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Original Article

Deep Learning-Based Body Shape Clustering Analysis Using 3D Body Scanner: Application of Transformer Algorithm

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Abstract

Background: This study was conducted to perform deep learning-based body shape cluster analysis using 3D Body Scanner.

Methods: For this study, 54 variables were measured using 3D Body Scanner on 366 adult men and women at Korea National Sport University in 2022. Transformer learning and dimensionality reduction models were used to perform cluster analysis on the measured data. Mann-Whitney test and Kruskal-Wallis test were applied to compare the principal component differences of new scale characteristics, and all statistical significance levels were set at .05.

Results: First, among the two methods for classifying body types, the transformer algorithm had a higher performance in body type classification. Second, in the classification of body type clusters, two clusters, endomorphic body type and ectomorphic body type, were divided into six clusters, two for cluster 1 and four for cluster 2.

Conclusion: The six clusters provide more granular information than previous body type classifications, and we believe that they can be used as basic information for predicting health and disease.

Keywords: Deep learning; 3D Body Scanner; Transformer algorithm; Body shape

Introduction

The classification of human body types has been the subject of much interest and research since the ancient Greek era. Body type is a type of body shape that is formed by environmental influences through genetic constitution and diseases, and studies are conducted by categorizing it into occupational body type and sports body type (1). Therefore, in the case of physique and constitution, it is determined through genetic factors, and in the case of posture, it is shown to be influenced through environmental factors.

Hippocrates of Greece was the first to introduce body type classification, categorizing it into habitus phthisicus and habitus apoplecticus (2, 3), and since then, many scholars have studied body type classification from their own perspectives. Specifically, we can introduce the Sigaud classification (respiratory type, digestive type, muscular type, cerebral type), the Kretchmer classification (pyknischer type, leptosomer type, athletischer type), and the Heath-Carter somatotype, which is currently the most used method. Heath-Carter's somatotype was introduced in 1967 and categorizes human body types into endomorphy, mesomorphy, and ectomorphy, and is currently applied in various fields, and interest in human body type classification continues to grow.

Previous studies on body shape classification using Heath-Carter have been conducted to predict diseases, identify nutritional status, and differentiate athletes by sport (4-6) and predict diseases (7, 8). Each of these studies has yielded features in their respective fields, and we can see that body shape can be used to generate a wide range of information.

Nevertheless, there are several limitations to Heath-Carter's somatotype as it is currently commonly applied (9). Report difficulties in ensuring the accuracy of the measurement process and results, such as the lack of experts to ensure the reliability of anthropometric measurements, unreliability of measurements in overweight subjects, problems with subjects removing their tops or bottoms, and problems with examiners contacting subjects to measure them.

In recent years, with various efforts, digitalized tools have been developed as modern society evolves. 3D Body Scanner can be introduced as a way to solve the aforementioned problems of reliability and contact. 3D body scanners have been used in many fields for anthropometric measurements (10-12) and because 3D body scanners utilize a light source camera for measurement, they have the advantages of harmlessness to the human body, simplicity of measurement, and large amount of data generation (13).

Heath-Carter's somatotype also has the advantage of classifying body types by considering width (upper arm, femur), circumference (upper arm, calf), subcutaneous fat (triceps, subscapularis, humerus, and calf), height, and weight variables. The problem with these methods is that the formulas are based on past body shapes and don't account for a wide range of measurement variables (9). For example, in the case of 3D Body Scanner, in addition to the aforementioned variables, it measures more variables such as height (knee height, chest height), circumference, and width for each part, so it has the advantage of considering more details to classify body types. In addition, there is a need for a new body type classification because human body types are changing in modern society.

On the other hand, the recent methodology for classification can give rise to the field of artificial intelligence, introduced as a powerful methodology for analyzing large amounts of data and complex patterns (14). In the case of artificial intelligence, it is applied to perform predictably in a wide range of areas, not only in the field of sports. Therefore, we aimed to perform deep learning-based body shape clustering analysis using 3D Body Scanner. One of the deep learning algorithms applied in this study, the Transformer algorithm, is reported to be more accurate than past clustering methodologies (14), so this study aimed to contribute to improving classification accuracy by utilizing it. This result is expected to be utilized as a more appropriate body type classification methodology in the current era through a new body type classification, and it is expected that this result can be used to predict disease prediction, nutritional status, and sports classification in the future.

Methods

Study participants

Adult men and women living in Seoul, South Korea in 2022 were selected as participants, and they were asked to participate only if they were willing to participate voluntarily after the purpose and contents of the study were explained to them by the principal investigator. At this time, those who refused to undress during the 3D Body Scanner measurement and those with limited mobility were excluded from the study, and the study was conducted after receiving informed consent.

Finally, there were 366 participants in the study, and the characteristics of the participants are as follows (Table 1).

Table 1: Study participant characteristics

Gender	Age(yr)	height(cm)	Weight(kg)	BMI (kg/m)2
Male(n=214)	37.7±16.83	174.2±7.79	77.1±14.23	25.3±4.03
Female(n=152)	42.8±17.76	161.9±7.21	62.2±12.05	23.8±4.74
Total(n=366)	39.8±17.38	169.1±9.69	70.9±15.26	24.7±4.40

Study participants Measures and study variables

The 3D Body Scanner is a device that extracts 3D images of the body while the camera module rotates the measurer 360 degrees to measure the circumference, cross-sectional area, and volume of height and body parts. Therefore, in this study, a 3D Body Scanner (Model PFS-304, PMT innovation) was used to measure the physical characteristics of the study participants. In addition, to reduce measurement errors, men wore a top and sports leggings, and women wore a sports top (underwear) and sports leggings, and wore a hat because the back of the neck should be exposed during measurement. There are 54 body data extracted through 3D Body Scanner as shown in (Table 2), and finally 57 variables were used as research variables in this study by adding age, gender, and BMI.

Table 2: Variables Extracted via 3D Body Scanner

NO	Variables	NO	Variables	NO	Variables
1	WCR	19	Shoulder Circumference	37	Navel-waist cross-sectional area
2	WHR	20	Chest Circumference	38	Belly button cross-sectional area
3	WHtR	21	Breast Circumference	39	Hip cross-sectional area
4	THR	22	Waist circumference	40	Cross-sectional area
5	Nape Height	23	Navel waist Circumference	41	Thick Thigh Cross Section
6	Shoulder height	24	Belly button Circumference	42	Mid-thigh cross-sectional area
7	Chest height	25	Hip Circumference	43	Knee cross-sectional area
8	Breast height	26	Girth	44	Calf cross-sectional area
9	Waist height	27	Bold Thigh Circumference	45	Total
10	Navel waist height	28	Mid-thigh circumference	46	Shoulder Volume
11	Belly button height	29	Knee Circumference	47	Chest Volume
12	Hip Height	30	Calf circumference	48	Upper Abdominal Volume
13	Height	31	Arm circumference	49	Lower abdominal volume
14	Boldt high height	32	Cross-sectional area of the back of the neck	50	Thigh Volume
15	Mid-thigh height	33	Shoulder cross-sectional area	51	Calf volume
16	Knee height	34	Chest cross-sectional area	52	Abdominal Body Fitness
17	Calf height	35	Breast cross-sectional area	53	Kidney
18	Back of neck Circumfer-ence	36	Waist cross-sectional area	54	Weight

Click Transformer

Transformer was first proposed by Vaswani et al, and it has shown excellent performance in natural language processing (14). It is organized around the Attention mechanism instead of the RNN mechanism to compensate for the problems of the existing recurrent neural network, Seq2Seq algorithm. The transformer consists of an encoder and a decoder, but only the encoder part of the transformer was utilized in this study.

The specific architecture of the transformer encoder part is as follows. First, the embedded data is merged with the location information. Second, the vector is divided into query, key, and value before entering the self-attention structure, and the query and key are internally softmaxed to produce a weight. This weight is eventually multiplied with value to produce a vector value that reflects the weight. This is the self-attention process of the transformer, and it is fed into the multi head attention structure to repeat the process. Third, through the skip connection technique, the output that has passed the multi head attention is added to the existing value that has not passed the multi head attention to preserve the existing value and perform normalization. Fourth, it goes through the feed forward process and adds it to the existing value through skip connection again. Repeating this process N times is the transformer encode structure.

Data processing method

For this study, the data handling methodology consisted of the following steps. First, the 57 study variables were standardized for gender. This was done to prevent gender from affecting the classification of body types, and the standardization was done with Z-score. Second, to understand the performance of clustering in this study, two clustering models were created to evaluate the performance. Model 1 is a model that reduces the dimensionality of the raw data by principal component analysis and applies the k-means algorithm. Model 2 is a model that reduces the dimensionality of the raw data by principal component analysis and applies the k-means algorithm after transposer embedding. The reason for reducing the dimensionality by principal component analysis in both models is to solve the problem that distance-based clustering algorithms, such as the k-means algorithm, may perform poorly when there are many independent variables. In Model 2, Transformer utilized the BERT model developed by Google. The processor of both models is shown in (Fig. 1).

Third, to evaluate the performance of the model, the silhouette index was calculated by setting the clusters from 2 to 9. The formula for calculating the silhouette index is as follows (Equation 1). The average value of the distance to the data in the cluster to which it belongs and is the minimum value of the average distance to the data in the cluster to which it does not belong. The higher the silhouette index, the better the model is evaluated. Fourth, we conducted a principal component analysis using the raw data to compare physical characteristics for clustering outcomes. This was done to solve the interpretation difficulty of comparing 55 physical variables for clustering outcomes. Fifth, we compared the principal component differences of the neonatal characteristics according to the clustering results. We applied the non-parametric Mann-Whitney test and Kruskal-Wallis test to test for differences. This was done to address the assumptions of normality and homogeneity of variance underlying parametric tests. All statistical significance levels were set at .05, and the program was developed using Python 3 and SPSS ver. 25.0 (IBM Corp., Armonk, NY, USA).

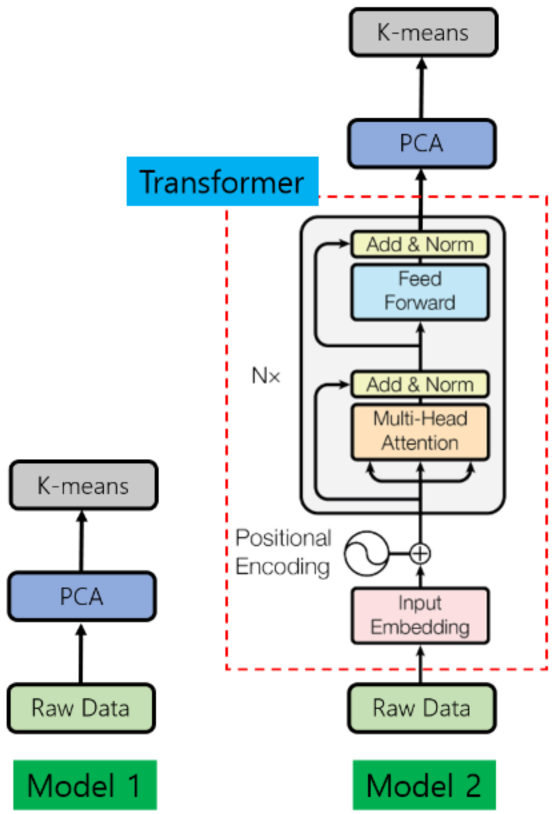

Fig. 1: Processes in the model

Ethics approval and consent to participate

This study was performed in compliance with the Helsinki Declaration guidelines and approved by the Ethical Review Committee of Korea National Sport University (Research Ethics No.: 1263-202204-HR-015-01). Each participant was voluntary, informed of the study objective and context and provided their written informed consent regarding privacy and information management policies.

Results

Silhouette index calculation result by clustering by model

We evaluated the performance of two models to classify body types: Model 1 is a model that reduces the dimensionality of 57 variables by principal component analysis and applies the k-means algorithm, and Model 2 is a model that pre-processes 57 variables with the transformer algorithm and expands them to 760 variables, then reduces the dimensionality by principal component analysis and applies the k-means algorithm. To evaluate the performance of the model, the number of clusters (k) was selected from 2 to 9, and the silhouette index was calculated, and the result is shown in (Table 3).

As a result of applying k-means to a total of 366 cases, both models showed the highest silhouette index when the number of clusters was set to 2, and Model 2 seemed to perform better than Model 1. In addition, k-means was applied to confirm the detailed classification of cluster 1 and cluster 2 based on the results of the first classification. The silhouette index was higher in model 2 than in model 1, indicating that the performance of model 2 was higher. Therefore, model 2 was selected as the final model in this study, and the optimal number of clusters was set to 2 in the first round, 2 for cluster 1, and 4 for cluster 2 to classify body shapes.

Table 3: SILHOUETTE INDEX calculation results for selecting the optimal cluster size for each model

Clustering (k)	Primary		Secondary			
	Model 1	Model 2	Model 1-1	Model 1-2	Model 2-1	Model 2-2
2	0.398	0.524	0.407	0.380	0.455	0.403
3	0.346	0.416	0.360	0.356	0.377	0.416
4	0.322	0.394	0.342	0.342	0.399	0.427
5	0.327	0.384	0.360	0.346	0.425	0.393
6	0.309	0.375	0.340	0.336	0.423	0.356
7	0.320	0.378	0.360	0.366	0.434	0.377
8	0.325	0.385	0.379	0.342	0.411	0.391
9	0.297	0.363	0.374	0.341	0.385	0.375

Principal component analysis results for comparing body characteristics based on clustering results

As an unsupervised learning model, the k-means algorithm is a distance-based algorithm that can classify similar data into a type of cluster, but the type of cluster is subjective to the researcher. In this study, we tried to compare 55 physical variables between clusters to determine the characteristics of the results of the clusters. However, considering the difficulty of interpretation due to the large number of variables, principal component analysis was conducted to reduce the 55 variables, and 6 components were extracted as a result of the initial principal component analysis, but WCR, chest circumference, and shoulder circumference variables that did not meet the criteria of loading value of 0.4 or more were deleted, and finally 5 components were extracted, as shown in the following (Table 4), and the cumulative variance of the 5 components was 87.0%.

Table 4: Principal component analysis results for comparing body characteristics based on clustering results

Component	Variables	Unique variance	Key Variables
Component1	23	38.4	Waist circumference, Upper abdominal volume, Waist cross-sectional area, Abdominal fit, Humidification volume, Belly waist cross-sectional area, Lower abdominal volume, Belly button cross-sectional area, WHtR, Bust cross-sectional area, Breast circumference, BMI, Volume, Weight, Hip cross-sectional area, Hip cross-sectional area, Shoulder volume, WHR, Hip circumference, Breast cross-sectional area, Arm circumference
Component2	13	24.5	Shoulder height, height, knee height, mid-thigh height, nape of neck height, chest height, below navel height, waist height, below belly button height, thick thigh height, hip height, breast height, hips height
Component3	11	16.9	Bold Thigh Circumference, Bold Thigh Area, THR, Mid-Thigh Circumference, Hip Circumference, Mid-Thigh Area, Thigh Volume, Knee Circumference, Knee Area, Calf Volume, Waist Circumference
Component4	3	4.6	Calf height, calf circumference, calf cross-sectional area
Component5	2	3.1	Back of neck circumference, Back of neck cross-sectional area

Compare Model 2 clustering results and body characteristics

Out of 366 participants, cluster 1 was classified as 149 and cluster 2 was classified as 217 (Fig. 2). To identify the characteristics of the classified clusters, we conducted a difference test of 5 components according to the clusters (Table 5). Except for component 5, the remaining components showed statistically significant differences, and cluster 1 was higher than cluster 2 (Table 5).

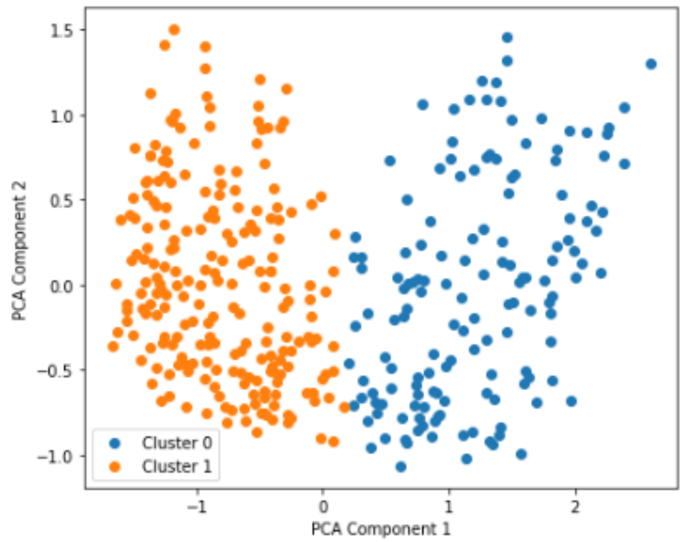

Fig. 2: Compare Model 2 clustering results

Table 5: Validation of differences in body characteristics based on clustering results in Model 2

Component	Clusters	Md	Q	z	P
Component1	Cluster1	0.695	0.581	11.950	<.001
	Cluster2	-0.484	0.504		
Component2	Cluster1	0.287	0.738	3.818	<.001
	Cluster2	-0.232	0.635		
Component3	Cluster1	0.474	0.637	7.954	<.001
	Cluster2	-0.342	0.503		
Component4	Cluster1	0.325	0.381	3.262	.001
	Cluster2	0.090	0.326		
Component5	Cluster1	-0.073	0.667	.360	.719
	Cluster2	-0.083	0.535		

Model 2-1 Comparison of clustering results and body characteristics

Out of 149 people, cluster 1-1 was classified as 82 and cluster 2 as 67 (Fig. 3). To identify the characteristics of the classified clusters, a five-component difference test was conducted according to the clusters. The results showed a statistically significant difference in component 1 and component 3, and cluster 1-1 was higher than cluster 1-2 (Table 6).

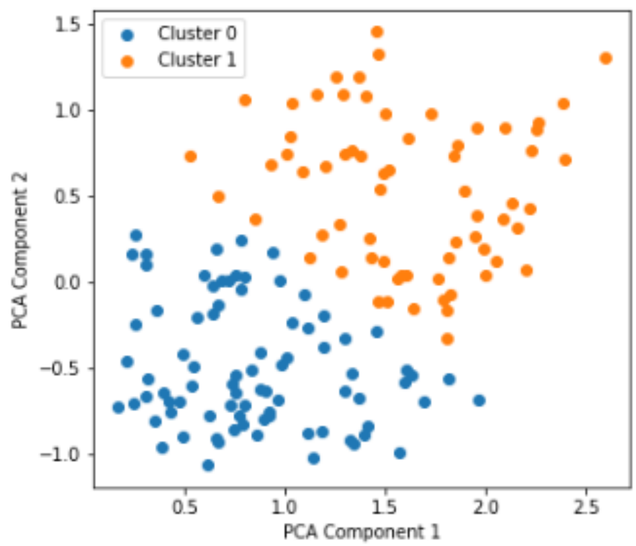

Fig. 3: Model 2-1 Comparison of clustering results

Table 6: Validation of differences in body characteristics based on the clustering results of Model 2-1

Component	Variables	Md	Q	z	P
Component1	Cluster1-1	1.150	0.484	6.487	<.001
	Cluster1-2	0.367	0.444		
Component2	Cluster1-1	0.302	0.996	.164	.164
	Cluster1-2	0.273	0.591		
Component3	Cluster1-1	0.827	0.836	2.892	.004
	Cluster1-2	0.241	0.588		
Component4	Cluster1-1	0.248	0.449	.698	.485
	Cluster1-2	0.362	0.361		
Component5	Cluster1-1	-0.073	0.828	.946	.344
	Cluster1-2	-0.070	0.641		

Model 2-2 Comparison of clustering results and body characteristics

Out of 217 participants, 46 were classified as cluster 2-1, 64 as cluster 2-2, 68 as cluster 2-3, and 39 as cluster 2-4 (Fig. 4). To identify the characteristics of the classified clusters, we conducted a five-component difference test according to the clusters, and found statistically significant differences in component 1, component 2, and component 4. Cluster 2-1 is the highest in component 2, second highest in component 1, and cluster 2-2 is the highest in component 4. Cluster 2-3 was highest in ingredient 1, and cluster 2-4 was lowest in ingredient 1, ingredient 2, and ingredient 3 (Table 7).

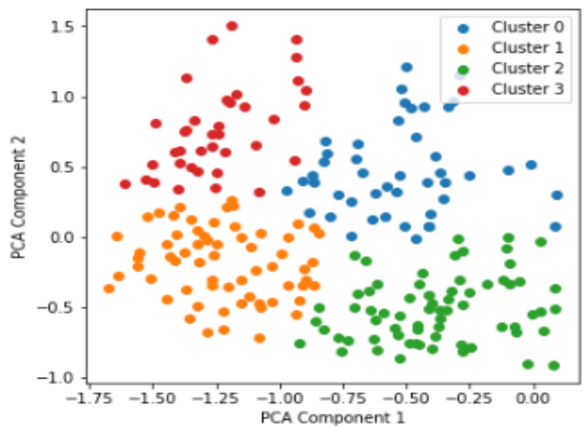

Fig. 4: Model 2-2 Comparison of clustering results

Table 7: Validation of differences in body characteristics based on the clustering results of Model 2-2

Component	Variables	Md	Q	H	P
Component1	Cluster2-1	-0.942	0.643	55.904	<.001
	Cluster2-2	-0.415	0.402		
	Clusters2-3	-0.102	0.436		
	Clusters2-4	-1.041	0.434		
Component2	Cluster2-1	0.814	1.079	48.802	<.001
	Cluster2-2	-0.457	0.341		
	Clusters2-3	0.260	0.527		
	Clusters2-4	-0.724	0.498		
Component3	Cluster2-1	-0.489	0.443	7.038	.071
	Cluster2-2	-0.364	0.455		
	Clusters2-3	-0.135	0.611		
	Clusters2-4	-0.674	0.576		
Component4	Cluster2-1	0.033	0.330	7.932	.047
	Cluster2-2	0.211	0.370		
	Clusters2-3	0.130	0.267		
	Clusters2-4	0.022	0.279		
Component5	Cluster2-1	-0.028	0.701	2.378	.498
	Cluster2-2	-0.195	0.458		
	Clusters2-3	-0.099	0.524		
	Clusters2-4	0.064	0.444		

Discussion

The purpose of this study was to perform deep learning-based body shape clustering analysis using 3D Body Scanner. We applied the transformer algorithm, based on deep learning, to perform clustering analysis.

First, the silhouette index was calculated according to the number of clusters by model, and the body types were categorized into two clusters for cluster 1 and four for cluster 2. Most of the previous studies have utilized the previously developed Heath-Carter's somatotype to classify body types based on ectomorphy, endomorphy, and mesomorphy through AI methodologies (9, 15). These studies have similar methodologies in that they utilize 3D body images rather than traditional body shape measurements. Nevertheless, while previous studies have classified body types based on three types, this study attempts to explain more detailed body types by classifying a total of six

body types. In addition, body types are changing as society changes, so the results of this study are likely to be less meaningful.
Looking at the body types categorized in this study, we can see that cluster 1 has an endomorphic body type. Endomorphism is a relatively large body type, and the two body types in cluster 1 are as follows. First, cluster 1-1 was categorized as having a "very large upper body and thighs," which is a highly developed body type among endomorphs, and cluster 1-2 was categorized as having an "above-average overall body size. In fact, endomorphs have been categorized as a single group in the past, so it is difficult to determine what characteristics they possess. However, if you look at Heath-Carter's somatotype body type category, divided into 13 categories based on 3 body types, endomorphs are described as ectomorphic endomorphs, balanced endomorphs, and mesomorphic endomorphs. Specifically, if we explain the 1-1 and 1-2 body types based on Heath-Carter's somatotype, we can explain that the 1-1 body point is similar to the body type corresponding to the endomorphy index of 8~9, and the 1-2 is similar to the body type corresponding to the endomorphy index of 5~7.
In cluster 2, four body types were identified. Cluster 2 is an extra-endodermal body type, and 2-1 is categorized as 'tall and thin', 2-2 is 'generally small in height but with well-developed calves', 2-3 is 'normal build but with well-developed calves', and 2-4 is 'short and thin'. If we look at cluster 2 as a whole, it describes four body types based on height, and the degree of development of the body type is described based on height. In the past, abdominal indicators were often used to classify body types, but in this study, calf indicators were used to classify body types. Cluster 2-2 is characterized by small stature but well-developed calves, suggesting that calf development is a key factor in distinguishing body types. The reason for this needs to be examined through further research, but they were classified based on calf features, which are indicators of the lower body, because they have characteristics such as recent office work, lack of physical activity, and lack of exercise.
On the other hand, this study utilized two methods to classify body types. Model 1 is a model that applies the k-means algorithm, and model 2 is preprocessed with the transformer algorithm and applied to the k-means algorithm. Traditionally, studies have been conducted based on model 1 in the past, but recently, studies have been conducted by preprocessing and applying the transformer algorithm. Transformer is a deep learning model that can embed variables and sentences and has the advantage of showing high performance in the field of natural language processing (16). Transformer algorithms are reported to be a superior methodology for learning data by embedding based on data location values and overall data context rather than identifying features of a single simple number (17). These methodologies are likely to be more accurate in classifying body types, suggesting that fine-grained classifications can be identified in describing body types.
Finally, this study was designed to perform deep learning-based body shape clustering analysis using 3D Body Scanner. We believe that this study is meaningful in that it applies 3D Body Scanner, which measures body shape, and the Transformer algorithm, a recent research methodology, to perform cluster analysis. However, this study has limitations in that it was not conducted on Korean subjects and additional features were not investigated. Therefore, in the future, it is possible to conduct follow-up studies on health, disease, and sporting activities based on the body types classified in this study. There is a need for further research as there are reports of studies that use body type to diagnose health and predict disease (18). These results can be utilized as a basis for calculating various outcomes through body shape.

Conclusion

Among the two methods for classifying body types, the performance of the transformer algorithm was found to be higher. The clustering of body types was divided into two clusters, endomorphic body type and ectomorphic body type, and further divided into six clusters, two for cluster 1 and four for cluster 2. The six clusters provide more detailed information than previous body type classifications, and we believe that they can be used as basic information for predicting health and disease.

Journalism Ethics considerations

Ethical issues (Including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc.) have been completely observed by the authors.

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Conflict of interest

The authors declare that there is no conflict of interests.

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