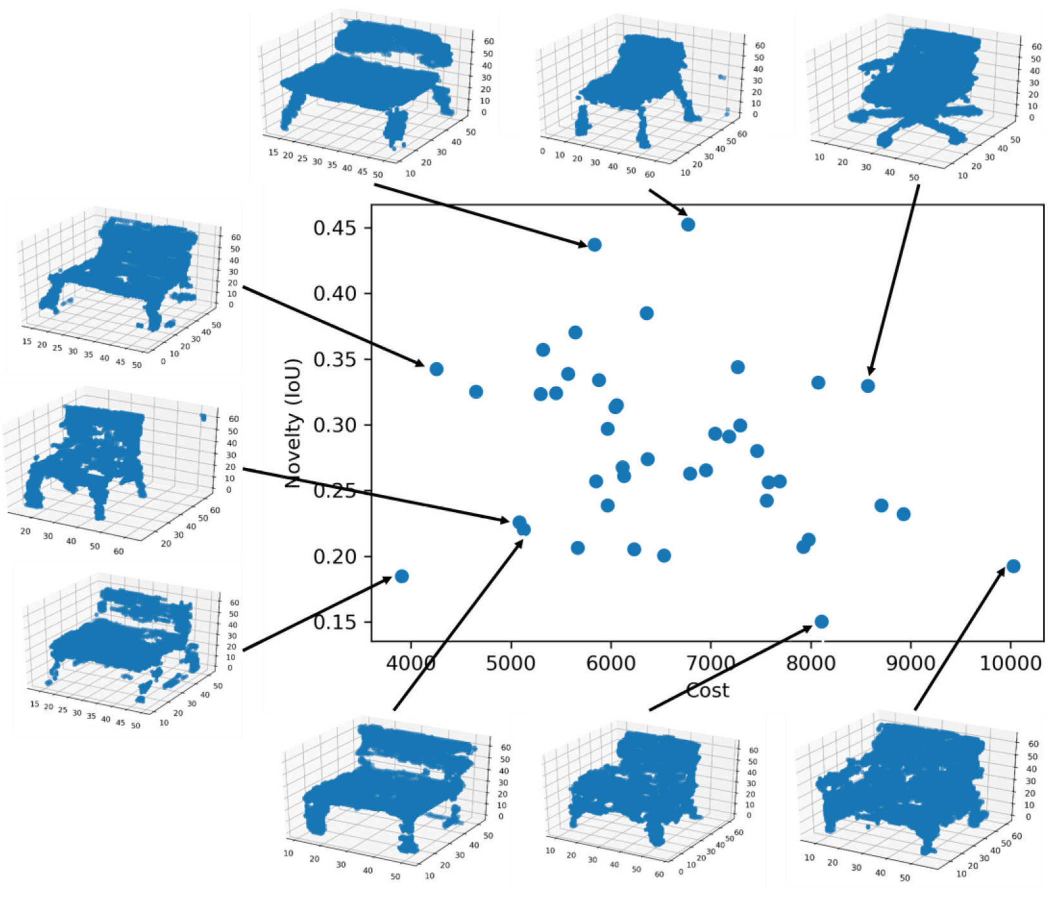


Figure 14. Cost and Novelty Graph

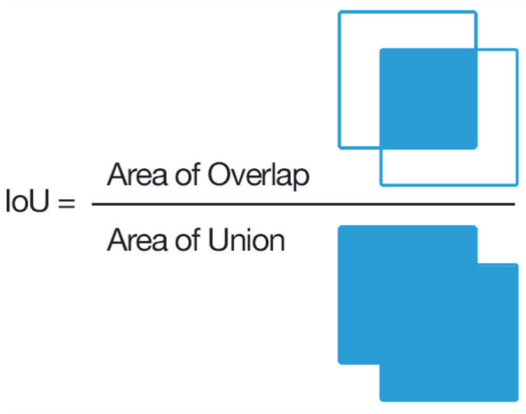


Figure 15. Concept of IoU

4.6. Collaborative design in virtual reality

Next, the collaborative design of the virtual reality makes the overall Voxel shape as a final concept model. More precisely, the final concept model is complemented by the conversion of Voxel to STL and by the recreation of shapes by design experts. In this experiment, the shape that received the highest score in Novelty was converted to STL and imported into collaborative VR. Each voxel is represented as the floating-point number. Thus, we assigned the threshold value for cells to transform voxels into a form in STL. This value varies from 0.0 to 1.0, and the STL form comes out with three threshold values of 0.1, 0.7 and 0.9. If you enter a number too small, the shape output will be a sort of block. In this experiment, the first form of the Figure 16 is the output with a threshold of 0.1. The collaborative virtual space of Gravity Sketch supports the analysis of STL forms from different angles. Several designers are able to check out unique parts of virtual reality. The new design of the chair had unusual shapes for legs, armrests, and corners of the support. The designer recreated a new model of connected volume chair with a virtual reality joystick of the voxel shape. The bottom right of Figure 16 is the result of the final concept step.

5. Discussion

In this study, we proposed a new approach for an automatic model to create new designs that are similar to previous designs. In actual manufacturing sites, many parts are automated, and deep learning used in most process. However, in the areas that require human intuition and creativity, such automation is not achieved, and thus, it cannot keep up with the ever-changing product trends and cannot keep up with

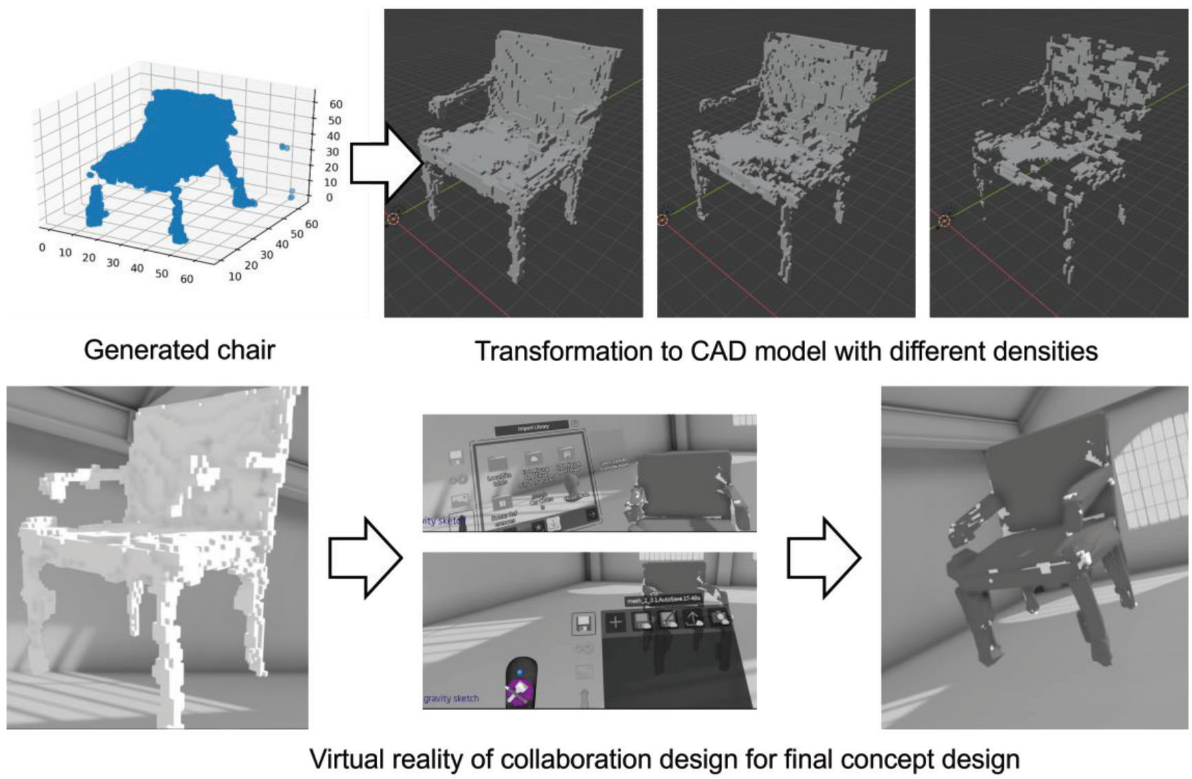


Figure 16. Experiment in virtual reality for collaborative design

the future manufacturing keywords of multi-variety, small-volume production. Therefore, we solved this problem by through generation for deep learning by creating an automated device that mimics human intuition and creativity in design. Existing studies are focused on generating 2D images using GAN and VAE, and 3D research has been limited to simple segmentation with no application purpose. In this study, generative deep learning was used in the product development process to create an automation model that can replace the overall design and design parts in actual manufacturing sites. By referring to the design of previously sold products, it is possible to create new things that have not yet been found in the learned probability distribution, while maximizing the existing characteristics. It is also possible to create new shapes that humans have never thought of. We summarize the comparison with different types of design generation methods in Figure 17.

However, this model is somewhat unstable, and unintended shapes may be created. In the actual process, this shape, which corresponds to a defect, needed to be filtered out manually in the past. However, it was possible to filter the defect-detection process using the 3D CNN deep learning model. The model was trained to classify the existing chair shape and other shapes, and it was judged whether the generated shape could be used as a chair. The filtering function was performed through the ship after creation. We expect the VAE to create shapes that are not designed by humans.

However, the VAE sometimes generates shapes that look exactly like the existing ones. Therefore, to verify the creativity of the shape generated by the VAE, a separate autoencoder model is trained and verified. The autoencoder model was trained to perform the function of restoring the shape of the existing chair data by inputting the existing chair data and using the same chair data. By inputting the shape that is generated from the VAE into this model, it is judged whether it is restored in the same way as the existing chair data, and the similarity with the existing chair data is studied. This was quantified using the IoU value obtained in an existing 2D segmentation vision study. Through the automation of a series of design, defect detection, and evaluation processes, the focus on automation was extended to processes that required human intuition and creativity, thereby enhancing production efficiency and preparing for the era of small-lot production of multiple products.

6. Conclusion

This study converts rapidly generated customer reviews into quantitative numbers which makes it possible to determine which shape of the product is the most preferred through numerical values. In addition, the use of the shape recognition model numerically indicates the types of shapes that are mixed along with the proportions, and it was possible to predict the preferred shape of customers by linking it to the review data. However, the limitation of the proposed method is that the back propagation of 3-stage learning models is disconnected. The disconnected learning leads to slow training and requires for more dataset than 1-stage model like GAN model (Generative Adversarial Network). On the other hand, Voxel data is sparse matrix and let 3-dimension neural network trains very slowly. The future works are the integration of all deep learning models to connect all back propagation and the pre-processing for reducing the space data of Voxel product data in order to apply GAN model. The proposed method has 3 stage deep learning models and disconnected the back-propagation of the models.

In conclusion, the proposed framework for generative design of 3D chairs represents an innovative departure from conventional approaches. By utilizing a variational autoencoder model based on a 3D

	Modify existing shapes	Generate new shapes	Classify given shapes	Evaluate creativities of new shapes	Stage	Method
Parametric Design	O (All dimensions)	X	X	X	Detail design	Given equations
Topology Optimization	O (Only boundary conditions)	X	X	X	Detail design	Finite element method
3D Recognition	X	X	O	X	Not available	Deep learning model
3D Generation	O	O	X	X	Concept generation	Deep learning model
Proposed method	O	O	O	O	Concept generation	3-stage Deep learning models

Figure 17. Comparison with different types of design generation methods

convolutional neural network, the longstanding research gap in the field has been effectively addressed. This approach not only enhances the efficiency and automation of 3D product generation but also significantly reduces the reliance on human involvement and decision-making when compared with established methods. Furthermore, the introduction of an automated deep learning model to appraise the uniqueness of generated designs redefines the standards for evaluating generative designs.

The proposed approach extends seamlessly to other product categories without limitations. By leveraging the existing product-form database, it generates new shapes through a VAE trained on pre-existing designs. Furthermore, a 3D CNN model is developed to recognize product types, laying the groundwork for an automated design system that can identify multiple product images in 3D and derive new recommended shapes. This underscores the framework's potential for application in various product domains by retraining the 3D CNN model on new datasets and employing the VAE to generate novel designs based on the established product-form database, providing a versatile and automated design solution for diverse product categories.

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