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Tissue Classification and Tactile Estimation using Convolutional Neural Networks with Physical Input Data

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I. Introduction

Tactile sensation is a key determinant of perceived product value and can significantly influence consumer purchasing behavior. Tissue paper, which is commonly used for applications such as nasal hygiene, comes into direct contact with the skin. Consequently, consumers often prioritize tactile properties—along with cost and composition—when assessing product quality, underscoring the importance of quantifying tactile sensation in product development.

Currently, the standard approach to quantifying tactile sensation is sensory evaluation [1], where subjects physically interact with samples and rate them based on their subjective impressions. While this method captures actual user experience and satisfaction, it suffers from several limitations. Sensory perception varies across individuals and can be affected by external factors such as temperature, humidity, and emotional state [2]. Additionally, evaluating multiple samples is time- and cost-intensive.

To address these challenges, this study aims to develop a new tactile evaluation method that is robust against environmental variability and individual differences. By leveraging machine learning with physically measurable data, we propose a cost-effective and objective approach to estimate tactile sensation.

II. Research Procedure

The research began with a sensory evaluation of tissue papers to quantify their tactile sensation and classify tissue samples based on perceived similarity. Based on the resulting clusters, physical features capable of producing similar classifications were selected. These physical features were then used to label data for training a convolutional neural network (CNN) model. The model outputs the similarity of a given sample's physical data to each cluster. Finally, tactile scores were estimated by computing a weighted sum of sensory evaluation values, based on the predicted cluster probabilities.

III. Sensory Evaluation

A total of 13 tissue paper samples with varying compositions and price ranges were evaluated through a sensory experiment involving 76 participants (47 males, 29 females). Each participant was asked to touch all samples using a specified tactile method and rate them using the semantic differential (SD) method on a 7-point scale across 18 evaluation terms in Japanese (Table I). The experiment protocol was approved in advance by the Bioethics Board of the Faculty of Science and Technology, Keio University (2024-004). The resulting data were analyzed using hierarchical clustering via Ward's method by SPSS (ver. 29, IBM).

The results of clustering are shown in Figure 1, where the horizontal axis represents the distance between clusters. The red dashed line indicates the first division into two clusters. Focusing on the blue dashed line, one of these clusters containing ten samples is further divided, resulting in three clusters in total. Beyond that point, the distances between samples are small, making further divisions less meaningful. Therefore, it can be inferred that the samples can be reasonably grouped into three clusters based on human tactile perception, and that the three high-grade lotion samples (Samples 9, 12, and 13) are particularly distinguishable.

IV. Selection of Significant Physical Data

To identify physical data capable of producing classifications comparable to those derived from sensory evaluation results, eight candidate features were selected as follows.

Six physical features: friction noise intensity, average friction coefficient (in both parallel and perpendicular directions relative to fiber orientation), tensile strength (in both directions), and resistance during indentation.

Two types of image data: surface texture (RGB images from a 3D microscope), and grayscale images of transmitted light from the backside.

For each physical feature, 52 graph-based images were prepared (4 measurements for 13 samples). These images were clustered using the unsupervised K-means method[3]. The clustering output was evaluated based on two criteria,

(1) whether the four measurements from each sample were consistently assigned to the same cluster

(2) whether the three perceptually distinguishable high-grade lotion samples (Samples 9, 12, and 13) were grouped together

Table II presents an example of clustering results that satisfy both conditions (1) and (2) when the average friction coefficient in the vertical direction is employed. Four physical features—average friction coefficient (both directions), tensile strength (perpendicular), and friction noise intensity—were found to meet these conditions. Among them, three features—average friction coefficients (both directions)

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and friction noise intensity—achieved high silhouette scores [4] and were selected as CNN input data.

Table I. Evaluation terms used in the sensory experiment

Subesube shiteiru (smooth)	*Tsurutsuru shiteiru* (slippery)	*Atatakai* (warm)
Shimeppoi (moist)	*Petapeta suru* (slighy sticky)	*Shikkuri kuru* (natural)
Yawarakai (soft)	*Shikkari shiteiru* (firm)	*Fukkura shiteiru* (fluffy)
Kawaita (dry)	*Koukyuukan no aru* (luxurious)	*Funwari shiteiru* (airy)
Tsumetai (cold)	*Shitashimi no aru* (familiar)	*Atumi ga aru* (thick)
Betabeta suru (sticky)	*Sawarigogochi ga yoi* (pleasant)	*Suki de aru* (liked)

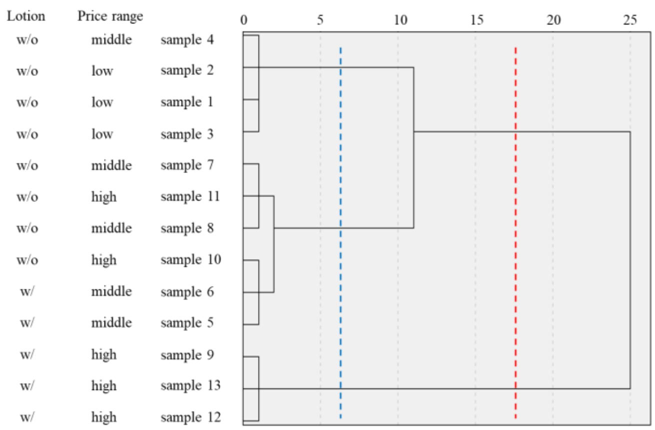

Figure 1. Results of sensory evaluation clustering

Table II. Number of graph-based images (out of 4) assigned to each cluster using the average friction coefficient (vertical direction)

Cluster \ Sample	1	2	3	4	5	6	7	8	9	10	11	12	13
0	0	0	0	3	1	0	1	0	0	0	3	0	0
1	4	4	4	1	0	0	3	4	0	4	1	0	0
2	0	0	0	0	3	4	0	0	4	0	0	4	4
Majority cluster	1	1	1	0	2	2	1	1	2	1	0	2	2
(1)	✓	✓	✓	×	×	✓	×	✓	✓	✓	×	✓	✓
(2)							✓						

*"Majority cluster" indicates the dominant assignment. ✓ marks conditions (1) and (2).

V. Tactile Estimation using CNN

To estimate the sensory evaluation values from the selected physical features, a CNN-based classification model was constructed. The model classifies a given sample into one of the three tactile clusters identified through the sensory evaluation.

As CNNs generally require thousands of images to learn effectively, and conducting thousands of physical measurements would be time-consuming and costly, composite images were generated by combining multiple graphical representations of the selected physical features, as illustrated in Figure 2.

This study utilized these composite images as input to the CNN model. For each tissue sample, 100 composite images were generated. Each image was labeled based on the cluster assignment obtained from the sensory evaluation results of the corresponding sample. To evaluate generalizability, we employed a leave-one-sample-out approach: the model was trained using 1,200 images derived from 12 of the 13 samples, with the remaining sample reserved for testing. This procedure was repeated for each of the 9 samples, excluding one representative sample from each cluster.

The predicted cluster proportions were used to linearly combine the sensory scores of the representative samples from each cluster, estimating each sample's sensory scores.

Figure 3 presents a representative result of the proposed estimation. For this sample, the mean absolute error across all evaluation terms was as low as 0.085, indicating high prediction accuracy. In 7 out of 9 test samples, the absolute error for all terms remained within 1 point. Considering that the SD method has a resolution of 1 point, these results suggest that the predicted tactile values closely approximated those obtained through human evaluation.

VI. Conclusions

This study proposed a tactile estimation model that takes physical measurement graphs of tissue samples as input and uses a convolutional neural network to classify them into tactile clusters. The sensory evaluation scores were then estimated based on the classification results. For 7 out of 9 test samples, the estimated scores for all 18 evaluation terms had absolute errors within 1 point of the actual sensory scores. These findings demonstrate that the tactile sensation of tissue paper can be accurately estimated using only physical measurement data.

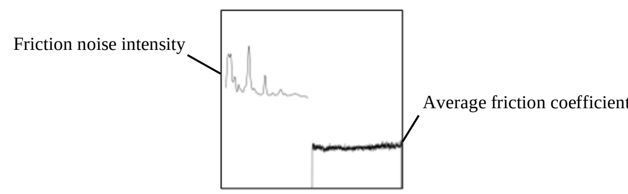

Figure 2. Combination image input to CNN

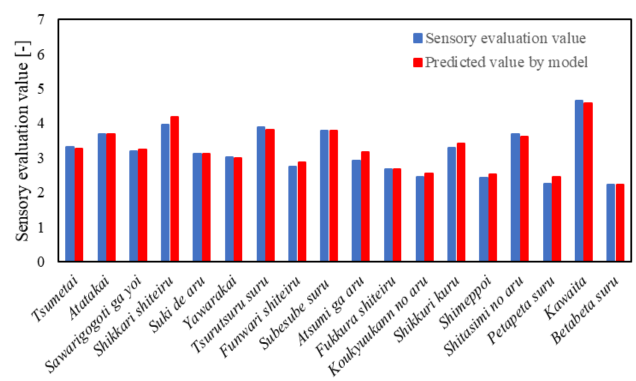

Figure 3. Estimated sensory evaluation values (Sample 2)

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