4-4　パブリック・プライベートデータを活用した予測モデリングを実現する連合学習によるエッジ AI

4-4　Edge AI with Federated Learning for Public-private Cooperative Predictive Modeling

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従来の機械学習パイプラインでは、モデルを学習するために単一のコーパスに収集されたデータを必要としていた。機械学習手法の一種である連合学習は、複数の分散型エッジデバイスやデータ収集にわたってモデルを学習する仕組みを提供する。エッジと中央サーバー間の通信要件や異種データの分布とインフラストラクチャは、実世界のアプリケーションにおける連合学習の課題となっている。本稿では、連合学習の包括的な定義を提供・分類し、本質的な課題について議論する。Non-IID 分布の問題や計算限界に対処するため、グローバル側での連合学習連携アルゴリズムとエッジ AI 適応アプローチを導入した。提案した技術の環境及びスマートホームサービスなどへの応用についても述べる。また、Beyond 5G / 6G 適応に向けた新しい研究の方向性について述べる。

Conventional machine learning pipelines require data collected into a single corpus to train models. Federated learning (FL), a type of machine learning technique, provides a mechanism to train models across multiple decentralized edge devices or data collection. The requirement of communication among edges and central server and the heterogeneous data distribution and infrastructure challenges federated learning in real world application. In this paper, we provide a comprehensive definition of federated learning, categorize it, and discuss essential challenges. To tackle non-IID distribution issues and computational limitations at edges, we introduced federated learning collaboration algorithms on the global side and Edge AI adaptation approach. The proposed techniques have been applied to environmental and smart home services, etc. We also address new research directions in the context of Beyond 5G / 6G adaptation.

1 Introduction

Today, the development of mobile devices and the Internet of Things (IoT) with many applications has recently brought benefits to society, from smart cities and intelligent transportation to smart cities and personalized health care support systems. Artificial intelligence (AI) [8] has support data from many different information sources that can be modeled through training processes. Therefore, the trained model is used in future forecasting tasks. Besides, the development of telecommunications technology has promoted the network infrastructure, especially in the 5G / 6G era. Today's intelligent systems have become more data-intensive and high-speed, with low latency and high communication capacity. In 2016, the Japanese government proposed building a Japanese Society 5.0[*1], a super-smart society. It takes advantage of the most outstanding achievements of the industrial revolution 4.0 (i.e., artificial intelligence, robotics, internet of things, big data) to solve complex social problems and bring a whole life to people in the future. Japanese Society 5.0 Beyond 5G / 6G [1] is an indispensable component supporting artificial intelligence, big data, and other ancillary technologies.

Although, modern deep learning models and big data analytics based on AI models often require enormous computing power and data consumption. However, thanks to the development of telecommunications technology,

＊1　https://www8.cao.go.jp/cstp/english/society5_0/index.html data can be transmitted with low latency. In addition, embedding model inference and training facilities in the network's edge (Artificial Intelligence Edge) [2] can also help solve the challenge of data-driven communication and enable marginal contribution to the entire infrastructure. Bringing training and inference close to hand also protects privacy and secrecy. It provides high security, thereby reducing network traffic congestion and energy consumption and reducing computational load at the server. To enable knowledge sharing across the edges to generalize AI models, the FL model [3][4] provides a framework for collaboratively training global statistical models that demand multiple edge participants without accessing private raw data locally.

The edge AI enabled in the federated learning framework can be depicted in Fig. 1. At the edge, devices can collect user data and pass it to the Edge AI server for local storage and model generation. Sometimes devices can also train and infer directly without edge AI server support, but users often have multiple device types. We will address these issues in the section related to Edge AI. On top of the advanced AI environment above, the federated learning framework can support collaborative training by collecting locally updated models from the edges and combining them with the global model. In this study, we aim to integrate the collaboration between public and private data training to overcome the problems of FL of heterogeneous data distribution for the users to join and limit local data.

This paper will provide a comprehensive picture of design FL systems that enable collaboratively training among edge AI and the association between models trained on private and public data. The contributions are in the following items.

- We convince the readers that combining edge AI and federated training paradigms distill knowledge from edge to central server. Thus, better performance in general while keeping the privacy of personal information on edge.
- We provide a system design that works with the IoT environment, processes on edge, and can share among participants. Furthermore, master models can be initially trained and updated through time using public data. They can be combined with local models trained on private data.
- We illustrate applications including environmental, healthcare, and traffic monitoring systems in many configurations of federated learning paradigm and edge AI suitable capacity.
- We address future research and development in general and direct to NICT innovation promotion which drives economic growth and society affluent, safe, and secure.

The paper is organized as follows: Following the first section, the second section will revise the background of federated learning and edge AI within the context of B5G promotion and Society 5.0. Section **3** subsequently introduces our current achievement with demonstration and ongoing research in the field. We will address challenges in Federated learning and edge AI research in section **4** before the conclusion in the last section.

2 Research Background

In this context, we describe the perspective of AI on cloud and edge environments, the collaboration, and challenges. As shown in Fig. 2, the differences and intricacies of AI modeling applications and availability across mobile

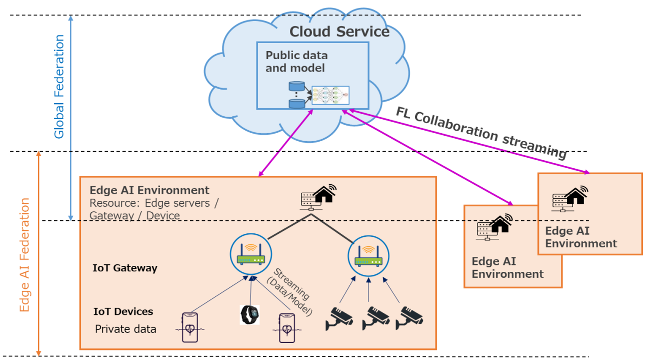


Fig. 1　Edge AI collaboration on Federated Learning Paradigms

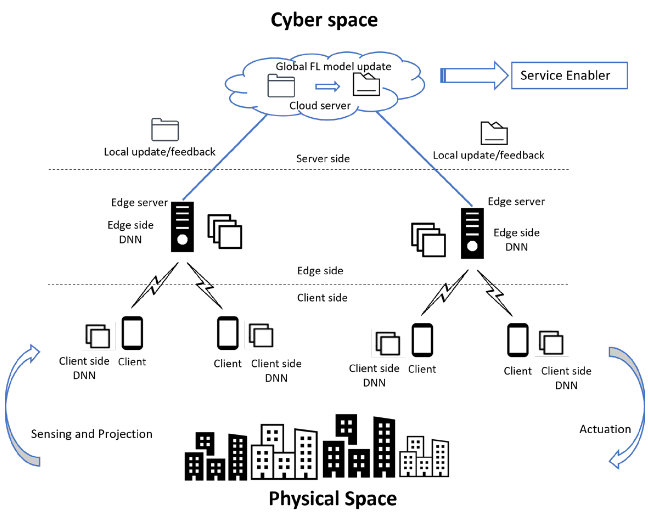


Fig. 2　Emerging Federated Learning and Edge AI in Cyber-Physical Spaces Infrastructure

devices, edge servers, and cloud machines integrated into CPS are depicted. FL is first a means to aggregate across edges and devices, enabled by low-latency data transmission to generalize predictive and forecasting ability to service enablers. Meanwhile, data processing and AI-based applications [5] on Edge AI involve processing with edge and client sides directly to physical space.

2.1 Federated Learning

2.1.1 Federated learning paradigm

In conventional machine learning approaches, data is often gathered into a centralized database. Then sample data is drawn to train machine learning models until convergence. In an ideal scenario where data can be transferred without communication cost, high computational capacity is available for training. There are non-issues of data privacy, a model trained on the whole corpus will capture the statistical distribution of general data and should provide the highest accuracy for the entire training dataset.

In the FL paradigm, each IoT device or Edge server owns its private data yet wants to cooperatively train a machine learning model without sharing individual data. The method of FL was first proposed by McMahan et. al. [3] in which each participant trains a local model on their own data before sending it to a global server for aggregation. The aggregated models are sent back to local for the next training round in an iterative way.

Formulary, as described in Fig. 3, there are a set of K participants along with their private data set. In each training round, a global model w is aggregated from many local models w_k trained locally on local datasets. Therefore, the objective of learning problem is to find an optimal aggregate function f such that $w = f(w_k)$. Note that local models and aggregated models are iteratively updated over time. In the federated learning paradigm, each (communication) round of federation often involves many training epochs at local clients.

Conventionally, Federated Averaging Aggregation (FedAvg) [3] shows a simple yet effective method to aggregate local models. In FedAvg, local models are optimized by stochastic gradient descent (SGD) using the same hyper-parameters including learning rate and training epochs over all participants.

2.1.2 Federated learning systems and challenges

Commonly, FL systems can be categorized into two types by the federation scale: cross-silo and cross-device federated learning [6][7]. Cross-silo federated learning is collaborative training between organizations such as hospitals and banks. In this type, the number of participants is small. However, local data is known to be significant, with high-performance servers to serve as local training tremendous capacity.

In contrast, in cross-devices FL, local models are trained collaboratively on end-user devices. In this type, the number of participants in active training rounds could reach to million, with small computational capacity. Participants in this type can be using mobile devices or IoT sensor devices. Instead of training large datasets, this type faces a high communication cost when many participants update their model to the central server for aggregation.

In our current research, instead of training on devices, data from end-user devices can be gathered to closed edge AI. AI models are then trained on edge before sending to cloud servers for aggregation. Edge AI may have a small capacity compared with local servers as cross-silo FL. Edge

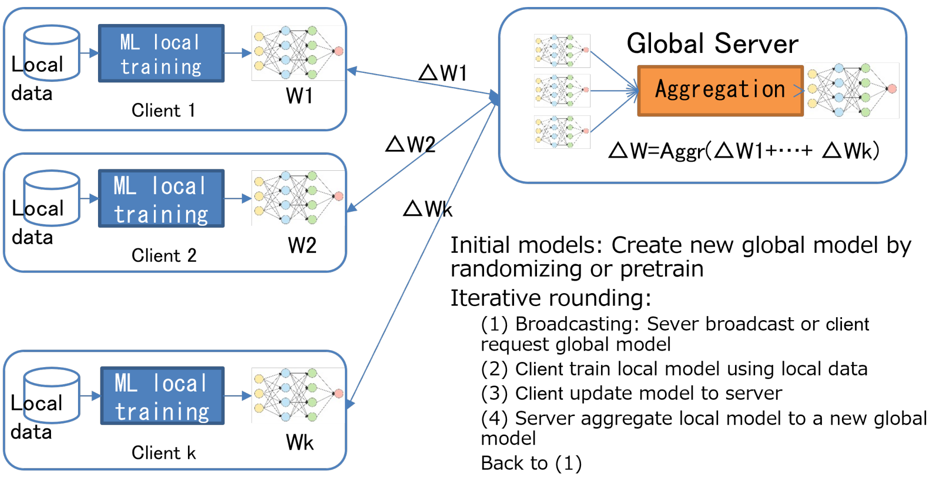


Fig. 3　Federated Learning Paradigm

AI served in tiny smart homes or buildings. Thus, the number of participants in FL is also higher than those in cross-silo. Moreover, Edge AI and devices also can collaboratively train local models by taking training responsibility on smaller parts of models that split from original local models.

There are some vital challenges that must be solved during the training distributed to various participants, with heterogeneous local data distribution and complex system configuration. The challenges include *expensive communication, system heterogeneity, statistical heterogeneity*, and *security and privacy concerns*. In addition to the main challenges, the other obstacles of federated learning can be pointed out: incentive mechanisms for participants, personalization and multi-task on local sites, and fairness among participants, to name a few. Those obstacles make FL more challenging when deploying into real-world applications, especially with the emerging Edge AI in heterogeneous IoT environments.

2.2　Edge AI and use case

2.2.1 Edge intelligence

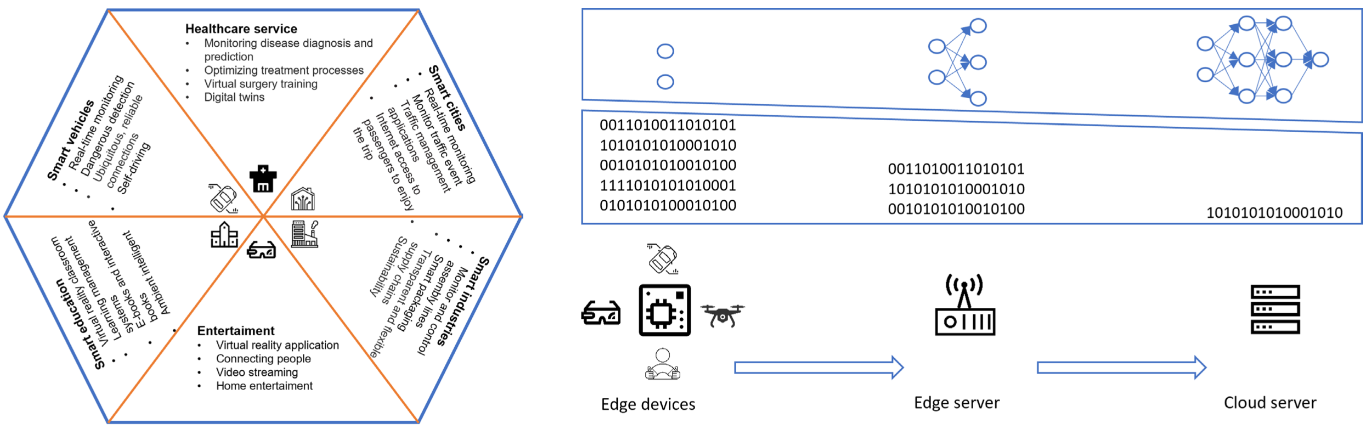
Big data processing requires more powerful methods, i.e., AI technologies, to extract insights that lead to better decisions and strategic business moves. In the last decade, with the great success of Deep Neural Networks (DNNs) [8], it has been possible to learn profound data representations and become the most popular machine learning architecture.

Considering that AI is functionally necessary to analyze vast volumes of data and extract insights quickly, a strong need exists to integrate Edge Computing and AI, creating Edge Intelligence. Edge Intelligence is not a simple combination of Edge Computing and AI. The topic of Edge Intelligence is enormous and highly complex, covering many concepts and technologies intertwined in a difficult attitude [9]. Figure 4a depicts vital conceptual studies from the perspective of building an intelligent wireless network on Edge.

2.2.2 Artificial intelligence meets edge computing

We believe the fusion of AI and Edge Computing is natural and inevitable. There is a close exchange and brings many outstanding advantages. On the one hand, AI provides EC with technologies and methods that enable Edge Computing to unleash its potential and scalability with AI. In another aspect, EC provides AI with scenarios and platforms, and AI can expand its applicability with EC.

The current research focuses on AI on Edge, including architecture, implementation, and application. AI on Edge is understood as deploying AI models on Edge. Edge AI for operating training and inference AI models combined with a device-cloud synergy. That aims to extract insights from large and scattered edges data with the satisfaction of algorithm performance, cost, privacy, reliability, efficiency, etc. Therefore, it can be interpreted as Edge AI. Fig. 4b. illustrates the differences, complexity of AI, and data availability across mobile, edge servers, and the cloud. The fact that data exists at devices such as edge clients, edge servers, and cloud is inversely proportional to its processing. As aforementioned, many solutions share data processing using methods such as split learning, a combination of split learning (SL), and FL [9][10]. The primary purpose is to solve the computation load for both edge clients and not need to share data for the server.



(a)　　　　(b)

Fig. 4　Artificial intelligence on Edge

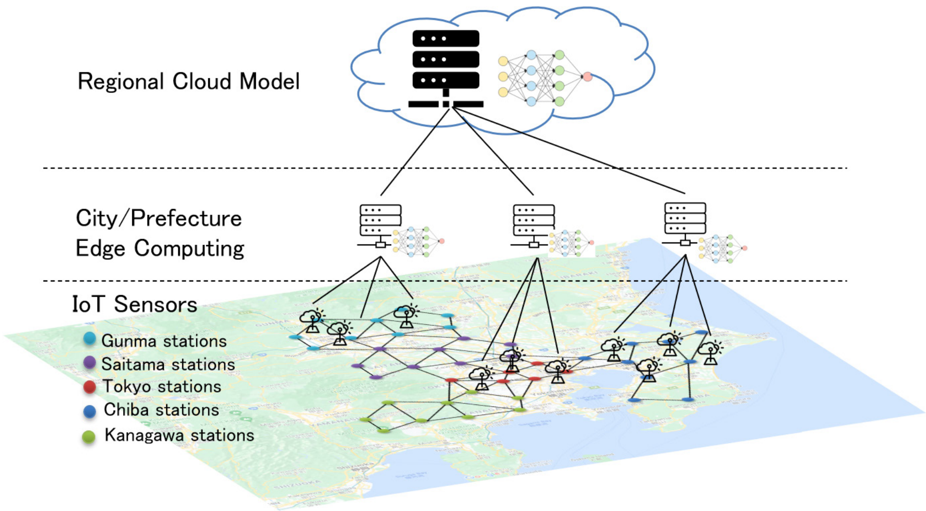


Fig. 5　Spatially distributed federated learning of regional pollution prediction system methodology

3 Research and Development on FL and Edge AI

Over recent years, along with research direction in cross-data analysis, building big data platforms, and going toward the era of CPS with B5G. We deeply study and propose global and edge federation methodologies. The first deals with non-IID spatial data distribution, while the latter assumes the edge environment consists of heterogeneous IoT devices. This research adapts FL and edge AI to applications, including environmental monitoring systems and smart-home applications.

3.1 Cooperative model training among edge AI servers

This research showed a FL system that overcomes heterogeneous IoT data issues among different edge sides of geographical areas [11]. In this system, edge AI emerged from training privately using local IoT data while aggregating with global model training on a public dataset. Leveraging CRNN studies on air pollution prediction [12], we contribute a study to design and develop a federated learning framework on air pollution prediction with an illustration of high-ranking oxidant warning prediction.

In applying pollution forecasting, data is collected from environmental stations in the Kanto region. Each station has a wide range of IoT sensors that measure environmental indicators. If using a centralized machine learning approach, all sensing data must be transferred to the central server for model training. Figure 5 shows the emerging edge computing environment in the system. Each prefecture is supposed to have its computational capacity with edge AI. Local models are trained on edge servers of the prefectures using environmental data. We also use public data to train the regional cloud model to enhance the accuracy of the master model while collaborating with models trained on local data. The global utilized training on public data experiments will be discussed afterward.

a. Methodology

On the local site, we employ the CRNN model [12] but the neural network structure is splitted into localized and (common) generalized parts to represent local distribution of monitoring station and sharing part across participants, respectively (Fig. 6a). Formally, $w_k \leftarrow \{w_{k,c}, w_{k,l}\}$, where $w_{k,c}, w_{k,l}$ are common and localized parts of participant k, respectively. There is also the same predictive CRNN model, but it is trained on the global site with a public dataset.

To aggregate on the global site, we adapt the average aggregation method [12] but with only common shared parts among participants are contribute to global update, such that $w_{G,c} = aggr(w_{1,c} \ldots w_{k,c})$ in each communication round (Fig. 6b).

b. Research outcome

The experimental result showed that local models are trained separately on different spatial distribution data. However, once aggregated, the delivered model can perform similarly to the centralized model. Furthermore, by using public data for initializing and frequently updating the global model, the performance of the whole region remains transferable to local areas, even to a new area that has not participated in any communication round.

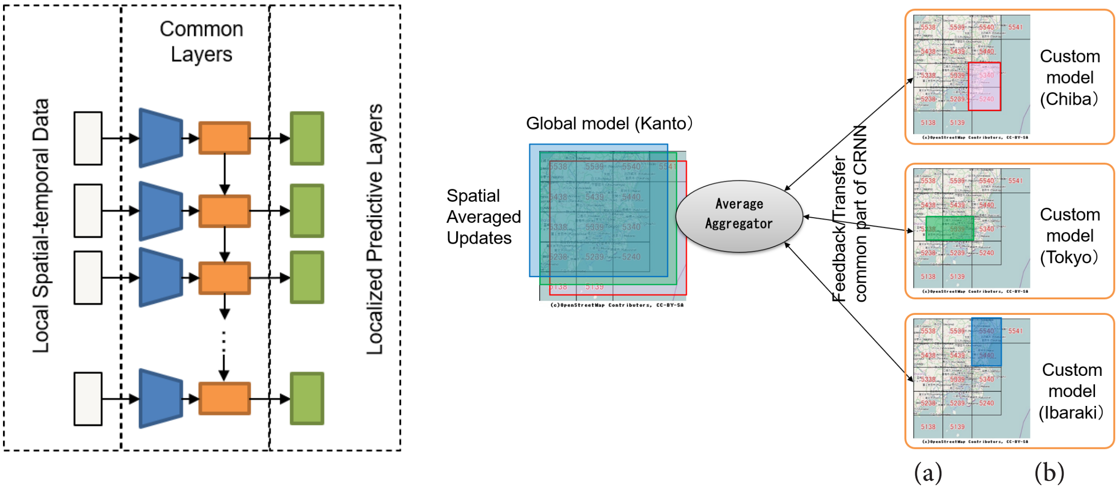


Fig. 6　Model structure design (a) and Spatial averaging aggregator (b) Research outcome

3.2　Federated Learning for Edge AI

Currently, the development trend of IoT is increasing gradually, and technology is always around us. Anyone can own a smartphone, bracelet, or various IoT devices with sensors attached. From the IoT data collected, many studies can be applied in healthcare services, such as predicting people's health status such as identifying cancer through photos, image detection because of Covid19, fall warning, health status prediction, sleep, etc. With the recent development of cloud-edge networks, smart devices can facilitate rapid access to patient's health information. Success has been achieved in the healthcare sector by training a federated learning model on large amounts of users' data.

However, some challenges in the Edge AI environment with IoT devices contributing to FL models have not yet been addressed. This subsection will introduce our two most recent studies on FL and its application in healthcare.

3.2.1 Fed xData: A Federated learning framework for enabling contextual health monitoring in a cloud-edge network

a. Health monitoring federated learning framework

We present the Fed xData framework (Fig. 7) for contextual health monitoring in cloud-edge networks to address the above challenges [13]. This research focuses on supporting and taking care of the elderly's health based on sensors collected on mobile devices.

The aging population in Japan chronically corresponds to a prevalence of diseases, physical disabilities, mental illness, and other comorbidities. This leads to problems linked to a shortage of health resources and a reduced quality of healthcare services. Consequently, this results in increasing demand for developing technologies that assist with caring for the elderly from hospital to home.

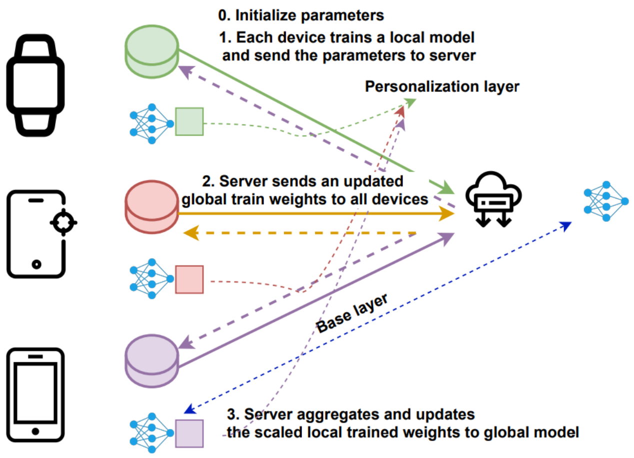


Fig. 7　Overview of the Fed xData framework.

With the ongoing proliferation of smart devices, mobile networks, computing infrastructure, and the IoT are poised to make significant advances in healthcare systems due to IoT devices' sensor integration, computing, and communication capabilities. Accordingly, IoT home health monitoring is envisioned as a promising model and has received significant research attention.

b. Framework components and edge AI federated learning approach

Our main contributions to Fed xData are summarized as follows: i) The generic FL process also faces the problem of data imbalance (i.e., not IID). This study introduces an additional structure that balances the continuous data using the RandomOverSample method, which addresses all data classes, ii) a novel Encode Depthwise Convolutions Network (EDCN) proposed, which reduces transmission data load when using transmission sockets. At the same time, it reduces the dimensionality of the extracted data for the client-side transfer learning combinator, which has various purposes; fine-tuning model enhances personal prediction for different purposes and personalizes user data when merging EDCN and Decoder to form AutoEncoder (AE) variant. Thus, the solution helps to reproduce new data with good characteristics associated with shared data (baseline), partially solving the non-IID problem, and achieving reinforced learning and repetition.

c. Research outcome

The excellent performance demonstrated by Fed xData in smartphone-based human activity recognition. The test results show that Fed xData significantly improves recognition accuracy compared to general and clearing models. Fed xData is extensible and can be the standard framework for many healthcare applications. Specifically, the Fed's xData framework is designed and applied to recognize falls and strokes in the elderly. User privacy is well protected and achieves good performance in real-life scenarios. This research can widely monitor health status and warn of falls and strokes in a narrow range such as houses, apartments, hospitals, and nursing homes.

3.2.2 FedMCRNN: Federated learning using Multiple Convolutional Recurrent Neural Networks for sleep quality prediction

a. Sleep quality prediction from IoT environmental data

Sleep plays a vital role in helping the body rest, restore and regenerate energy for the operation of organs in the body, especially the brain. The circadian clock regulates the human sleep-wake cycle in the brain, constantly balancing the sleep and wake times of the human body. Good sleep is a fundamental part of a healthy life, which improves all bodily functions and mental state. Using the data collected in daily activities such as IoT, such as a smartwatch, [14] introduced an FL application solution to predict sleep quality.

b. Methodology

In this study, the first important issue is data processing since daily human activities include many different activities. So, what actions affect the quality of sleep is a top concern. We have researched and found that in this dataset, only six important activity categories were used to assess sleep quality effectively (calories, distance, sedentary minutes, lightly activity minutes, active minutes, and very active minutes). Those categories are used to predict sleep-related outputs, and the outcome is a per-sleep breakdown of the rest into periods of light, deep, REM sleeps, and time awake, where sleep efficiency is the most concerning part. Next, we introduce how to choose the future prediction by the data windowing method. The purpose is that we can predict outcomes by adding data appropriately. And finally, In the same direction on Edge AI federated learning with IoT devices, we also proposed operating federated multiple convolutional neural networks (FedMCRNN) (Fig. 8) to predict sleep quality. The advantage of this model is to benefit from traditional CRNN to develop a new neural network model.

c. Research outcome

In experimental results, we measure the performance of the FedMCRNN in many-to-one and many-to-many cases using a variety of metrics and compare it with traditional machine learning models. The results show that FedMCRNN predicts quality intention reliably, with 96.774% and 68.721% accuracies for the two cases, many-to-one and many-to-many, respectively. Besides, other metrics have better value than methods. The results also show that FedMCRNN performs better than previous most advanced methods for predicting sleep quality and clearly shows which features influence sleep quality. Our findings have implications for developing AI doctors.

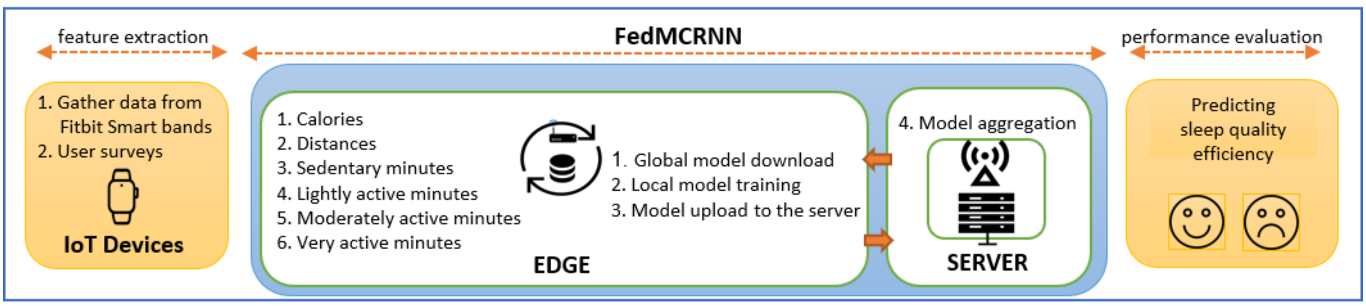


Fig. 8　Federated Multiple Convolutional Recurrent Neural Networks for Sleep Quality Prediction

4 Open Research Direction to Edge AI Collaboration on Federated Learning

In a conventional AI system, triggers take place in the cloud to provide customer service. However, in this distributed system, we assume that customers also contribute to training AI models using their own local data. To illustrate, local authorities can use weather and atmospheric data related to congestion [15]. Transport companies can use the cameras and sensors of trucks and taxis inside to predict traffic events, for example, using the MM [16] traffic event model. Additionally, we're considering using public data on our platform to train models in the cloud to generalize AI models to participants. However, the above studies bring a lot of points and benefits to the community. However, the AI model still uses distributed ML models, making it challenging to deploy in large spaces such as cities, transportation companies, taxis, etc. Another solution that opens a new direction is FL applied to solve the above difficulty. However, FL offers many advantages in distributed ML models for customers with compact design configurations. And the FL faces the challenge of selecting such models as proximity, ensuring data collection from different sensors. Because clients have configurable structures (e.g., processor, memory, computer, power, etc.), it's hard to respond in constant time. So, to overcome this difficulty and challenge, we are developing the solution using federated & split learning for the EDGE AI application. We hope our solution can overcome the problem in FL and still ensure computing power, data processing, and security in sharing private data.

5 Conclusion

From the viewpoint of data privacy, federated learning provides a mechanism to cooperatively train machine learning models while preventing any information leakage. On the other hand, federated learning challenges many deployment obstacles in real application with heterogeneous participant data distribution and information and communication technology infrastructure.

In our recent research, we deeply discover the frontier of using edge computing by delivering Edge AI in the context of federate learning paradigm along with application in smart-home including sleep quality prediction and health monitoring. We also tackle the problem of non-IID distribution by introducing public-private data cooperation and the newly adopted cross-silo federation on spatial skewness when providing environmental pollution prediction services on a large region that consist of many local areas.

In the era of cyber-physical integration along with the advanced in telecommunication, e.g., 5G / 6G, we address the challenges and research direction on federated learning with edge computing by emerging Edge AI for training and reasoning while delivering robust aggregation algorithms dealing with various types of data distribution skewness.

In the context of Beyond 5G / 6G adaptation, especially on *the Edge AI behavior support* study [1] whereas the advantage of Edge AI as the combines of edge computing and AI to train ML models and inference in high-capacity edge server, low-latency data transferring and heterogeneous IoT data, we open the research to leverage Edge AI throughout the participants on Federated learning paradigms.

In such a system, we address research obstacles that adopt Beyond 5G / 6G requirements in both Federated learning and Edge AI consideration. Firstly, Edge AI needs to optimize machine learning processing within the edge environment including network conditions and resources available. For that purpose, it must be possible to adjust the size of the respective ML models. This can be done by shrinking them with techniques such as Split Neural Network [17] on edge environments. To illustrate, small computing in smart cars or trucks cannot serve to train models but they can send IoT data and share resources with Edge AI by partially training models leveraging split neural network techniques.

Secondly, it will also be necessary to develop federated learning technology that combines supper-diverse data streams and heterogenous and non-IID data distribution [18], for example different data IoT data capturing between transportation companies and mobility service providers, to improve performance of prediction outcomes. To overcome these obstacles, in the near future, we are conducting aggregation methods that deal with skewness in data features, spatial-temporal sampling by leveraging individual distribution from edge sites.

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