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Analysing the Effectiveness of a Generative Adversarial Network Model for the Creation of New Datasets of 3D Human Body and Garment Sizes in the Clothing Industry

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ABSTRACT

Apparel designers and manufacturers are now using virtual garment simulation technology to evaluate 3D prototypes in virtual environments, which reduces the waste of raw materials in the sampling process. With the immediate visualization of the 3D prototypes, designers and manufacturers can communicate with each other to adjust the virtual garments seamlessly, and thereby the production process has become simplified using simulation technologies. Nevertheless, there are several limitations to the current practice. Apparel companies do not have a universal sizing standard, which leads to problems because customers need to identify their sizes in different stores, and a high return rate is expected in this case. Additionally, the psychological preferences of the wearers are not taken into account when evaluating fit. Production teams in apparel companies are only concerned with the physical fit of their targeted customer groups; they neglect the actual will of a specific customer. For example, some may like to wear oversized garments, and a just-fit size is not what they want. It is valuable to find a method to adapt the psychographic orientations of the customers to the design and production process of a garment. Therefore, we had proposed our method for developing a virtual garment fitting prediction model to predict the garment pattern parameters with anthropometric data and psychographic orientations of subjects, and previous work had proven that the prediction model has high accuracy and stability. Nevertheless, a limitation was found in that the subject data was difficult to obtain. It would be advantageous if there were more data to test in the prediction model. Thus, this study proposes the build of generative adversarial network (GAN) models to generate new body dimension data and garment parameter data. The new datasets produced by the GAN models would be favourable for an improvement in the virtual garment fitting prediction model with more training and testing data to be processed. Moreover, the synthetic datasets can be employed by designers to do research in their garment evaluation process since they have more data on similar body dimensions and preferred garment sizes to assess. A more comprehensive appraisal of the garment fit can be attained by this approach, which accelerates the design process in the apparel production stage.

Keywords: Body measurements and psychographic preferences, Generative adversarial networks, 3D virtual clothing simulation

INTRODUCTION

Apparel designers and manufacturers are currently using 3D technology to assist in the production of garments, where body scanners and digital rendering software are employed in the process. Though technological innovations have benefited the apparel industry and customer satisfaction has also been enhanced with more efficient tools, some limitations are still observed. First of all, each garment brand has its own sizing system, which leads to confusion among customers when they purchase clothes in different stores and creates a high return rate at the end. Moreover, the sizing systems of the brands are only defined for physical fit. Customers' psychographic orientations toward wearing a garment are neglected in this case; for example, customers have different tastes towards fashion. In a prior suggestion, we recommended employing an artificial neural network (ANN) model to forecast the parameters of clothing pattern design for manufacturers and designers during the pre-production stage (Chan et al., 2022; Dik et al., 2023). By giving the final users the ideal fit, it facilitates mass customization and customized orientation, and eventually, new sizing methods are delivered to enhance end-user satisfaction with clothing fit and create better ease preference charts. Nevertheless, a limitation was found in that the number of records was small (i.e., 120 records) due to the difficulty in finding subjects to participate in the body scan and survey sessions. Even though the coefficient of determination (R^2) for the model's effectiveness was significant, it is still preferable to add more records and some special cases for extremely large or small sizes. Over-training is also another issue that may happen in the previous algorithm with large training iterations due to the limited training data (Yin et al., 2003). Therefore, to come up with a solution, using the generative adversarial network (GAN) model seems to be effective to produce large tabular data synthesis from our obtained amounts. The data creation method in this study used a variety of open-source GAN models, notably the well-known CTGAN and CopulaGAN models. Those synthetic data would include anthropometric data and cognitive inclinations. Two ANN models were trained with the synthetic data generated by the two GAN models, respectively, and in contrast, the testing data would be using the real data from the respondents in the project (i.e., 50 sets). At the end, the performance and computational efficiency of the ANN model were evaluated to determine its significance.

METHODS

The objective of this study is to assess how well new synthetic datasets produced using GAN models can be used to train an ANN prediction model for parameters relating to clothing patterns. Overall, there were three sections to conduct the study. The first part piloted the synthetic data generation with the chosen GAN models. They produced anthropometric data, survey parameters for retrieving the psychographic orientations of a person in choosing garments and fitted garment pattern parameters for design sketching. Table 1 is a list of column headers for the data. The second part would apply the synthetic data from each GAN model to train two prediction models. The principle of the ANN models is to forecast the most-fit garment pattern parameters for the garment designers when they obtain the data from their customers. With real data gathered from the body scan sessions with participants, the last phase would assess how well the synthetic data produced by the GAN models performed. In this study, short-sleeved shirts are the garment type to be considered in the development.

As in our prior work, we had 120 subjects who were 18 years of age or older for body scans and surveys to assess body dimension data and psychological orientation in fashion and clothing selection, respectively. Due to the GAN model's potential to generate realistic data and the restriction on subject engagement, 70 sets of real data were used to build the 500 dummy records, while the remaining 50 sets were used for validation. Two GAN models for synthetic tabular data generation, which are CTGAN and CopulaGAN, were available as open-sourced libraries. Many recent articles have indicated these algorithms for generating synthetic text data (An et al., 2021; Bourou et al., 2021; Gupta et al., 2021; Habibi et al., 2023; Han et al., 2022). CTGAN uses GAN to shape the dispersal of tabular data and choose the required number of sample rows (Huang & Wu, 2022; Xu et al., 2019), while CopulaGAN is a model variant that simplifies the CTGAN model training by using Cumulative Distribution Function (CDF)-based transformation

Table 1. List of column headers for synthetic data (short-sleeved shirts).

Anthropometric data		
Gender	Height	Weight
Across Back	Armscye	Bicep
Centre Back to Hip	Centre Back to Waist	Chest
High Hip	Hip	High Point Shoulder to Bust Point
High Point Shoulder to Hip	High Point Shoulder to Waist	Inseam
Natural Waist	Neck	Outseam
Pant Waist	Pant Waist Height	Rise Back
Rise Front	Rise Total	Shoulder Back
Sleeve Length Back Neck	Sleeve Length HPS	Sleeve Length Shoulder
Thigh	Under Bust	
Survey Parameters to Obtain Psychographic Orientations in choosing garments		
Occupation	Monthly Income	
Age Range		
Parameters related to Brand Consciousness	Parameters related to Sensational	
Parameters related to Practical	Parameters related to Informational	
Garment Pattern Parameters for Design Sketching		
Neck Drop- Back	Neck Drop- Front	
Neck- Width	Shoulder- Length	
Across Shoulder	Front Length from HPS	
Back length from CB	HPS to Underarm	
Across Chest	Across Waist	
Side- Length	Bottom Edge Opening (Sweep)	
Sleeve Length from CB (3 Point Measure)		

(Bourou et al., 2021). The GAN and ANN models were developed using the Python language, where Synthetic Data Vault (SDV) and PyTorch packages were employed. Last of all, to evaluate the ANN model trained with the synthetic data, coefficients of determination (R^2) for the 50 testing sets would be presented to show the effectiveness of the ANN model.

RESULTS AND DISCUSSION

Time Complexity in GAN and ANN Models

Overall, the models' time complexity for creating synthetic data and training with it was reasonable. CTGAN and CopulaGAN spent around 10 seconds producing synthetic records into two Excel files, while the training time for the ANN models for the two synthetic datasets was between 3 and 5 minutes. It is anticipated that time complexity won't be an issue in the future, even if data size increases.

Option in Flattening ANN Structure

In our prior work, the ANN structure was in 7 hidden layers to obtain high prediction accuracy since the model handled multiple inputs and outputs in the training process and the amount of data (i.e., 70 training sets) was not sufficient to train a high-quality model in a few epochs. Therefore, the proposed method of increasing the number of data points using the GAN model created 500 synthetic data points and helped reduce hidden layers in the ANN model. The current ANN model was found to be effective with only one hidden layer. Despite a dramatic increase in hidden neurons as compared to the preceding ANN model, the training time remained relatively constant even as the data size grew. The structure of the ANN has improved and is eventually supportive of a larger dataset.

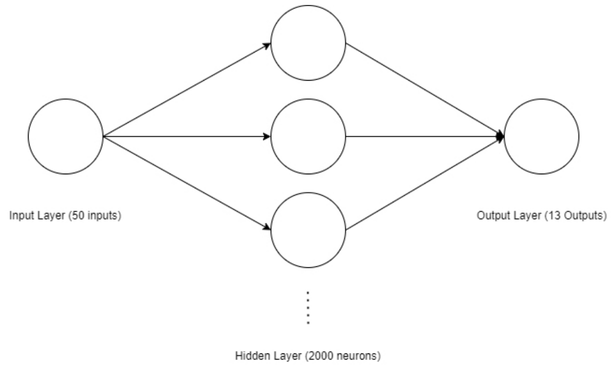

Figure 1: ANN structure in the model development.

Prediction Accuracy From ANN Model Using Synthetic Data

The ANN model was employed to predict the garment pattern parameters for designers and manufacturers to apply in 3D prototype software. The performance of the model was so effective that it had a significant R^2 for both training (synthetic) and testing (real) data. The model parameters are indicated in Table 2. As mentioned before, two synthetic datasets were generated by CTGAN and CopulaGAN, each producing 500 records. Five rounds of training and testing were performed for each dataset. R^2 for the training data generated using CTGAN were between 0.65 and 0.75, while that generated using CopulaGAN were between 0.6 and 0.8. On the other hand, when the ANN model was trained with CTGAN's data, R^2 for the testing were between 0.96 and 0.99, and in the opposite case, R^2 for the testing data were between 0.87 and 0.99 when the ANN model was trained with CopulaGAN's data. The synthetic data generated by two GAN models did not differ much from one another when they were applied to the ANN training. Table 3 presents the findings from the training cycles.

Table 2. Model hyperparameters for the ANN model using synthetic data.

Hyperparameters	Values
Activation function	Rectified Linear Unit (ReLU)
Input parameters	Psychological Orientation of Consumers' Options of Fitting Factors Anthropometric Data
Output parameters	Garment Pattern Parameters for Design Sketching
Hidden layer	1
Hidden neurons in hidden layer	1500
Number of training rows	500
Number of testing rows	50
Learning rate	0.001
Loss function	Mean Squared Error
Optimizer	Adaptive Moment Estimation (Adam)

Table 3. R^2 Values from ANN training and testing.

ANN Model Trained by CTGAN's data		ANN Model Trained by CopulaGAN's data	
Round 1			
Training	Testing	Training	Testing
0.6753	0.9894	0.7383	0.9910
Round 2			
Training	Testing	Training	Testing
0.6514	0.9962	0.6766	0.8713
Round 3			
Training	Testing	Training	Testing
0.7478	0.9670	0.7879	0.9919
Round 4			
Training	Testing	Training	Testing
0.7405	0.9732	0.6041	0.9114
Round 5			
Training	Testing	Training	Testing
0.6862	0.9877	0.7834	0.9987

DISCUSSION FROM THE RESULTS

The performance of the ANN model suggested that the synthetic text generation models (CTGAN and CopulaGAN) had nothing in common when it came to ANN model training because the R^2 values for both training and testing were significant. The advantage of CopulaGAN as a variation of CTGAN is said to be easier data learning (Anande et al., 2023; Bourou et al., 2021; Desai et al., 2022), though it has little impact in our case. There was no significant change from the control in this instance. Also, it was found that data generation for the tabular data synthesis was relatively simple for our study, and those produced data can be utilized if the number of participants is insufficient for training the ANN model.

CONCLUSION

This study has evaluated the potential of using GAN models to generate tabular data synthesis when the data is scarce to train or test the ANN prediction model. Our prior work has proposed developing a prediction model for garment pattern parameters based on consumers' preferences for wearing apparel and their body dimensions. However, it was challenging to recruit subjects, and only limited real data were acquired. Therefore, CTGAN and CopulaGAN were assessed to produce 500 dummy data points to replicate the training data for the prediction model. Results indicated that synthetic training data were effective in training the model, and the prediction accuracies were satisfactory for the five trials. When the real data is insufficient, it is encouraged to use the approach of multiplying tabular data. Given that the current progress primarily focuses on short-sleeved shirts, in future work we will adapt the training data synthesis to the four apparel types (long-sleeved shirts, short-sleeved shirts, blazers, and long pants) when subject shortages continue to exist.

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