LIFTING POSTURE RECOGNITION FOR OCCUPATIONAL HEALTH USING DIGITAL IMAGE AND MACHINE LEARNING

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ABSTRACT

Lower back pain (LBP) due to awkward posture during manual lifting has been a serious problem in various workplaces. Stooping and squatting are the major postures for manual lifting. Previous studies have recommended the use of a squatting posture during lifting to prevent LBP. Monitoring and feedback of these stooping and squatting postures are necessary to ensure the use of the squatting posture. The objective of this study was to develop and evaluate a method for recognizing stooping and squatting postures during manual lifting. The proposed method recognizes stooping and squatting postures by using machine learning and digital images obtained from an ordinary monocular camera. The proposed method was tested on lifting posture images from the OrthoLoad database. The results showed that the proposed method could recognize stooping and squatting postures with 0.75 accuracy. Furthermore, the awkward stooping posture could be recognized by the proposed method with 0.80 recall (sensitivity). These results indicate the possibility that the proposed method can be used for lifting posture monitoring to prevent LBP.

Keywords: manual lifting, stooping, squatting, posture recognition, digital image, machine learning.

1. INTRODUCTION

Lower back pain (LBP) due to an awkward posture during manual lifting has been a serious problem in various workplaces, such as construction [1], [2], [3]. In the construction field, worker experience LBP due to manual handling for materials such as brick and stone [4], [5]. These lifting motions are required for specific tasks of construction such as laying out plates, sorting wall materials, and standing wall [6]. Furthermore, LBPs due to manual lifting are caused in other workplaces such as medical and industry fields [7], [8], [9]. Thus, preventing LBP due to manual lifting is important for occupational health.

Stooping and squatting are the major postures for manual lifting [10]. The stooping posture involves lifting by back bending [10]. The squatting posture involves lifting by flexion and extension of the knee [10]. Previous studies have indicated the possibility that squatting posture could reduce lumbar loads during manual lifting by using lower limb movements [11], [12]. In addition, the Japanese Minister of Health, Labour and Welfare have been recommending to use squatting posture for preventing LBP [13]. From this background, it is considered that instruction in the squatting posture is important for preventing LBP. Furthermore, monitoring and feedback of stooping and squatting postures are necessary for instruction in squatting posture. Note possibility that stooping posture will be recommended in some cases because other previous study reported some musculoskeletal loads of stooping were smaller than squatting [14]. Whether squatting or stooping is suitable, monitoring of these postures is considered necessary.

The objective of this study was to develop and evaluate a method for recognizing stooping and squatting postures during manual lifting.

2. LITERATURE REVIEW

Generally, occupational postures are recorded and evaluated by human observers [15], [16], [17]. However, there are several limitations, such as repeatability and sampling intervals in human observation [15], [16], [17]. In addition, it is considered that human observation of many occupational postures causes fatigue in observers. Therefore, an automatic posture recognition system is required for occupational health.

Posture recognition systems for occupational health were developed by various devices. Combination of wearable textile sensor shirt and machine learning could recognize sitting postures [18]. Insole pressure sensors contributed to recognize various postures such as walking, standing, and manual handling in construction fields [19], [20], [21]. Images and depth information obtained from RGB-D sensors such as Kinect were used for recognition

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of upper limb, trunk, and lower limb for occupational health [22], [23], [24], [25]. Inertial sensors can measure postures and movements related to occupational health [26], [27], [28]. Furthermore, light detection and ranging (LiDAR) is used to obtain depth information for posture recognition in occupational health [29]. These sensors can be used for posture recognition for occupational health. However, it is considered that specific sensors such as textile sensor shirt, insole pressure sensors, Kinect, and LiDAR are difficult to apply various fields because these specific sensors are not common for workers. In addition, it is difficult to inertial sensors in long term measurement since inertial sensors have problems due to drift [30].

Digital images obtained from ordinary monocular cameras are considered useful input data for posture recognition systems because they are also used in current human observations [16]. A previous study developed a posture recognition method for lifting postures using ordinary monocular images and image processing [31]. This method can recognize lifting postures based on the height to width ratio of the bounding box for a worker [31]. However, the height and width ratio of the bounding box may be affected by the body shape or object size for lifting. Combination of monocular camera and techniques of computer vision such as convolutional neural network (CNN) could measure postures and movements for occupational health [32], [33], [34], [35]. However, previous studies using CNN did not focus on suitable and unsuitable manual lifting such as squatting and stooping.

From these literature reviews, we propose the monocular digital image-based automatic lifting posture recognition method without specific sensors. In addition, bounding box is not used for image processing of the proposed method for avoiding effects from the body shape or object size.

3. PROPOSED METHOD

An overview of the proposed method is shown in Figure 1. The proposed method recognizes stooping and squatting postures by using monocular digital images and machine learning. In this study, machine learning model was trained via Teachable Machine that is web service for developing machine learning model [36], [37]. Teachable Machine had been applied for recognition model for various targets in science, engineering, and clinical field [38], [39], [40], [41]. Teachable Machine was selected for this study because this platform using graphical user interface (GUI) is easy to use for health managers who are not experts in computer vision.

The proposed method recognizes stooping and squatting postures by trained MobileNets model [42] via Teachable Machine. MobileNets is selected for the proposed method because MobileNets could be used in previous studies for applications using image recognition [43]. The parameters of the machine learning model are listed in Table 1. The trained machine learning model calculated the probability for both stooping and squatting postures. A posture with a higher probability is the output of recognition.

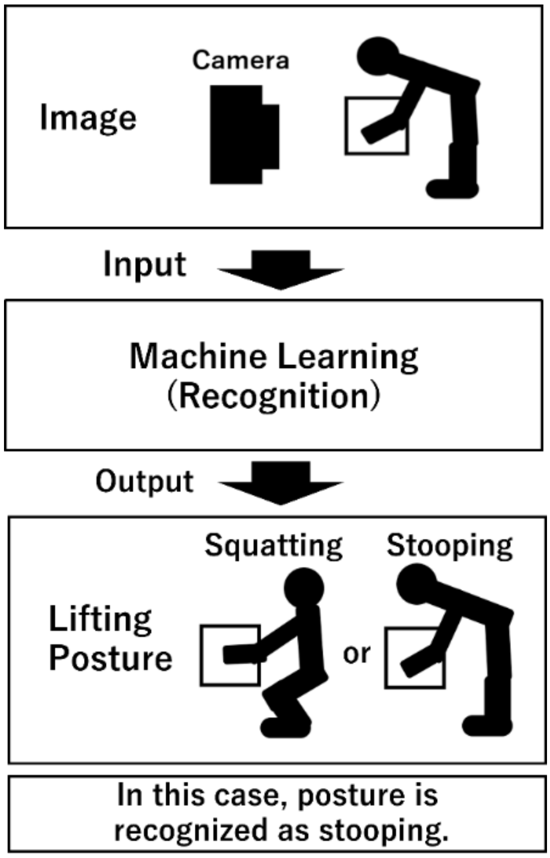

Figure 1. Overview of proposed method

Table 1. Specification of machine learning model

Parameter	Value
Algorithm	**MobileNets** [42]
Environment	**Teachable Machine** [36]
Epoch	**200**
Batch Size	**16**
Learning Rate	**0.0001**

4. EVALUATION

The proposed method was tested using stooping and squatting images from a public database. Stooping and squatting images were extracted from the OrthoLoad database [44]. Extracted images of stooping and squatting postures on the sagittal plane were labeled based on descriptions of knee and back postures (bent or straight) provided in the OrthoLoad database. A total of 100 images (50 images for each posture) were extracted and labeled from the OrthoLoad database. Table 2 shows the examples of ID list for images which were used in this evaluation. These images can be accessed via the listed ID and the OrthoLoad database [44]. Details of images such as background, brightness and contrast can be confirmed by these images at OrthoLoad database [44].

The proposed method was trained and tested using 10-folds cross validation with the labeled images. Figure 2 shows an example of a screen shot for training and testing of the proposed method via Teachable Machine.

Accuracy, precision, recall (sensitivity), and F1 score were calculated as evaluation indices from the confusion matrix of posture recognition. These values are used in evaluation of machine learning models in various fields [45]. Accuracy measures the overall proportion of correct recognized postures. Precision is an indicator for the proportion of correct recognition for each posture. Recall is an indicator of completeness of recognition for each posture. F1 score is calculated by harmonic means of precision and recall. F1 score is an indicator of balance of precision and recall. A great F1 score means that both precision and recall are great. These values were calculated using Equations 1–4:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1\ Score = \frac{2*Precision*Recall}{Precision+Recall} \quad (4)$$

where TP is the true positive, TN is the true negative, FP is the false positive, and FN is the false negative. Note that the precision, recall, and F1 score were calculated for each posture class.

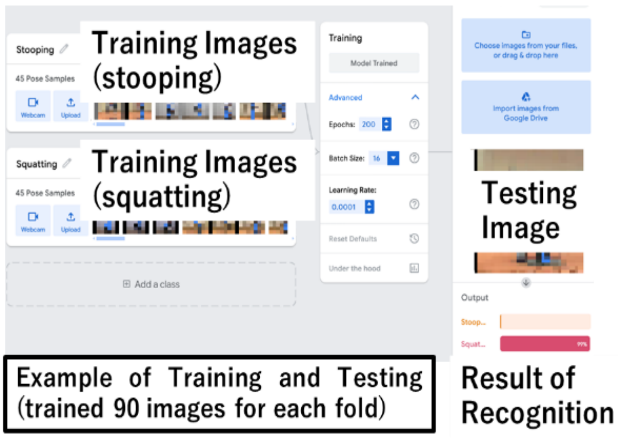

Figure 2. Training and testing via Teachable Machine

Table 2. Examples of References at OrthoLoad [44]

Data ID at OrthoLoad [44]	**Lifting Posture**
wp1_101210_1_101	**Stooping**
wp2_071207_1_79	**Stooping**
wp4_270808_1_46	**Stooping**
wp5_280311_1_122	**Stooping**
wp1_270808_1_42	**Squatting**
wp2_071207_1_75	**Squatting**
wp4_101210_1_151	**Squatting**
wp5_280311_1_126	**Squatting**

5. RESULTS

A confusion matrix for posture recognition is presented in Table 3. A total of 40 stooping postures could be correctly recognized by the proposed method. In addition, a total of 35 squatting postures could be correctly recognized by the proposed method. On the other hand, the other 10 squatting postures were incorrectly recognized as stooping posture. Furthermore, the other 15 stooping postures were incorrectly recognized as squatting postures.

The results showed that the proposed method could recognize stooping and squatting postures with 0.75 accuracy. Figure 3 to 5 show the precision, recall, and F1 scores of the proposed method. The precision, recall, and F1 score were greater than 0.70 in both stooping and squatting. The precision and confusion matrix indicated that squatting postures were more correctly recognized than stooping postures were. The recall and confusion matrix indicated that stooping postures were recognized more comprehensively than squatting postures.

Table 3. Confusion matrix of posture recognition

Confusion Matrix		**Predicted**	
		Stooping	**Squatting**
Actual	**Stooping**	**40**	**10**
	Squatting	**15**	**35**

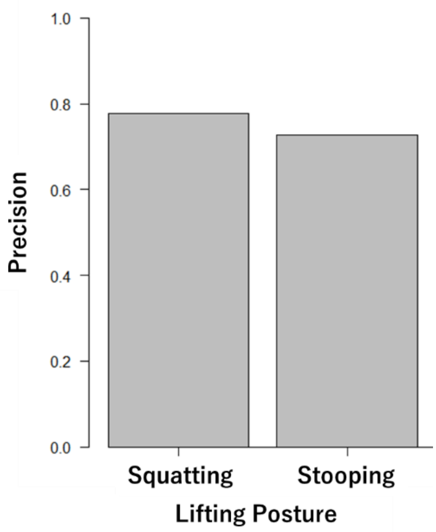

Figure 3. Precision of posture recognition

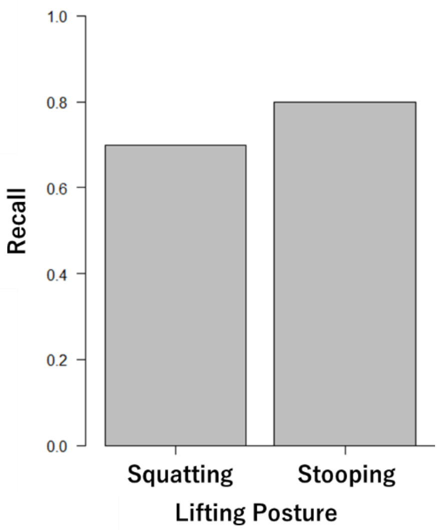

Figure 4. Recall of posture recognition

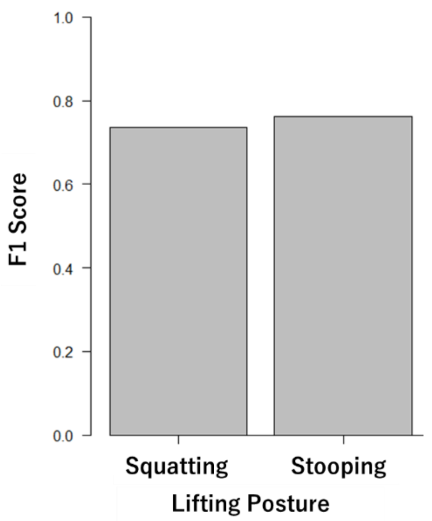

Figure 5. F1 Score of posture recognition

6. DISCUSSION

The experimental results showed that the proposed method could recognize stooping and squatting with 0.75 accuracy. A previous study reported that the inter-observer reliability of lower limb posture recognition in human observation was 0.66 to 0.97 [46]. From this previous report, it is considered that 0.75 accuracy of the proposed method is comparable to that of human observations.

As mentioned previously, this study suggests that stooping postures should be recognized and improved to prevent LBP due to manual lifting. The proposed method could comprehensively recognize stooping postures with 0.80 recall (sensitivity). These results indicate the possibility that the proposed method can be applied to the automatic monitoring of manual lifting postures to prevent LBP. Note that a recognition method between lifting and other postures such as standing and sitting might be required because an automatic monitoring system should initially recognize lifting activities from occupational activities in the workspace.

The limitation of this study was that the posture images were limited to the sagittal plane. Camera angles might affect accuracy, precision, recall, and F1 score in posture recognition. Thus, machine learning models should be trained and tested by further images with various camera angles for improving performances of posture recognition. In addition, light conditions of images which were used in this study were only day light conditions. The proposed method should be tested for night light conditions. In this study, the number of trained images was only 90 for each fold in 10-folds cross validation. More trained images might contribute to improving accuracy of the proposed method. In the future works, the number of images might be increased for improving the proposed method. In addition, several techniques of computer vision such as data augmentation [47], [48] will be applied for increasing the number of images.

Vision-based measurement methods, including the proposed method, can accurately measure human movement [49]. However, these vision-based methods have limitations in their measurement ranges. Thus, it is possible that the proposed method will be used concomitantly with wearable sensor-based methods [50] for posture monitoring in the workspace.

7. CONCLUSION

In this study, we propose a recognition method for stooping and squatting postures during manual lifting. The experimental results indicate that the proposed method can recognize stooping and squatting postures in manual lifting. The findings of this study provide an approach using only a monocular camera for preventing LBP due to manual lifting in occupational health. In a future study, the proposed method will be modified and investigated under various conditions.

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