International Journal of Innovative Computing, Information and Control
Volume **18**, Number **4**, August **2022**
ICIC International ©2022 ISSN 1349-4198
pp. 1235–1245

ESTIMATION OF OPTIMAL META-PARAMETERS FOR USER IN ORAL MUCOSAL DISEASE DIAGNOSIS SUPPORT SYSTEM

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Received December 2021; revised April 2022

Abstract. *In this paper, we propose a method to improve the accuracy of the oral mucosal disease diagnosis support system in which users intervene in the inference process by estimating appropriate parameters specialized for the user. Intraoral images are non-standard images, the shooting angle, shooting distance, brightness, and so on are not constant, and furthermore teeth and fixing devices are sometimes included in the image. Thus, the variations of the images are very wide, and full-automatic diagnosis is very difficult. Therefore, in our previous system, by specifying the part of the oral image that seems to be a disease, the variation due to the difference in imaging conditions was reduced. However, depending on the user, it is not possible to cut out the appropriate disease area, so ensemble classification was employed to improve robustness. However, there are parameters that determine the characteristics of the ensemble classification, and there is a problem that the optimum parameters differ depending on the users. Therefore, in this study, we proposed a method to quantify the characteristics of the user's cutting area and determine the parameters accordingly. From the experiment, it was shown that the accuracy was improved compared with the general-purpose parameters by setting the parameters appropriately according to the user.*
Keywords: Oral mucosal disease, Diagnosis support system, Ensemble classification, Parameters optimization

1. **Introduction.** Oral mucosal diseases that develop in the oral cavity range from serious diseases to diseases that do not require treatment. In the case of serious diseases such as oral cancer, delayed corespondence often increases the risk of death and often leaves speech disorders and eating disorders after treatment, so early detection and appropriate diagnosis are important. Many of these oral mucosal diseases are found during dental treatment in a general dental clinic. However, many clinical dentists do not have specialized knowledge about oral mucosal diseases, and refer patients to specialist, oral surgeons, even in the case of mild diseases. This situation only increases the burden on

DOI: 10.24507/ijicic.18.04.1235

the patient and the oral surgeon, and in particular, the oral surgeon is wasting time to see a patient with a serious disease. There are several studies on diagnostic support systems based on images of oral mucosal tissue and images under special light sources [1-4]. These methods are very time-consuming, such as the need to collect tissue and observe it under a microscope, so it is not practical to perform it in a general dental clinic. If there is a system that supports the diagnosis of the disease when the clinical dentist discovers the disease in a general dental clinic, it will help to improve this situation.

We have been developing an oral mucosal disease diagnosis support system based on intraoral images taken by clinical dentists [5-10]. It seems to be the first diagnosis support system based on intraoral images taken with a general digital camera without using special equipment, lights or chemicals. In recent years, several studies have been reported aiming at the realization of a similar diagnosis support system using deep learning [11-16]. Deep learning is a powerful classifier, and it is possible to realize highly accurate classification in case that there is a sufficient amount of training data. Thus, deep learning is currently applied to a wide range of problems. The most important feature of the intraoral image targeted in this study is that it is not a standard image unlike other medical images, e.g., chest x-ray. That is, since the subject is a diseased part that occurs in various places in the oral cavity, the shooting angle, distance, lighting condition and so on are not constant, and the image includes teeth, fixtures and other items that are unnecessary for diagnosis. Figure 1 shows examples of intraoral images used in this study. From Figure 1, it is shown that there is a wide range of variations of intraoral images due to the inability to standardize how to take the image. Summarizing the above, there are three possible reasons why research on diagnostic support systems that directly utilize oral images has not progressed in recent years: 1) variation of intraoral images is extremely wide, 2) target area is a relatively narrow in the intraoral image and 3) collecting the enough amount of training data for deep learning is almost impossible.

FIGURE 1. Examples of intraoral images used in this study. These images show the wide range of variations of intraoral images due to the inability to standardize the shooting method.

The biggest difference between the above methods using deep learning and our method is that the dentist who is the user specifies the diseased area in the intraoral image. In other words, in our system, the system does not make a fully automatic diagnosis from the intraoral image, but the dentist specifies the area considered to be a disease in the intraoral image, and the system makes a diagnosis based on the specified area. In our previous studies, we have mentioned features that are effective for diagnosis, and as a result, we have adopted five features such as the shape of vitiligo and the presence or absence of redness. Of course, in the future, we believe that a method that can be identified with high accuracy and fully automatically from intraoral images including feature extraction can be realized by utilizing deep learning. However, at present, the realization of the system is not realistic due to the difficulty of collecting the required number of images for the variation of the image.

However, in our method, it is necessary for the dentist to specify the area that seems to be a disease, and there is a problem that the area specified by each dentist is different, that is, individual differences occur. Figure 2 shows examples in which four dentists specified

Figure 2. (color online) Individual difference in extracted ranges. Yellow: Two years career dentist, Light Blue: Five years career dentist, Blue: Thirty years career dentist, Green: Specialist (Oral surgeon).

an area of diseases for two intraoral images. From the figure, it can be seen that the width and position of the area designation range are different from each other. In order to reduce the influence of this individual difference in the diagnosis results, it is necessary to find out the characteristics of each dentist regarding the area designation and take appropriate measures, and this is the purpose of this research. There are parameters in the identification part of this method for the purpose of improving robustness, but in our previous studies, the parameters were set to general-purpose values. In other words, it was set to a value that seems to be good for many users. The method of setting such parameters is common. In this research, when setting these parameters, we propose a method to make the parameters specific to each user in consideration of the characteristics of the user. In this method, a relationship between the tendency when the disease area is extracted, that is, the tendency of the vertical and horizontal lengths of the extraction range and the appropriate parameters in the discriminator is firstly found. The new user dentist is required to extract the diseased part from multiple images prepared in advance. Appropriate parameters are set based on the extraction tendency. It is possible to set the parameters of the classifier that is not general and specialized for each dentist, and it is expected that the discrimination accuracy will be improved.

The remainder of this paper is structured as follows. In Section 2, we briefly present mucosal diseases and data used in this study. Overview of the mucosal disease diagnosis support system we developed so far, the features for the classification and the problems of the previous system are described in Section 3. In Sections 4 and 5, we explain the proposed method and experimental results, respectively. The summary and discussion are given in Section 6.

2. Mucosal Diseases and Dataset Used in this Study.

Intraoral images which were used in this study were provided by Kyushu Dental University. The method of taking an image is not standardized, unlike CT image and MR image. Therefore, distance between a camera and an affected area, shooting angle and lighting conditions differ for each case. There are 117 intraoral images in which 30, 41 and 46 are for squamous cell carcinoma (SCC), leukoplakia (LEU) and lichen planus (LP), respectively. Oral mucosal diseases of each intraoral image were given final diagnosis by specialists (oral surgeons). Our final goal is to classify an intraoral image to four categories (above three diseases and normal) and to propose a candidate for a diagnosis result.

Serious diseases that require clinical treatment are SCC and LEU. In contrast, LP is not a serious disease. SCC produces complex vitiligo, which is white spots, and uneven bumps and granules. LEU produces plate-like vitiligo and uniform bumps, with no granules. LP produces lacy vitiligo and redness, without bulge. Therefore, we focus on five features: vitiligo, vitiligo shape, redding, bulge, and granular pattern.

3. Previous Oral Mucosal Disease Diagnosis Support System.

3.1. **Overview of system.** Figure 3 shows an overview of our previous oral mucosal diagnosis support system. Input image of the system is an intraoral image. A dentist as a user manually detects area that seems to be a disease from the intraoral image. And resolution of cutout image is reduced 0.2 times, because, it has been reported that resolution reduction eliminates unnecessary information and improves identification rate in our previous researches. Feature refers to five of vitiligo, vitiligo shape, redding, bulge, and granular pattern. Support vector machine (SVM) which is a learning model with high generalization performance is used for classification, and ensemble classification is employed. Since images extracted by some dentists are different from each other, the reason for employing ensemble classification is to reduce the individual differences by creating several local images in the extracted image and using them for classification. To create the local images, there are two parameters, σ and N. In case that size of the extracted image is $l_x \times l_y$, size of local images is $\sigma l_x \times \sigma l_y$. Parameter δ $(0 < \delta < 1)$ is a coefficient for deciding the size of local images. Parameter N is a number of local images, it means the total number of classifier is $N + 1$, including that for the extracted image. The positions of the local images are randomly set. To decide the final result, majority vote is employed. If the number of votes is the same, it is decided according to the following priority, SCC > LEU > LP > normal.

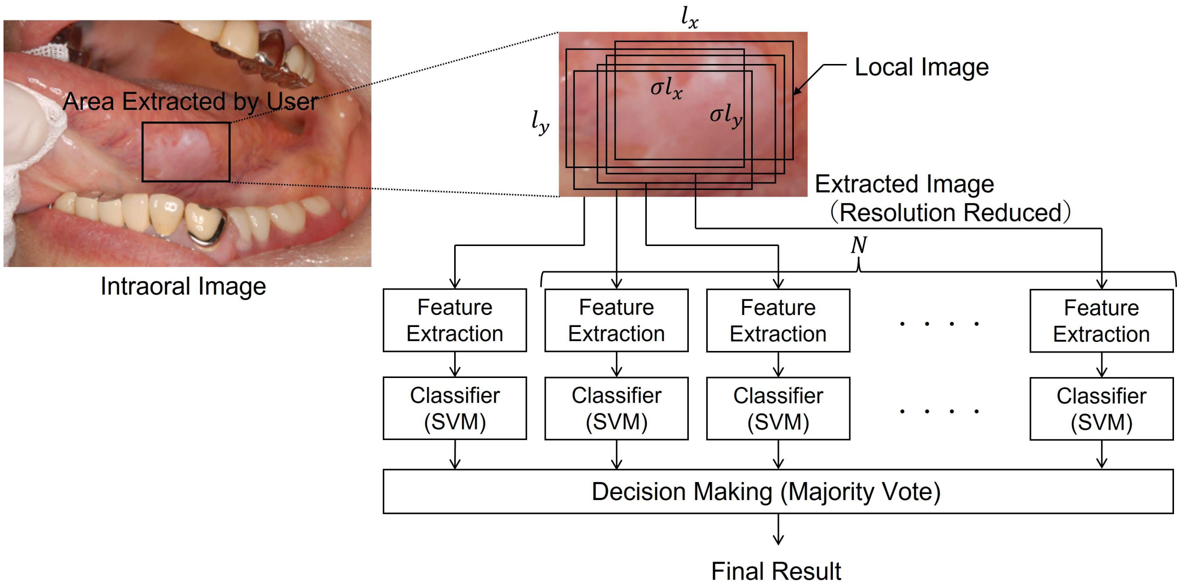

FIGURE 3. Overview of our previous oral mucosal diagnosis support system

3.2. **Features used for classification.** In this section, five features used for the classification are briefly explained. These features are not changed from our previous study. Please refer [9, 10] for detail. The features used in this study are based on the knowledge of oral surgeons. In recent years, end-to-end learning represented by deep learning has become popular. However, when images for learning cannot be sufficiently obtained for a variation of the images as in the target here, it is important to set an appropriate feature amount [17].

3.2.1. *Vitiligo feature and vitiligo shape feature.* Firstly, the vitiligo area is extracted from the extracted image. To extract the vitiligo area, histogram of saturation (S) in HSV color space of the extracted image is used. In the histogram of S, mean of maximum and minimum values is used as a threshold, and pixels whose S are less than threshold are assigned as the vitiligo area.

Although LP has an intricately-shaped vitiligo, LEU has a spatially-uniform vitiligo. Based on this knowledge, a degree of circularity F is used for definition of the vitiligo shape, and F is given by

$$F = 4\pi \frac{N_v}{L^2}, \tag{1}$$

where N_v is the number of the pixels which are assigned as a vitiligo, and L means the number of the pixels which are bordering pixels between vitiligo and non-vitiligo area.

3.2.2. *Redding feature.* LP presents redding area around the vitiligo area. Thus, mean of S value of the pixels which are not assigned as the vitiligo is defined as the redding feature.

3.2.3. *Bulge feature.* The bulge in the image is expressed by the shadow of the object. However, there is a problem that the change of color is extracted as a shadow in the intraoral image. Therefore, the bulge feature is calculated based on a gradient of intensity V in HSV color space to extract the information only for bulge effectively. The intensity V of pixel (x, y) is provided by

$$V(x, y) = \max(R(x, y), G(x, y), B(x, y)), \tag{2}$$

where $R(x, y)$, $G(x, y)$ and $B(x, y)$ are a level of the RGB components in the color image. $V(x, y)$ expresses the strength of the light. Therefore, $V(x, y)$ of vitiligo area and oral mucosal area are included in a same plane when their strengths of the light are the same, even if the change of a color exists. In other words, it is thought that an image expressing the bulges of the intraoral image is obtained by using a value image. The gradient $v(x, y)$ of intensity $V(x, y)$ is calculated, and the mean of them for pixels which are assigned as the vitiligo can be given by

$$M = \sum_{p \in P} v(p), \tag{3}$$

where p and P are pixel index and set of pixels which are assigned as the vitiligo.

3.2.4. *Granular pattern feature.* Granular patters are the characteristic structure of squamous cancer and are an important element which determines squamous cancer. The intraoral images are transformed into value image, and then the gradient intensity of each pixel is calculated. Furthermore, the binarization processing is performed with the threshold value 20. Based on edge images set to the binarization, extraction of granular patterns is tried by the opening operation which is one of the morphological operations. In order to extract granular patterns, an opening operation is performed to edge images with an 11×11 pixels circular small gure. It enlarges two pixels of small gures for all directions, and the opening operation is performed using a 15×15 pixels circular small gure. The opening operation with a 15×15 pixels circular small gure is carried out to the image. When the second image is compared with the third image, it turns out that the area of white pixels is decreasing. The area where white pixels are decreasing is an area which is applied to 11×11 pixels circular small gure and is not applied to 15×15 pixels small gure. Therefore, it turns out that it is possible to get to know the domain containing a 11×11 pixels circular small gure by calculating for the difference of the third image and the second image. The size of an area is expressed by the number of pixels. Therefore, the number in which a small gure is contained can be calculated by dividing the number of pixels by the value corresponding to a small gure. Similarly, the number in the image corresponding to a small gure can be known by enlarging the size of a small gure gradually. In this study, since squamous cancer can be considered granular patterns of various sizes, it makes a total of the number of each small gure which calculated based on each small gure in the images the amount of the characteristics of granular patterns.

3.3. **Ensemble classification.** As mentioned above, each dentist has to detect the disease area from an intraoral image in our system. If the extraction area is not appropriate, the classification rate will decrease. To improve robustness for the variation in extraction area, N local images which are smaller than the extracted image are created from the inside of the extracted image as shown in Figure 3. Five features are calculated from the extracted image and each local image, and each classifier outputs the result. The final decision is made by majority vote from the output of each classifier. In these processes, there are two important parameters which affect the result. Two parameters σ and N determine the size and the number of local images.

Table 1 shows the classification rate of one dental surgeon and 7 dentists corresponding to two parameters. In the table, the case of $\sigma = 1.0$ and $N = 1$ means the results without ensemble classification. Since the oral surgeon is an expert in oral mucosal diseases and can perform appropriate region extraction, as a result, highly accurate identification can be realized even if the ensemble classification is not adopted. From the table, it can be seen that in the ensemble classification, the discrimination rate is high when the number of the local images is small in average. However, when focusing on individuals, it can be seen that the optimum parameters differ from person to person. If aiming for a general-purpose system, the value of the parameter with the highest classification rate of multiple users ($\sigma = 0.7$, $N = 10$) should be adopted.

Table 1. Identification results of all subjects (Specialist and 8 dentists)

σ	1.0	0.9		0.8		0.7	
N	1	10	30	10	30	10	30
Dental surgeon	0.90	**0.91**	0.90	0.90	0.90	0.85	0.82
Dentist 1 (2 years career)	0.76	0.80	0.78	0.80	0.80	**0.85**	0.82
Dentist 2 (5 years career)	0.67	0.69	0.67	0.75	0.75	0.79	**0.82**
Dentist 3 (15 years career)	0.72	0.82	0.72	0.82	0.73	**0.87**	0.71
Dentist 4 (15 years career)	**0.82**	**0.82**	0.76	0.79	0.75	0.76	0.70
Dentist 5 (30 years career)	0.84	0.84	0.72	0.84	0.72	**0.87**	0.71
Dentist 6 (30 years career)	**0.88**	0.86	0.74	0.84	0.74	0.82	0.72
Dentist 7 (30 years career)	0.68	0.76	0.69	0.81	0.72	**0.83**	0.69
Average	0.78	0.81	0.75	0.82	0.76	**0.83**	0.75

3.4. **Motivation of this study.** In our diagnosis support system, the dentist who is the user extracts the part of the intraoral image that seems to be a disease, and the system performs feature extraction and classification to obtain the final result. Individual differences and lack of reproducibility are serious problems in such human-related systems. In our system, robustness was improved by using ensemble classification, but the problem remains that the optimum values of the parameters included in the ensemble classification differ for each user. In this study, we quantitatively express the characteristics of each user when extracting a region that seems to be a disease from an intraoral image. Then, appropriate parameters in the ensemble classification are estimated from the characteristics.

4. Optimal Parameter Estimation.

4.1. **Expression of detection characteristics.** In order to express the characteristics of each user's extraction, P users are required to extract the area that seems to be the diseased part from M intraoral images as shown in Figure 4. In the figure, i and j are the indexes for users and intraoral images, respectively. $x_{i,j}$, $y_{i,j}$, $w_{i,j}$, $h_{i,j}$ mean the x coordinate, y coordinate, width and height of extracted area, respectively. In order to find out what kind of bias a specific user has for a certain image among all users, normalize each of the four indicators so that the average is 0 and the variance is 1. For example, the relative x coordinate of user i for image j, $lx_{i,j}$, is expressed by the following equation.

$$lx_{i,j} = \frac{x_{i,j} - x_{ave,j}}{x_{ver,j}}, \tag{4}$$

$x_{ave,j}$ and $x_{ver,j}$ are the mean and the variance of $x_{1,j}, x_{2,j}, \ldots, x_{P,j}$, respectively. The bias of user i for all images bx_i is calculated by averaging the biases of user i for each image $lx_{i,j}$. The bias of a user for each image is averaged for all images. For user i, it is given by

$$bx_i = \frac{1}{M} \sum_{j=1}^{M} lx_{i,j}. \tag{5}$$

As a result, it is possible to obtain the characteristics of the area center coordinates, the width, and the height when each user extracts the area. For example, one user may extract a wider area compared to another. That is, the characteristics of user i are represented by four variables, bx_i, by_i, bw_i and bh_i.

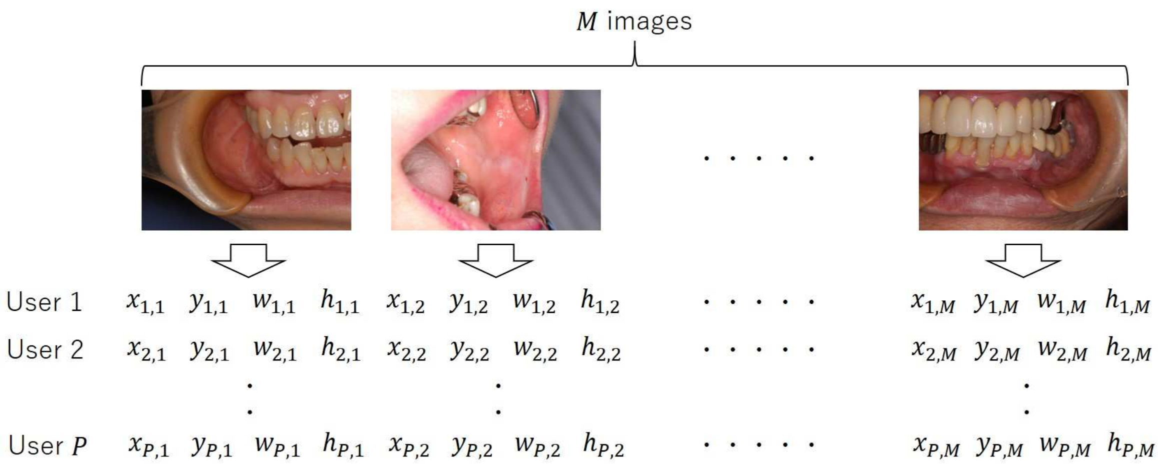

FIGURE 4. P users extract the area that seems to be the diseased part from M intraoral images.

4.2. **Estimation of optimal parameters.** On the other hand, the classification accuracy for each parameter of each user is known, and the set of the parameters which perform the best classification accuracy σ_{best} and N_{best} is the optimum solution for that user. In other words, it is possible to approximate the relationship between the bias of each user obtained in the previous section and the parameters showing the highest accuracy. This problem can be reduced to a regression problem. In this study, we consider only a finite number of parameter combinations. Specifically, considering that σ is 0.9, 0.8 and 0.7, and N is 10 and 30, there are 6 combinations. Adding a parameter with $\sigma = 1$ and $N = 1$ without ensemble, seven types of combination of parameters are defined. Here, we consider a regression problem in which four biases are input and the classification accuracy in a combination of seven parameters is output for a certain user. The bias of multiple users and the classification accuracy of each parameter are collected using the images specified in advance, and the regression model is trained based on them. For new users, the extraction bias is calculated by extracting the region that seems to be a disease from the specified intraoral image before using the system. By inputting the bias into the regression model, the classification accuracy of each parameter is predicted, so the parameter showing the maximum accuracy is regarded as the optimum parameter for the user. Figure 5 shows the processing flow.

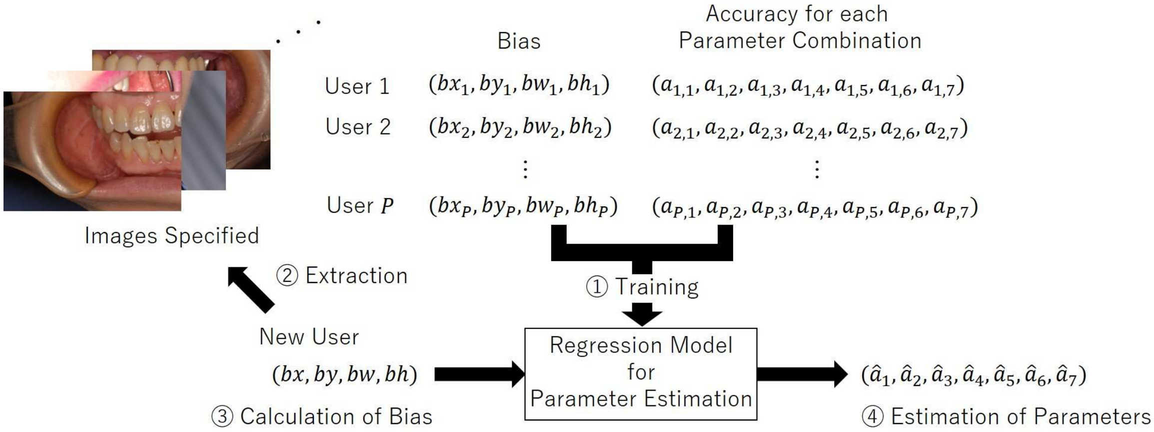

FIGURE 5. The processing flow of the procedure to estimate the specified parameters for a new user

5. **Experimental Results.** In the proposed system, three methods, linear multiple regression model, ridge regression model and canonical correlation analysis, are tested as regression models. In the experiment, the regression model was trained using the data of other users, assuming that the user is a new user. For the corresponding user, area extraction was performed on 70 images, and the classification rate was calculated for the remaining images. This experiment was performed 10 times while randomly changing the image used for region extraction, and the average of discrimination rate was calculated. Ridge regression model showed the best classification rate, and it was employed as a regression model for estimating the best parameters from the characteristics of the area extraction in the proposed method.

Figure 6 shows the results which indicate classification rate for conventional methods and the proposed method. In the figure, "Conventional (not Ensemble)" is the methods without ensemble classification, and "Conventional (Ensemble with General Parameters)" means the method with ensemble classification in which the parameters σ anf N are 0.7 and 10, respectively. These parameters are decided based on the best classification rate for all users in average as shown in Table 1. And "Conventional (Ensemble with Best Parameters" in figure means the result with the best parameters for each user which are represented in bold font in Table 1, but they are unknown in advance. In the figure, "Proposed (Ensemble Estimated Specified Parameters)" is the proposed method, in which the parameters for each user are estimated from the characteristics of area extraction by ridge regression model trained with other users data.

From these results, it can be seen that the classification rate was improved by adopting the user specified parameters compared to the general parameters. It means the characteristics of the area extraction of the individual user are appropriately extracted, and the

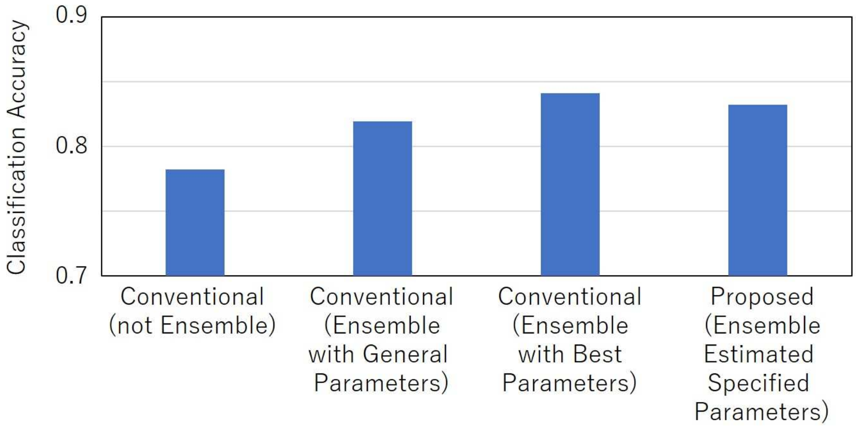

FIGURE 6. Comparison of classification accuracy

appropriate parameters are estimated by using the regression model. Of course the result with the best parameters is superior to the proposed method, and the best parameters cannot be known in advance. In the experiments, we have only about 130 intraoral images and 70 images were used for training of estimating the parameters. If more intraoral images are available, the classification rate of the proposed method can be expected to be close to the discrimination rate when the best parameters are used. Furthermore, it can be expected that the accuracy will be improved by increasing the number of subjects.

6. **Conclusions.** In this study, we proposed a method for estimating the appropriate parameters for a specific user for the ensemble identification parameters in the oral mucosal disease diagnosis support system that we are continuing to develop. In the proposed method, the characteristics of the user's area extraction are expressed as a relative bias with other users, and the appropriate parameters are obtained by estimating the accuracy of various combinations of parameters using a regression model. The effectiveness of the proposed method was shown by a classification experiment of oral mucosal diseases.

In this paper, we discussed the oral mucosal disease diagnostic system, but the idea described in this study is widely applicable to systems in which humans are involved in the process of determining the output of the system.

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