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Deep Learning Frameworks for Cervical Mobilization Based on Website Images

Background: Deep learning related research works on website medical images have been actively conducted in the field of health care, however, articles related to the musculoskeletal system have been introduced insufficiently, deep learning-based studies on classifying orthopedic manual therapy images would also just be entered.
Objectives: To create a deep learning model that categorizes cervical mobilization images and establish a web application to find out its clinical utility.
Design: Research and development.
Methods: Three types of cervical mobilization images (central posteroanterior (CPA) mobilization, unilateral posteroanterior (UPA) mobilization, and anteroposterior (AP) mobilization) were obtained using functions of 'Download All Images' and a web crawler. Unnecessary images were filtered from 'Auslogics Duplicate File Finder' to obtain the final 144 data (CPA=62, UPA=46, AP=36). Training classified into 3 classes was conducted in Teachable Machine. The next procedures, the trained model source was uploaded to the web application cloud integrated development environment (https://ide.goorm.io/) and the frame was built. The trained model was tested in three environments: Teachable Machine File Upload (TMFU), Teachable Machine Webcam (TMW), and Web Service webcam (WSW).
Results: In three environments (TMFU, TMW, WSW), the accuracy of CPA mobilization images was 81-96%. The accuracy of the UPA mobilization image was 43~94%, and the accuracy deviation was greater than that of CPA. The accuracy of the AP mobilization image was 65-75%, and the deviation was not large compared to the other groups. In the three environments, the average accuracy of CPA was 92%, and the accuracy of UPA and AP was similar up to 70%.
Conclusion: This study suggests that training of images of orthopedic manual therapy using machine learning open software is possible, and that web applications made using this training model can be used clinically.

Keywords: *Mobilization; Medical images*

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INTRODUCTION

Predicting the presence and progression of brain tumors, heart disease, lung cancer, etc., it has been influential and so prolific in domain of this scholarship about incorporating artificial intelligence (AI). Researchers perceived this issue as being actively conducted whole area. AI in the field of radiology and pathology has already begun to significantly exceed the discriminant ability of doctors, and is currently making diagnosis in collaboration with AI.[1,2] Consilience through such artificial intelligence is expanding to various fields of health care beyond the work of medical doctors, and AI research would also have been published in the physical therapy scopes. In recent years, big data tasks to collect images and videos related to the musculoskeletal system are actively underway,[3] and this data is expected to be an excellent foundation for supervised learning.

In the preceding studies linking to the musculoskeletal system and AI, there are few studies on unsupervised learning, and studies on supervised learning are mainly conducted in relation to medical imaging, pain, wearable technology, risk prediction, and decision support.[4,5] Even in the case of medical imaging research related to invigilated learning, it can be seen as a research in radiology rather than a field of physical therapy because it is a study that might reads fractures and the like with x-rays.[6] Since supervised learning studies related to the musculoskeletal system including image classification are insufficient, there are also few studies on image classification related to posture or hand grip for orthopedic manual therapy.

Deep learning (DL) is a set of machine learning (ML) algorithms that attempts high-level abstractions (abstractions, the task of summarizing key contents or functions in a large amount of data or complex data) through a combination of several nonlinear transformation methods. It is defined and can be described as a branch of ML that teaches computers how to think in a large frame.[7]

When there is any data, it is represented in a form that can be understood by a computer (for example, in the case of an image, pixel information is expressed as a column vector, etc.) and a lot of research (how to do better) to apply it to learning. And how to make a model for learning them, and as result of these efforts, various deep learning techniques such as deep neural networks, convolutional deep neural networks, and deep belief networks are being used in computer vision and speech recognition. Natural language processing, voice/signal processing, etc., showing cutting-edge results.[8] This is a part that scholars and clinicians should consider in the part of grafting physical therapy and rehabilitation medicine in line with the changing times, and it is expected that better educational outcomes and clinical performance may be improved. In the meantime, it may be possible to solve the limitations of traditional teaching materials and training through apprenticeship training or group practice on clinical skills.

When computer learns an image of certain operation that performs orthopedic manual therapy through machine learning and the recognition accuracy is increased, it is possible to provide audio-visual feedback on the manual therapy operation performed by a person in real time. Learning results could be applied to web services in a few steps, and be used at any time by simply accessing the web address.[9] Since a webcam or camera can monitor the practitioners and give feedback on the correctness, error, and accuracy of the movement on behalf of the supervisor or supervisor, it might be anticipated for online lessons or even study by oneself.[10,11] In addition, such web services will be enable more objective and clean evaluation without the existing authoritative and subjective judgments in test evaluation, etc.[12] These artificial intelligence interventions would anticipate to help fill the expectations in education caused by the COVID-19 Outbreak and retrench education costs.[13]

Therefore, in this study, frameworks for recognizing an orthopedic manual therapy image through supervised learning was created, and the possibility of clinical application was suggested through a web service test.

METHODS

Preparing Image Datasets

In this study, training was conducted to classify different images by collecting cervical mobilization images. Images were collected in Google browser using a web crawler developed in Python and the 'Download All Images' app. The search words (32 terms) using the crawling are introduced in Table 1. A total of 9907 images were obtained through the search, and duplicate files and unsuitable files were removed using the 'Auslogics Duplicate File Finder' program, and the final 144 images were obtained. The class classification of cervical mobilization images consisted of central posteroanterior (CPA) (62), unilateral posteroanterior (UPA) (46, left/right), and anteroposterior (AP) (36, left/right).

Model Training

The image was trained using the Teachable Machine[12] developed by Google. The image was uploaded by configuring 3 classes in the 'Image Project' section. The ratio of training data: test data randomly selected for each class is 80%: 20%. Epochs 50, batch size 16, and learning rate were set to 0.001. The initial time spent training is 13 seconds. Pressing the training button repeatedly shortens the training time to around 3-4 seconds.

Web Service Application

After learning was completed, we entered a new window on the 'Teachable Machine' screen (Figure 1).

Table 1. Index search words

Body parts	Search terms
Neck	neck_mobilization, neck_mobilisation, neck_postero_anterior_mobilization, neck_postero_anterior_mobilisation, neck_pa_mobilization, neck_pa_mobilisation, neck_anterior_mobilisation, neck_anterior_mobilization, neck_unilateral_mobilization, neck_unilateral_mobilisation, neck_anteroposterior_mobilisation, neck_ap_mobilization, neck_ap_mobilisation, neck_posterior_mobilisation, neck_posterior_mobilization,
Cervical	cervical_anteroposterior_mobilization, cervical_anteroposterior_mobilisation, cervical_ap_mobilization, cervical_ap_mobilization, cervical_mobilization, cervical_posterior_mobilization, cervical_posterior_mobilisation, cervical_posterior_mobilization, cervical_posterior_mobilisation, cervical_posterior_mobilization, cervical_posterior_mobilisation, cervical_posterior_mobilization, cervical_posterior_mobilisation, cervical_posterior_mobilization, cervical_posterior_mobilisation, cervical_posterior_mobilization, cervical_posterior_mobilisation. cervical_mobilization, cervical_mobilisation, cervical_postero_anterior_mobilization, cervical_postero_anterior_mobilisation, cervical_pa_mobilization, cervical_pa_mobilisation, cervical_anterior_mobilisation, cervical_anterior_mobilization, cervical_unilateral_mobilization, cervical_unilateral_mobilisation, neck_anteroposterior_mobilization,

1) Click the 'Export Model' button to enter a new window. Then, after selecting'Tensorflow.js' and 'Javascript' in order, we downloaded 'my model'. TensorFlow.js is a library that develops and trains machine learning models with JavaScript and distributes them to browsers or Node.js.
2) After logging in to 'goormide (https://ide.goorm.io/)',[14] which provides an integrated cloud development environment, click on 'Dashboard' to create a new container. After setting the title, region, and scope of disclo-sure, we selected HTML/CSS/JS' and clicked the 'Create' button to create the container. It took about 10 seconds to create the container, and then I entered the container by pressing the 'Run Container' button.
3) Click the'+' button in the container to create a 'my_model' folder, then put the 3 downloaded files (metadata.json, model.json, weight.bin) into this folder to set up the model. Then dou-ble-click on'index.html' and check that 'head' and 'body' are written. Then, I copied the Javascript code generated by "Teachable Machine" and replaced the body tag '〈div class = "title"〉 Hello, goorm! 〈/ div〉'. Next, select the code format (html format), save it, and click the 'Open Preview' button to create a web page window. After accessing the web page, press the 'Start' button and press the 'Allow Camera' button to display the web camera on the screen.

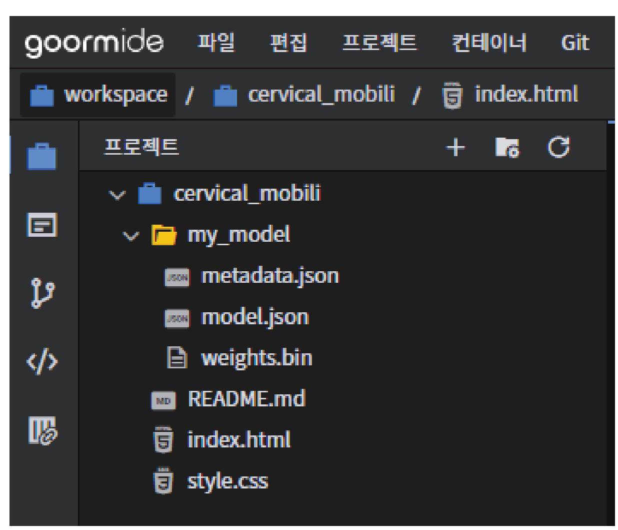

Figure 1. File structure of web application

Data Test

The test set images are 13 CPAs, 11 UPAs, and 8 APs, which are 20% of the total data for each class. The images used in the train set and validation set are 80% of the total and are automatically classified within the program. After creating the web service, the test data was loaded from the mobile phone screen, and the image recognition performance was tested by facing the laptop webcam. The hardware system used in the study was Intel i7-10875h (2.3GHz), memory 64GB, GeForce RTX 2060, and the mobile phone was Galaxy S10 5G, and the mobile phone screen and laptop screen kept a horizontal distance of 10cm. In order to maintain the consistency of image recognition, the light brightness was kept constant, and a mobile phone holder was used to prevent shaking of the mobile phone (Figure 2, 3).

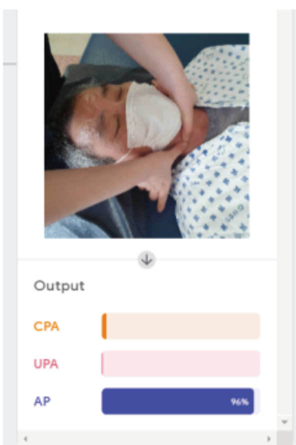

Figure 2. Output screen in Teachable machine (file upload, webcam)

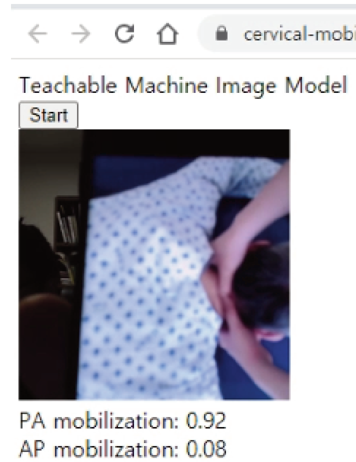

Figure 3. Main screen of a web application

RESULTS

Teachable Machine File Upload (TMFU) is a result of recognizing the file uploaded on the Teachable Machine screen, and the accuracy was highest in CPA, followed by AP and UPA. Teachable Machine Webcam (TMW) is the result of the Teachable Machine's webcam recognition, and the accuracy is the same as in TMFU, with the highest CPA, followed by AP and UPA. Web Service Webcam (WSW) is the result of recognizing a web application developed by our research team based on the Teachable Machine model, and the accuracy was highest in CPA, followed by UPA and AP. In addition, CPA images had the highest accuracy in WSW, followed by TMW and TMFU in order. UPA images had the highest accuracy in WSW, followed by TMFU and TMW. AP images were highest in TMFU, followed by WSW and TMW (Table 2).

Table 2. Comparison of accuracy in teachable machine and web application

	Each Image Test Accuracy (%)													
	Teachable Machine File Upload (TMFU)													
	No.	1	2	3	4	5	6	7	8	9	10	11	12	13
Image Class	CPA	18	100	100	100	7	99	98	99	88	99	100	100	53
	UPA	0	100	0	99	92	100	98	0	100	99	100		
	AP	0	99	96	99	99	100	37	73					
	Teachable Machine Webcam (TMW)													
	CPA	99	98	97	99	95	84	99	98	100	99	98	92	97
	UPA	15	97	0	92	3	58	17	8	75	33	84		
	AP	2	99	75	78	87	100	25	57					

Table 2. Cont'd

	Each Image Test Accuracy (%)													
	Web Service Webcam (WSW)													
	No.	1	2	3	4	5	6	7	8	9	10	11	12	13
Image Class	CPA	100	100	100	99	100	87	97	99	99	100	100	75	100
	UPA	100	65	100	98	98	82	99	100	99	96	98		
	AP	100	85	92	93	72	97	2	2					
	MTA (%)													
		TMFU				TMW				WSW				
	CPA	81.62				96.54				96.62				
	UPA	71.64				43.82				94.09				
	AP	75.38				65.38				67.88				

CPA: central posteroanterior, UPA: unilateral posteroanterior, AP: anteroposterior, TMFU: teachable machine file upload, TMW: teachable machine webcam, WSW: web service webcam, MTA: mean test accuracy

CONCLUSION

In this study, we implemented machine learning that can classify cervical mobilization images based on the 'Teachable Machine' developed by Google. The image classification accuracy was compared with the file upload and webcam methods provided by Teachable Machine, and the web application we developed. The developed web application can be accessed directly from a computer by copying and entering the web address during testing. If you use this web application, you can identify cervical mobilization images at any time.

In the manual therapy web application implemented in this paper, when a cervical mobilization image was projected on a web camera, the server classified three classes of images. Using this web application, you can predict 3 types of cervical mobilization images trained with a 'Teachable Machine'. As a result of testing the application implemented in this study, in the case of CPA, the accuracy is about 81–96%, but in the case of UPA and AP, the accuracy is 43–94%. It is believed that the reason why CPA has the highest accuracy is that the number of CPA images is relatively large among the three classes. On the other hand, there was a case that an AP image wearing a mask was incorrectly recognized as a CPA image. Overall, the reason the accuracy is not high is thought to be because images with masks and images without masks are mixed, and the images were taken in various environments. For improving the classification accuracy, it is necessary to secure more training images of various types.

In the era of precision medicine, data-based medical care is essential, and from the point of view of data collection, it will become important how to utilize data collection on patients, which increases at a faster rate than the development of treatments within the scope of big data in the medical field. Now, clinicians are faced with an era in which data produced in hospitals should not be discarded and used for patient treatment. This research is at the level of inexperienced preliminary research in the early stages, and I hope that the domestic research in this field that is still inadequate will be established by the research of these authors.

In addition, it is considered necessary to try supervised learning by grafting transfer learning such as VGG16, Resnet50, and Resnet50V2, and supplement the number of images that are insufficient through augmentation. Meanwhile, we plan to improve the accessibility of web applications by focusing on convenience and fast speed in subsequent research.

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