New AI model uses federated learning for multi-organ segmentation based on medical image data

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Researchers have successfully developed the technology that can accurately segment different body organs by effectively learning medical

image data used for different purposes in different hospitals, which is expected to greatly contribute to the development of large-scale medical AI models in the future.

The study, published in the journal *Medical Image Analysis*, was led by Professors Kilian Pohl and Ehsan Adeli at Stanford University and Professor Sanghyun Park at the Department of Robotics and Mechatronics Engineering, the Daegu Gyeongbuk Institute of Science & Technology.

Hospitals and other health care institutions have organ image data for various parts of the body for different purposes. To facilitate and provide health care more accurately, however, it is necessary to develop an AI model for multi-organ segmentation based on the medical data that individual institutions do not have.

In the past, image data from different health care institutions was collected and learned on a central server, and therefore, it was difficult to apply the above method in the health care field, which is sensitive to data breaches and leaks. Furthermore, different health care institutions have different areas of interest for the use of images, which results in a limitation in training a model that can analyze and simultaneously segment multiple areas.

Against this backdrop, Professor Park proposed a multi-organ segmentation model based on federated learning to effectively utilize distributed data with different organ labels without data breaches and leaks. Federated learning makes it possible to train an AI model by allowing different institutions to work with each other without directly sharing distributed data.

However, during the process where the information obtained from distributed data is compiled, information is lost, which is also known as

the problem of "catastrophic forgetting," and the data with different labels for different areas of interest makes learning unstable, leading to the shortcomings that the model is not established or the learning speed slows down.

To tackle this problem, Park's team proposed the knowledge distillation technique. To begin with, the research team used a multi-head U-Net model to segment the image data of different body organs from different institutions, and shared the segmented images with shared embedding learning, which enabled different institutions to perform federated learning by using the knowledge of the global model and the pre-trained specific organ segmentation model when training the AI model.

Consequently, Park's team successfully developed a novel technique that uses fewer parameters and computations with better performance than previously proposed models.

To verify the developed technique, the research team applied the technique to an abdominal CT dataset with seven different segmentation labels. Validation revealed that while the traditional multi-organ segmentation models had the performance of 66.82% on average in federated learning, the newly developed technique had the higher performance of 71.00% on average and reduced the inference time with shared embedding learning.

Park said, "In this study, we successfully developed the technology to segment different organs of interest so that medical AI can be effectively trained and utilized even though medical image data from multiple health care institutions are not shared. I think that the newly developed technology will be greatly helpful in medical image analysis, and it is expected to contribute to the development of large-scale medical AI models in the future."

More information: Soopil Kim et al, Federated learning with knowledge distillation for multi-organ segmentation with partially labeled datasets, *Medical Image Analysis* (2024). DOI: 10.1016/j.media.2024.103156