Determining When to Replace a Stoma Faceplate Using Image Processing and Machine Learning

Michiru Mizoguchi[1], Tomaya Kokaji[2], Masaya Nakahara[2], and Hiroshi Noborio[2,*]

[1] Department of Nursing Science, Naragakuen University, Nara, Japan
[2] Department of Computer Science, Osaka Electro-Communication University, Osaka, Japan
Email: michiru-m@nara-su.ac.jp (M.M.); ht21a037@oecu.jp (T.K.); nakahara@osakac.ac.jp (M.N.); nobori@osakac.ac.jp (H.N.)
*Corresponding author

***Abstract*—This study was conducted to determine the optimal time for changing stoma appliances. One of the problems with stoma appliances is that it is difficult to regularly change the faceplate. The faceplate is sticky and is attached around the stoma. If it is used for a long time, urine or feces may seep between the faceplate and the stoma, causing the faceplate to come off and urine or feces to leak. However, patients themselves need to be accustomed to changing stoma appliances. In addition, if nurses who are not used to changing the appliance do the job, there are cases where the timing of the change is mistaken. The timing of changing the stoma appliance is determined by the amount of urine and feces of the patient, the color change of the appliance, and the degree of dissolution. Therefore, it is expected that if the patients themselves change the appliance, it will prevent mistakes in the timing of the change and leakage of urine and feces, through image processing and machine learning.**

***Keywords*—stoma, machine learning, teachable machine, NMKD stable diffusion, grayscale HSV, smoothing, sharpening, Gaussian filter, overlearning**

I. Introduction

As a research background, this study was conducted to verify the accuracy of detecting when to change a stoma appliance by editing various images and comparing them. A stoma is a colostomy used to discharge urine and feces, with the patient's own intestines and ureters protruding from the abdomen. A stoma pouch is used to store urine and feces from the stoma, and a faceplate is an adhesive plate that is directly attached to the abdomen. Some faceplates and pouches are integrated, while others are separate. These are collectively called stoma appliances (in this study, only the faceplate was photographed without the pouch to see changes in the faceplate). After a period of use, urine and feces enter the space between the faceplate and the stoma, causing skin problems and staining of clothing due to discharge. Therefore, it is necessary to change the stoma brace periodically. In the conventional method, the timing of replacement is determined by looking at the color of the faceplate, the degree of skin irritation, and the degree of melting of the brace, etc. Patients need to become accustomed to changing the stoma themselves, and nurses who are not accustomed to changing stomas may make mistakes. If patients are able to know when to change their stoma appliance and change it autonomously, it is expected to prevent leakage of discharges. In this study, we used a machine-learning tool to learn the replacement photos of artificial faceplates, and studied whether the system could detect the timing of replacement and how to improve the detection of such changes [1–8].

In this study, we used Teachable Machine, a learning tool from Google, to detect when to replace a stoma appliance. We asked subjects to send us images of their stomas in use, which we used as the correct answer data. However, due to the lack of image data, we decided to use a mock stoma that resembles a real stoma for the training data. The color change and stains on the faceplate caused by the dissolution of the discharge that soaks into faceplate 2 were used as discriminative elements. The stoma was classified into two categories: when not to replace the stoma (when the stoma has been attached for a while and there is still time to replace it) and when to replace it (when it has been attached for a while and replacement is recommended), and the changes in these categories were analyzed using a machine learning tool [9].

The system learns from the images and detects when to replace them. The accuracy was verified by comparing images without processing to those without processing in order to focus on reducing the amount of information, by editing images in different ways, such as gray scaling, HSV, smoothing, changing resolution, sharpening, and Gaussian filtering, and by using a larger or smaller number of epochs. From the viewpoint of the verification results, we felt that preventing leakage from the faceplate should be a priority, so we set the target values at around 80 to 90% correct for "when to replace" and the same or slightly lower for "when not to replace" (70% correct was the limit in this case), which we believe is appropriate in an area where overlearning has not taken place.

The finding of this study is that if an image is edited in a way that is difficult for humans to distinguish visually, the same thing will happen in machine learning, and

Manuscript received February 19, 2025; accepted June 1, 2025; published September 25, 2025.

accurate results will not be obtained. Therefore, it was found that verification should be conducted on the premise that the images can be distinguished by humans. We sought a better combination of various image edits. We expected to improve the accuracy of the results by reducing the amount of information by gray scaling and decreasing the resolution.

In the organization of the paper, the contents of each chapter are briefly described so that the flow of the paper can be understood. The structure of this paper is as follows. Section II describes the Teachable Machine, OpenCV, and NMKD Stable Diffusion GUI software, Section III describes each verification experiment and its results, Section IV discusses the results of each verification, and Section V concludes the paper.

II. Software to Be Used

We evaluated a Teachable Machine was used as the machine learning tool for this study [10]. OpenCV was used for gray scaling [11], HSV, sharpening, and Gaussian filtering. NMKD Stable Diffusion GUI was used as AI image generation software [12].

A. Google Teachable Machine

Google Teachable Machine [10] is a machine learning tool using Artificial Intelligence (hereinafter referred to as AI) provided free of charge by Google. It can be accessed from a browser and can be used without writing any code. By inserting arbitrary images (training data) into multiple labels and training them, the tool determines which label matches the image to be discriminated against (correct data). The number of epochs, batch size, and learning rate can be adjusted during training.

B. OpenCV

OpenCV, officially called the Open-Source Computer Vision Library, is an open-source library for image processing, image analysis, and machine learning. In this study, gray scaling, HSV, sharpening, and Gaussian filtering were performed using OpenCV [11]. Python was used as the language.

C. NMKD Stable Diffusion GUI

NMKD Stable Diffusion GUI is a Windows GUI tool for Stability AI's Stable Diffusion, which generates images based on text (prompts) [12]. Anyone can use image generation based on text (prompts) without the need to prepare a Python runtime environment or to execute it from a command line.

To use this function, enter the type of image to be generated in the "Prompt" field. "Init Image Strength" allows the user to set how much the generated image should resemble the original image, with values from 0.1 to 0.9, the higher the number, the more the image should resemble the original. In this study, we wanted to create a similar image of the artificial faceplate, so we entered "Resemble the original image" in the "Prompt" field, which is an English translation of the phrase "Resemble the original image". "Init Image Strength" was set to 0.9.

III. Verification Experiment

A. Creation of Simulated Stoma and Artificial Faceplate

In this study, there were not many images of the subjects, so we artificially reproduced the face plates and used them as training data for machine learning. The face plates are real. The intestines were made from red paper clay, and the gloss was reproduced using salad oil. The face plates were divided into those that were not replaced and those that were replaced, and the ones that were replaced were coated with miso to reproduce dirt. The face plates were photographed using a smartphone (iPhone 13 mini).

B. Verification Experiment without Image Processing

For the training data for the Teachable Machine:

- 200 images of the artificial faceplate copied from the "non-replacement period";
- 200 images of the artificial faceplate copied from the "replacement period" were used (Figs. 1 and 2).

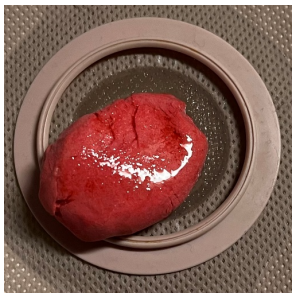

Fig. 1. When not to replace (artificial faceplate).

Fig. 2. When to replace (artificial faceplate).

On the other hand, for the correct data:

- 50 images of the subjects from the "non-replacement period";
- 50 images of the subjects from the "replacement period" were used (Figs. 3 and 4).

Fig. 3. Time when not exchanging (subject).

Fig. 4. Timing of exchange (subject).

We conducted training with 100, 200, 300, 400, and 500 epochs (Table I). Here, the number of epochs refers to the number of times a single piece of training data is repeated for learning, and if the number is too large, over-learning may occur.

TABLE I. THE PERCENTAGE OF CORRECT ANSWERS IN EACH CASE IN THE UNTOUCHED IMAGE, USING MACHINE LEARNING

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
100	50/50 (100%)	1/50 piece (2%)
200	50/50 (100%)	1/50 piece (2%)
300	50/50 (100%)	1/50 piece (2%)
400	50/50 (100%)	1/50 piece (2%)
500	50/50 (100%)	1/50 piece (2%)

C. Verification Experiment with HSV

In this section, we will examine images of HSV size [13]. HSV refers to "Hue", "Saturation", and "Value". H (Hue) is the hue of a color, and is the pure hue of a color without including its tint or brightness. S (Saturation) is the vividness of a color, and is high, the color appears vivid, while if the saturation is low, the color appears black or gray. V (Value) is the brightness of the color, and if the value is high, the color approaches white, while if the value is low, the color approaches black. The purpose of this study is to clarify how the brightness, lightness, and saturation of colors affect the accuracy of estimating the time to replace the pouch.

The details of some experiments are shown below. The images were converted to HSV using OpenCV (Figs. 5 and 6). The training data included 200 images of artificial faceplates (no replacement required) of HSV size, labeled as "no replacement required". In addition, 200 images of artificial faceplates (replacement required) enlarged to HSV size are included with the label "replacement required". Using these correct data, we will perform machine learning, and evaluate the learning effect with 50 subject images of HSV size "not replacement required" and 50 subject images of HSV size "replacement required".

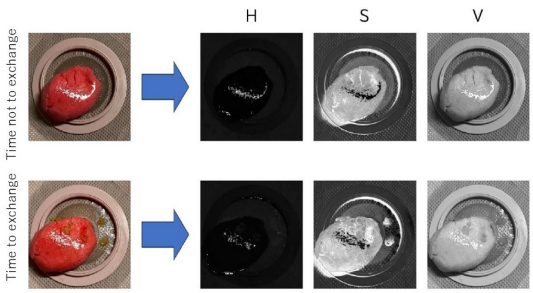

Fig. 5. Comparison of HSV-enhanced images (artificial faceplate).

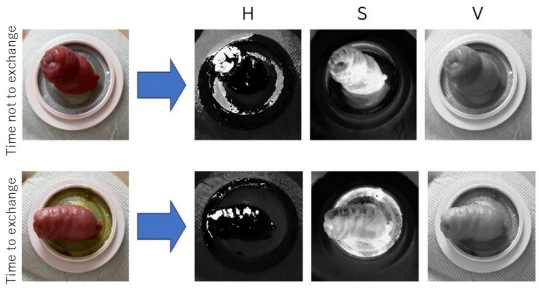

Fig. 6. Comparison of HSV-sized images (subject).

The results are shown in the following table. The correct rate of machine learning is shown for each of 100, 200, 300, 400, and 500 epochs (Tables II–IV).

TABLE II. H-ALTERATION: THE NUMBER OF EPOCHS WAS VERIFIED FOR FIVE EACH OF 100, 200, 300, 400, AND 500

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
100	2/50 (4%)	47/50 (94%)
200	3/50 (6%)	47/50 (94%)
300	2/50 (4%)	46/50 (92%)
400	3/50 (6%)	45/50 (90%)
500	3/50 (6%)	48/50 (96%)

TABLE III. S-INACTION: THE PERCENTAGE OF CORRECT ANSWERS IN EACH CASE IN THE UNTOUCHED IMAGE, USING MACHINE LEARNING

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
100	49/50 (98%)	6/50 (12%)
200	47/50 (94%)	8/50 (16%)
300	47/50 (94%)	5/50 (10%)
400	48/50 (96%)	6/50 (12%)
500	46/50 (92%)	6/50 (12%)

TABLE IV. V-INACTION: THE PERCENTAGE OF CORRECT ANSWERS IN EACH CASE IN THE UNTOUCHED IMAGE, USING MACHINE LEARNING

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
100	50/50 (100%)	2/50 (4%)
200	50/50 (100%)	2/50 (4%)
300	50/50 (100%)	2/50 (4%)
400	50/50 (100%)	2/50 (4%)
500	50/50 (100%)	3/50 (6%)

D. Verification Experiment with Gray Scaling

Here, we will examine the effect of grayscaling on machine learning for pouch replacement timing [14]. Grayscaling is a method of expressing gradations (i.e., gradations) from white to black, and is characterized by the presence of intermediate gray colors, which can express subtle shades. Here, we will look at the difference in replacement accuracy for machine learning when the number of colors is reduced.

Here, we will show the details of some experiments. First, all images were converted to grayscale using OpenCV (Figs. 7 and 8). Then, as before, the learning data used was:

- 200 grayscale artificial faceplate duplicate images (when no replacement is required) attached with a "no replacement required" label;
- 200 grayscale artificial faceplate duplicate images (when replacing) attached to "when replacing" labels are used as training data.

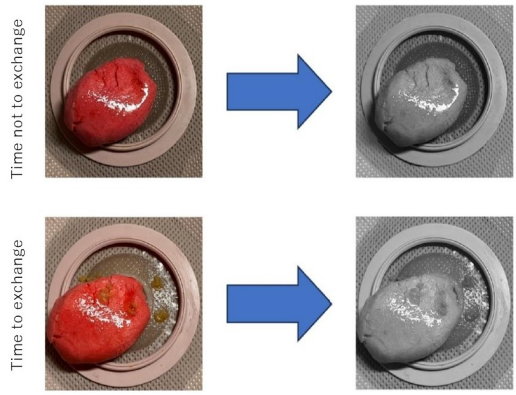

Fig. 7. Comparison of gray scaled images (artificial faceplate).

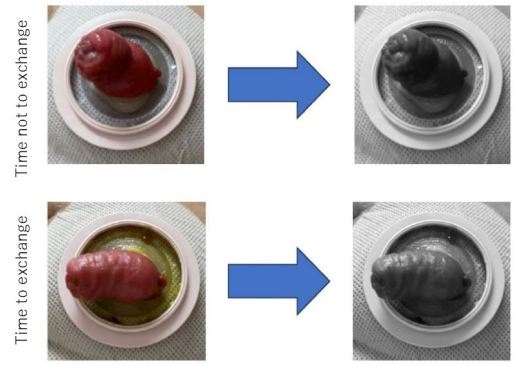

Fig. 8. Comparison of gray scaled images (subject).

On the other hand, as before, the correct data used were:

- 50 grayscale subject images (when not replacing);
- 50 grayscale subject images (when replacing).

The following table shows the results. The number of epochs was set to 100, 200, 300, 400, and 500. The table shows the correct response rate for the gray-scale images for each case where machine learning was performed (Table V).

TABLE V. VERIFICATION EXPERIMENT WITH GRAY SCALING

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
100	45/50 (90%)	19/50 (38%)
200	44/50 (88%)	15/50 (30%)
300	45/50 (90%)	13/50 (26%)
400	46/50 (92%)	15/50 (30%)
500	46/50 (92%)	15/50 (30%)

E. Verification Experiment in Smoothing

In this section, we will examine the effect of smoothing on the images. Smoothing is a process that blurs an image [15]. Smoothing can be used to make noise and edges less noticeable. The aim of this section is to investigate the effect of reducing the amount of information by reducing details such as the fibers on the faceplate. We used a tool called Data Chef for the smoothing process. This tool can blur any image with a radius of 1 pixel to 50 pixels. In order to achieve the blurring effect, the value of each pixel is replaced with the average or weighted average of the surrounding pixels. The larger the blurring radius, the more pixels are taken into account, so the blurring effect is more extensive. In the following verification, the grayscale images in Section D above are used as the target for comparison with the images processed using the +α method.

We will now show the details of some of the experiments. In Data Chef, the grayscale images were smoothed at 4px, 5px, 6px, and 10px (Figs. 9 and 10).

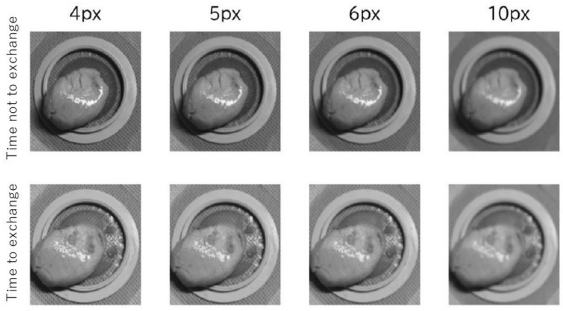

Fig. 9. Smoothing image comparison (artificial faceplate).

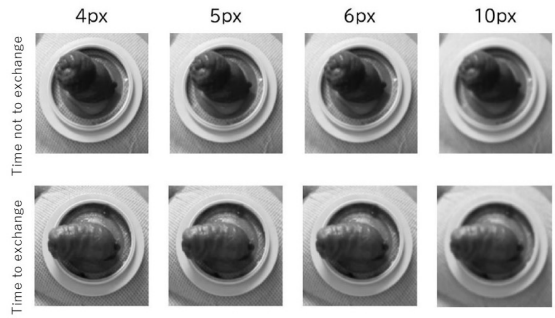

Fig. 10. Smoothed image comparison (subject).

First, as training data, we used:

- 200 smoothed artificial faceplate images labeled “not time for replacement”;
- 200 images of artificial faceplates with the label “It is time to replace them” that have been smoothed;

On the other hand, the correct answers have been trained using the correct data.

- 50 images of “It is not time to replace them” that have been smoothed (in the case of not replacing them);
- 50 images of “It is time to replace them” that have been smoothed (in the case of replacing them).

The following table shows the results. The number of epochs was tested for 100, 200, 300, 400, and 500. The following tables show some of the test results (Tables VI–IX).

TABLE VI. THE RESULTS IN THE SMOOTHED IMAGE BY 4PX

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
100	47/50 (94%)	17/50 (34%)
200	48/50 (96%)	21/50 (42%)
300	47/50 (94%)	23/50 (46%)
400	45/50 (90%)	27/50 (54%)
500	47/50 (94%)	22/50 (44%)

TABLE VII. THE RESULTS IN THE SMOOTHED IMAGE BY 5PX

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
100	38/50(76%)	31/50 (62%)
200	28/50(56%)	29/50 (58%)
300	25/50(50%)	32/50 (64%)
400	36/50(72%)	25/50 (50%)
500	33/50(66%)	33/50 (66%)

TABLE VIII. THE RESULTS IN THE SMOOTHED IMAGE BY 6PX

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
100	14/50 (28%)	48/50 (96%)
200	13/50 (26%)	48/50 (96%)
300	11/50 (22%)	49/50 (98%)
400	16/50 (32%)	48/50 (96%)
500	16/50 (32%)	48/50 (96%)

TABLE IX. THE RESULTS IN THE SMOOTHED IMAGE BY 10PX

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
100	17/50 (34%)	49/50 (98%)
200	17/50 (34%)	49/50 (98%)
300	15/50 (30%)	50/50 (100%)
400	13/50 (26%)	50/50 (100%)
500	19/50 (38%)	50/50 (100%)

F. Verification Experiment with Resolution Change

In this section, we will try to improve the accuracy of the machine learning-based replacement timing decision by changing the resolution of the image. The original image used in this experiment has a resolution of 1200px × 1200px, but we will temporarily reduce the resolution to a specified value and then return it to 1200px × 1200px. This will allow us to reduce the quality of the image. The purpose of this is to investigate how reducing the image quality affects the accuracy of the replacement (Figs. 11 and 12). The resolution was changed using the Windows 11 Photos application.

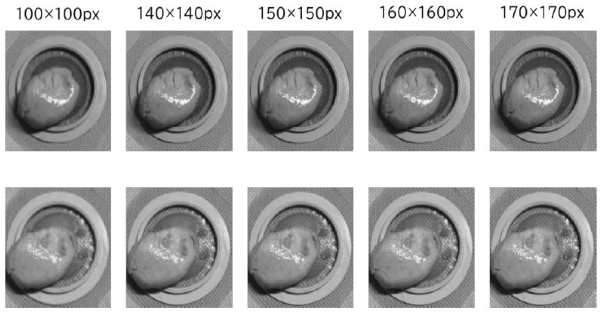

Fig. 11. Comparison of resolution change images (artificial faceplate).

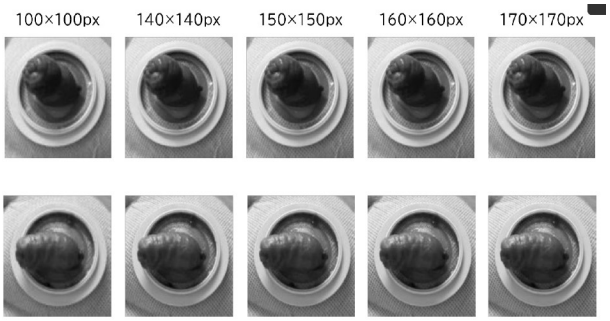

Fig. 12. Comparison of images with different resolutions (subjects).

Here, we will show the details of some of the experimental results. The grayscale images were degraded from 1200px × 1200px to 100px × 100px and 100px × 100px, respectively, within the photo application. In other words, the resolution was changed to 140 × 140px, 150 × 150px, 160 × 160px, and 170 × 170px.

As usual, the training data consisted of:

- 200 duplicate images of the artificial panel with the "No replacement required" label (when no replacement is required);
- 200 duplicate images of the artificial panel with the "Replacement required" label (when replacement is required);

On the other hand, the evaluation data consisted of:

- 50 images with the "No replacement required" label that were subject to resolution change;
- 50 images with the "Replacement required" label that were subject to resolution change as the correct answers.

The results are as follows. As usual, we verified the number of epochs 100, 200, 300, 400, and 500, each five times. And the correct answer rate when machine learning is performed on images with different resolutions is shown in Tables X–XIV, respectively.

TABLE X. THE RESULTS IN THE SMOOTHED IMAGE BY 100 × 100PX

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
100	50/50 (100%)	15/50 (30%)
200	50/50 (100%)	13/50 (26%)
300	50/50 (100%)	15/50 (30%)
400	50/50 (100%)	23/50 (46%)
500	50/50 (100%)	9/50 (18%)

TABLE XI. THE RESULTS IN THE SMOOTHED IMAGE BY 140 × 140PX

Number of epochs	Percentage correct (not to replace)	Percentage correct (to replace)
100	38/50 (76%)	36/50 (72%)
200	39/50 (78%)	35/50 (70%)
300	39/50 (78%)	36/50 (72%)
400	38/50 (76%)	38/50 (76%)
500	40/50 (80%)	34/50 (68%)

TABLE XII. THE RESULTS IN THE SMOOTHED IMAGE BY 150 × 150PX

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
100	46/50 (92%)	32/50 (64%)
200	46/50 (92%)	30/50 (60%)
300	49/50 (98%)	27/50 (54%)
400	48/50 (96%)	24/50 (48%)
500	46/50 (92%)	26/50 (52%)

TABLE XIII. THE RESULTS IN THE SMOOTHED IMAGE BY 160 × 160PX

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
100	40/50 (80%)	36/50 (72%)
200	37/50 (74%)	37/50 (74%)
300	40/50 (80%)	30/50 (60%)
400	37/50 (74%)	44/50 (88%)
500	33/50 (66%)	41/50 (82%)

Note: This dark gray result is the best.

TABLE XIV. THE RESULTS IN THE SMOOTHED IMAGE BY 170 × 170PX

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
100	49/50 (98%)	19/50 (38%)
200	48/50 (96%)	13/50 (26%)
300	48/50 (96%)	15/50 (30%)
400	45/50 (90%)	14/50 (28%)
500	47/50 (94%)	15/50 (30%)

G. Verification Experiment in Sharpening

In this section, we examine the sharpening process on a sharpened image [15]. Sharpening is the opposite of smoothing. The purpose of this section is to examine the effect of sharpening on accuracy, since the density of information is clearly differentiated.

We indicate many experimental results. Sharpening was performed in OpenCV (Figs. 13 and 14). The resolution of the image was set to 160px based on the results of the above section F. The training data includes the 200 images duplicating the sharpened artificial faceplate (when not to replace) on the "when not to replace" label. 200 images duplicating the sharpened artificial faceplate (time to replace) on the "time to replace" label. The correct answers are trained using the correct data contains 50 images of sharpened subjects (when not to be replaced) and 50 images of sharpened subjects (when to be replaced). The following table shows the results. The number of epochs was verified for five each of 100, 200, 300, 400, and 500.

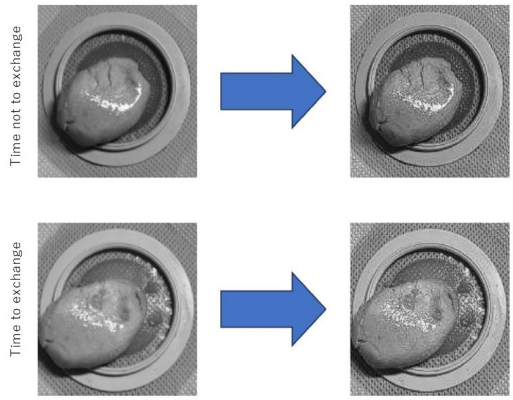

Fig. 13. Sharpening image comparison (artificial faceplate).

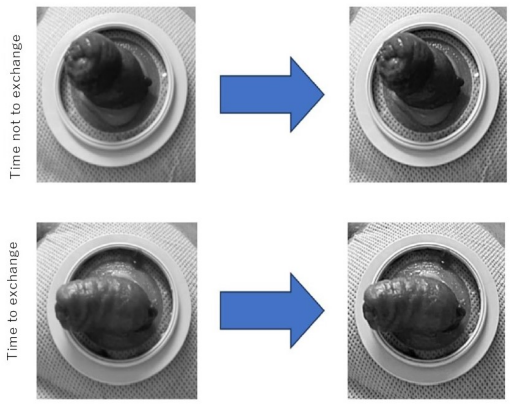

Fig. 14. Sharpening image comparison (subject).

We describe the percentage of correct answers in each case in the sharpened image that was subjected to machine learning (Table XV). Sharpening generates extra information for faceplate changing.

TABLE XV. THE RESULTS IN SHARPENING

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
10	50/50 (100%)	1/50 (2%)
20	50/50 (100%)	1/50 (2%)
30	50/50 (100%)	1/50 (2%)
40	50/50 (100%)	1/50 (2%)
50	50/50 (100%)	1/50 (2%)

H. Verification Experiment with Gaussian Filter Processing

Here, we will examine the results obtained using images [16] that have been subjected to Gaussian filtering. We thought that by combining the processes that achieved the highest accuracy rates, we would be able to obtain an even higher accuracy rate. Gaussian filtering has the effect of smoothing out noise by calculating the average values around the pixels and reducing blurring and edge loss in the image. The aim of this research is to see how smoothing out the image affects its accuracy.

The details of some of the experiments are shown below. Here, Gaussian filtering is performed using OpenCV (Fig. 15) [16], and a resolution of 160px is used based on the verification results in Section F. For the training data, the correct answers are learned using 200 images of duplicated artificial facial plates (when not swapped) that have been Gaussian filtered and labeled as "when not swapped", and 200 images of artificial facial plates (when to be swapped) that have been Gaussian filtered. On the other hand, the correct data is evaluated using 50 images of the subject (when not replaced) and 50 images of the subject (when replaced) that have been subjected to Gaussian filtering.

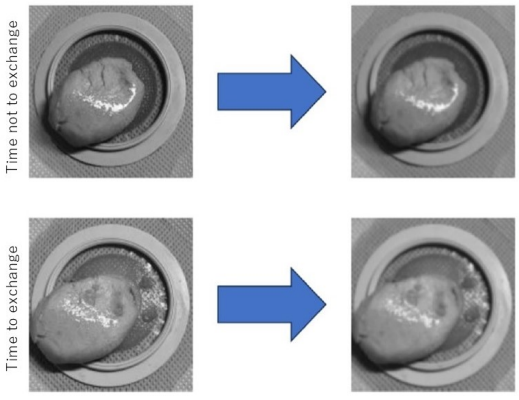

Fig. 15. Comparison of Gaussian filtered images (artificial faceplate).

The number of epochs was divided into five groups of 100, 200, 300, 400, and 500, respectively. In addition, because there is a possibility of over-learning, the number of epochs was reduced by 10 each time between 10 and 90. In each case, the correct response rate of the images with Gaussian filters applied by machine learning is shown (Fig. 16 and Table XVI).

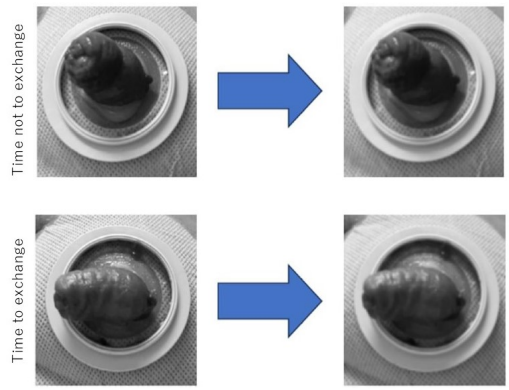

Fig. 16. Comparison of Gaussian filtered images (subject).

TABLE XVI. THE PERCENTAGE OF CORRECT ANSWERS IN THE GAUSSIAN-FILTERED IMAGE IN EACH CASE, USING MACHINE LEARNING

Number of epochs	Percentage correct (when not to replace)	Percentage correct (when to replace)
10	35/50 (70%)	48/50 (96%)
20	35/50 (70%)	48/50 (96%)
30	36/50 (72%)	48/50 (96%)
40	35/50 (70%)	48/50 (96%)
50	35/50 (70%)	48/50 (96%)
60	37/50 (74%)	49/50 (98%)
70	34/50 (68%)	49/50 (98%)
80	33/50 (66%)	49/50 (98%)
90	32/50 (64%)	49/50 (98%)
100	30/50 (60%)	49/50 (98%)
200	33/50 (66%)	50/50 (100%)
300	32/50 (64%)	50/50 (100%)
400	33/50 (66%)	50/50 (100%)
500	29/50 (58%)	50/50 (100%)

Note: The dark gray is the best result.

I. Summary of Results

The results of the validation experiment are summarized in this diagram (Fig. 17). The best results were obtained by gray scaling, setting the resolution to 160x160px, applying a Gaussian filter, and setting the number of epochs to 60.

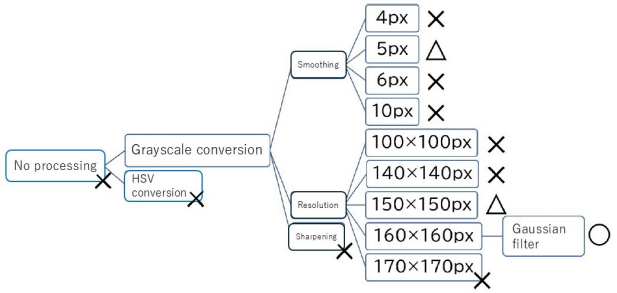

Fig. 17. Summary of results of experiments conducted.

IV. CONCLUSION

In this study, we thought that it would be possible to accurately determine the timing of stoma appliance (pouch) replacement by using image processing to bring out the dirt on the appliance and then using machine learning. For this reason, we initially proceeded with research in the direction of sharpening and using information-rich color images and information sharpening. However, we were unable to obtain any useful results. Therefore, we proceeded with research in the direction of reducing the amount of image information, and we were able to obtain useful results.

In this study, we used the machine learning tool Teachable Machine to process both the artificial faceplate and subject images using unprocessed images, gray scaling, HSV, smoothing, resolution change, sharpening, and Gaussian filtering, and compared the results in terms of the number of epochs.

In summary, the best results were obtained when the images were gray scaled, the resolution was set to 160px, the Gaussian filtering was performed, and the number of epochs was set to 60, to increase the rate of correct answers by machine learning for determining when to replace the stoma. In other words, we conclude that there is a moderate reduction in the amount of information that is good.

As a future task, we believe that priority should be given to adjusting the values of the Gaussian filtering process, which could not be verified this time due to lack of time. By doing so, it may be possible to further increase the percentage of correct answers to the question of "when not to replace". It might also be a good idea to use the D435 camera that was used in the early stages of the study to take pictures of the faceplates, as the image quality of the D435 camera was inferior to that of a smartphone, and we decided not to continue using it. However, since this study showed that the inferior image quality leads to an improvement in the percentage of correct answers, a similar verification experiment using images of faceplates taken with the D435 may yield new results.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Michiru Mizoguchi, Tomaya Kokaji, Masaya Nakahara, and Hiroshi Noborio contributed to the research concept and design, and conceived the project and the study hypothesis; Michiru Mizoguchi and Tomaya Kokaji designed and participated in performing the experiments; Michiru Mizoguchi, Tomaya Kokaji, and Masaya Nakahara tested the software and analyzed the data; Michiru Mizoguchi, Tomaya Kokaji, and Masaya Nakahara executed implementation and evaluation of programming; Tomaya Kokaji and Hiroshi Noborio clearly wrote the paper by manuscript rewriting; all authors had approved the final version.

ACKNOWLEDGMENT

This study was supported partly by the 2023 Cooperation Research Fund from the Graduate School at Osaka Electro-Communication University.

REFERENCES

[1] T. Shigeno, T. Umemura, M. Ii, and Y. Michiken, "The relationship between the self-care situation, anxiety, and QOL of people with stomas," *Japanese Journal of Stoma and Continence*, vol. 33, no. 3, pp. 71–80, Dec. 2017.

[2] K. Araki and Y. Takemoto, "Psychological status of ostomates at each stage of treatment from the time of diagnosis to the present," *Medical Care and Welfare*, vol. 45, no. 2, pp. 34–40, 2012.

[3] Ministry of Health, Labor and Welfare. (January 20, 2017). Policy name: Aiming to optimize medium- to long-term medical expenses through measures such as lifestyle-related disease countermeasures and the correction of long-term hospitalization. [Online]. Available: http://www.mhlw.go.jp/jigyo_shiwake/gyousei_review_sheet/2014/h25_1-9-2.html

[4] Y. Tanaka and E. Takamizawa, "Factors related to the indication for ileostomy construction," *Japanese Journal of Wound, Ostomy and Continence Management*, vol. 13, no. 2, pp. 26–33, 2010.

[5] A. Murauchi, C. Isomi, and T. Maeda, "Difficulties and coping strategies in the daily lives of elderly ostomates," *Japanese Journal of Nursing Science, Adult Nursing H*, vol. 42, pp. 206–209, 2012.

[6] Y. Shimizu, M. Ota, N. Saito, *et al.*, "Survey of problems experienced by permanent ostomate patients after discharge from hospital: Towards the establishment of a support system," *Japanese Journal of Nursing Science, Adult Nursing K*, vol. 42, pp. 222–225, 2012.

[7] Japan Ostomy Association. (January 20, 2017). Life and welfare of people with artificial anus and bladder. [Online]. Available: http://www.joa-net.org/contents/report1/pdf/seikatsu-fukushi-1.pdf

[8] WOC Support Office - Cancer Institute Hospital-. About stoma (artificial anus). [Online]. Available: https://www.jfcr.or.jp/hospital/conference/total_care/woc/artificial_anus.html

[9] M. Mizoguchi, S. Watanabe, M. Nakahara, and H. Noborio, "Comparison of the accuracy of pouch replacement timing decisions using image generation artificial intelligence and machine learning," in *Lecture Notes in Computer Science*, M. Kurosu and A. Hashizume, Eds., Springer, 2023, vol. 14014, pp. 107–120. https://doi.org/10.1007/978-3-031-35572-1_8

[10] Teachable Machine. [Online]. Available: https://teachablemachine.withgoogle.com/

[11] OpenCV. [Online]. Available: https://opencv.org/

[12] NMKD Stable Diffusion GUI for easy command-free use of Stable Diffusion for image generation AI. [Online]. Available: https://github.com/StableDiffusionGui/StableDiffusionGui

[13] HSL and HSV. [Online]. Available: https://en.wikipedia.org/wiki/HSL_and_HSV

[14] Grayscaling Images Made Simple with OpenCV. [Online]. Available: https://www.jeremymorgan.com/tutorials/opencv/how-to-grayscale-image/

[15] Y. Zhang, "Development and applications of filters for smoothing and sharpening of images," Ph.D. dissertation, Kyushu University Institutional Repository, April 2016.

[16] S. C. Kumain, Maheep, Singh, N. Singh, and K. Kumar, "An efficient Gaussian noise reduction technique for noisy images using optimized filter approach," in *Proc. of the 2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC)*, 15–17 December 2018.