FedAssist: Federated Learning in AI-Powered Prosthetics for Sustainable and Collaborative Learning

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***Abstract*—This paper explores the integration of federated learning in developing deep learning-powered surface electromyography decoding methods for AI-controlled prosthetics. Our proposed FL framework, FedAssist, aims to preserve data ownership while fostering decentralized collaborative modeling. Specifically, it focuses on mitigating the non-independent and identically distributed (non-IID) nature of sEMG datasets. Through collaborative local-level and global-level warm-start strategies, FedAssist achieves superior performance in non-IID scenarios compared to conventional learning paradigms. This research contributes to advancing decentralized machine learning approaches in the context of sEMG, with potential applications to improve prosthetic precision and rehabilitation effectiveness.**

***Index Terms*—distributed environment, electromyography, federated learning, non-independent and identically distributed data, rehabilitation engineering**

I. Introduction

Surface electromyography (sEMG) signal processing plays an important role in prosthetics and rehabilitation by capturing and decoding muscular activities [1]. In recent years, deep learning-based sEMG decoding methods have been developed to recognize patterns in sEMG signals corresponding to specific muscle activities or gestures [2], significantly improving the precision of prosthetic devices. Such capabilities enable the creation of personalized rehabilitation programs, addressing diverse challenges faced by individuals recovering from injuries or adapting to prosthetic limbs.

The development of sEMG signal decoding models has been following a centralized machine learning paradigm, which involves collecting raw sEMG data from diverse sources, preprocessing it for noise removal and feature extraction, and aggregating the processed data in a central dataset [3] for training and evaluating models. As the user base expands, there is a substantial increase in the volume of generated datasets. According to [4], it has been reported that the artificial prosthetic limb market is projected to witness a 130% growth by the end of 2025, driven by the rising number of users contributing to dataset generation. Consequently, the significant upsurge in data production renders the centralized storage and analysis of extensive datasets from diverse devices impractical. This challenges the applicability of conventional machine learning, reliant on centralizing training data in a singular data center, for efficient application development. Furthermore, privacy concerns impose additional constraints on centralized operations in healthcare contexts, as they may compromise sensitive medical information. Therefore, the pressing need to efficiently manage distributed individual information, coupled with the broader impact on improving prosthetic devices and rehabilitation, propels our motivation to explore new approaches.

To address this challenge, federated learning (FL) [5] emerges as a solution that preserves data ownership within each service provider while fostering collaborative modeling. It allows model training to occur locally on individual devices, with only model updates shared centrally. This ensures that raw patient data remains decentralized, reducing the risk of privacy breaches while maintaining model accuracy and generalization across decentralized datasets [6].

However, FL encounters a notable challenge when applied to real-world scenarios due to the non-independent and identically distributed (non-IID) data attributes. This non-IID data severely limits the FL operation, especially in the medical domain, where the bio-features obtained from different individuals may significantly differ due to various reasons such as personal physiological factors, living patterns, health issues, and others. To effectively integrate FL technology within such a distributed environment characterized by non-IID EMG data from diverse individuals, this study introduces *FedAssist*, a novel FL framework aiming to establish a sustainable upper-limb gesture classification model amidst distributed heterogeneous user groups. FedAssist operates through collaborative local-level and global-level warm-start strategies, effectively fine-tuning both local and global-end models to alleviate the impact of non-IID datasets. Through this, our research seeks to contribute a deeper understanding of how decentralized machine learning approaches, specifically FL, can elevate the precision of prosthetic devices and the effectiveness of rehabilitation strategies.

To summarize, the key contributions of this paper are

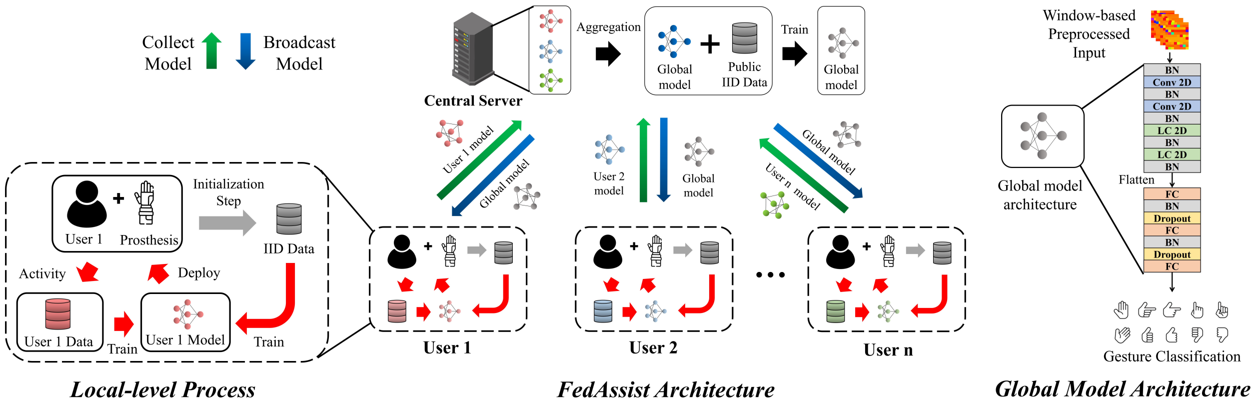

Fig. 1. The visual representation delineates the conceptual framework of FedAssist, a specialized system for continuous learning in upper-limb EMG gesture recognition. It emphasizes integration into an efficient distributed rehabilitation strategy within a non-IID environment with multiple users.

categorized as follows:

- We provide a detailed examination of the application of FL in the domain of upper-limb gesture classification using sEMG signal, and propose FedAssist, a novel FL framework to foster decentralized collaborative modeling for prosthetic devices and rehabilitation applications.
- Our FL framework specifically focuses on addressing the non-IID nature of decentralized sEMG datasets with the inclusion of supplemented IID datasets and subsequent model fine-tuning.
- We conduct comprehensive experiments to demonstrate the effectiveness of FedAssist within three prevalent non-IID scenarios. The results show that FedAssist achieves significantly improved performance compared to various learning paradigms.

II. Methodology

A. Federated Learning in Non-IID Dataset

FL [5] is a decentralized machine learning method that trains models across distributed datasets. FedAvg [5], the standard FL procedure, initializes a global model on a central server and deploys it to selected edge devices. Each device optimizes the model with its local data and sends updates back to the server for aggregation into a new global model, reflecting the collective knowledge of all participating devices. This refined global model is then redistributed to the edge devices, initiating a new cycle of learning with fresh user data. These iterative cycles enhance the global model's adaptability to diverse datasets and conditions.

In FL, non-IID data distribution across diverse edge devices has been a significant challenge [7]. Non-IID data refers to situations where data across clients lack uniformity or have varying statistical properties. This discrepancy can arise due to factors like different user behaviors, device capabilities, or diverse environmental conditions. In FL, non-IID data on edge devices can compromise the global model's performance, as aggregating disparate models trained on such data may not yield robust performance. FL in medical and bio-domains encounter a similar challenge. Human data often exhibits considerable variability across individuals and environments, showing diverse features and characteristics within bio-signals. Managing such non-IID data poses a complex challenge, and addressing this diversity stands critical in enhancing the robustness and performance of FL systems across distributed users in healthcare and rehabilitation environments.

B. FedAssist Architecture

To address the non-IID challenges, we introduce a new FL architecture, *FedAssist*, that mitigates the non-IID effect in distributed user environments. Various optimization strategies have been presented to handle non-IID scenarios in FL [7]. However, most algorithm-level approaches tend to specialize in particular environments, often without enhancing the fundamental adaptability of the algorithm. Our framework is essentially structured to alleviate the impact of non-IID datasets by augmenting the inherent capacity of the model to adeptly handle such variations. FedAssist ensures the robust learning effect through two key strategies: auxiliary local-level dataset supplementation and global-level model fine-tuning.

The auxiliary local-level dataset aids in achieving stable learning in non-IID scenarios. This method integrates previously collected IID datasets into the new training data, translating each model's loss into aligned global optima with the collective dataset during local training. Consequently, this approach helps hinge the learning process, aiming to adapt and perform more robustly in non-IID environments. Following local-level processing, our combined global model undergoes refinement by fine-tuning using an IID dataset stored in the central server. This warm-start approach serves as a crucial checkpoint, actively verifying and alleviating the adverse impacts of non-IID dynamics to achieve optimal convergence. Moreover, we freeze the training parameters of the local layers before the flattening layer to keep the model retained with the previously learned representations and the variants of features.

The integration of both local and global-level adjustments within our framework presents a compelling avenue for effectively mitigating the challenges posed by non-IID data. This multifaceted approach bolsters our capacity to achieve robust training performance and ensures a sustained promotion of the model's capabilities. This proactive methodology fosters an environment conducive to the seamless accumulation of collective knowledge from diverse users and environments. The algorithm pseudocode is described in Algorithm 1.

Algorithm 1 : FedAssist Algorithm

Input: Local datasets $D^{(T)}$, $\hat{D}^{(T)}$, Public dataset $\mathbf{D}$
Output: Global model $\mathbf{W}^{(T)}$

Initialize all participant client i's model
for *global epoch* T = 1,2,..., **T do**
  if *global epoch* > 1 **then**
    $D_i^{(T)}$ = merge($D_i^{(T)}$, $\hat{D}_i^{(T-1)}$)
  for *local epoch* t = 1,2,...,**t do** in all clients
    Freeze layer before the flattening layer
    Train local model with b mini-batches
  Aggregate local models and build model $\mathbf{W}$
  for *epoch* p = 1,2,...,**p do**
    Train $\mathbf{W}^{(T)}$ using $\mathbf{D}$ with b mini-batches
  Broadcast $\mathbf{W}^{(T)}$ to all clients
return $\mathbf{W}^{(T)}$

III. Experiments

A. Dataset

SEMG signals are typically captured by electrodes placed on the skin, providing information on muscle activation dynamics through intensity and temporal characteristics. In rehabilitation EMG data analysis, tasks like gesture recognition, motion classification, and muscle activity assessment are commonly involved, where our focus is on gesture classification using deep neural networks.

The experiments were conducted using the upper-limb gesture sEMG dataset Ninapro DB6 [8]. It consists of 14-channel sEMG data from 10 intact subjects performing 8 hand grasp gesture types (including rest). The acquisition protocol involved repeating 7 grasps 12 times, twice daily for 5 days, resulting in 120 repetitions per gesture per subject. DB6 presents an ideal setting for FL, aiming to iteratively train diverse subject datasets in each stage, where the dataset allocation protocol is visually illustrated in Fig.2. The window length was set to 150 ms and 10 ms incremental size, following experimental protocol in [9]. The deactivated sensors 8 and 9 were deleted in all DB6 data, and files subject2-day2-trial2 and subject9-day1-trial1 were excluded from the training set due to their noisiness.

B. Non-IID Scenarios

Based on the previous works of non-IID in FL [10], we establish three prevalent non-IID scenarios in a distributed environment comprised of multiple edge users conducting identical gesture types.

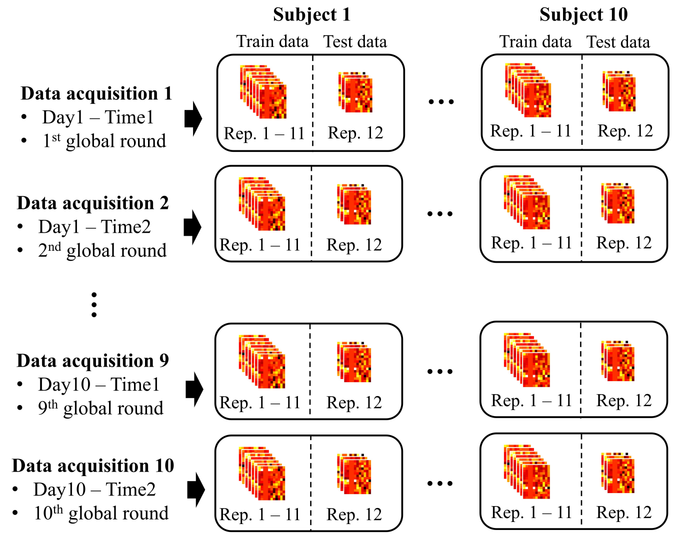

Fig. 2. Dataset allocation protocol for distributed structure. Note that 'Rep.' in the figure indicates Repetition.

1) Scenario 1. Heterogeneous Label Distribution: While acquiring local datasets from individual devices, users engage in a spectrum of activities associated with gesture labels. This diversity leads to class label imbalance across local edges and temporal updates, potentially introducing bias to the resultant model. To simulate this scenario, we independently assigned random probabilities ranging from 10 to 90% for each label within every local training dataset across each global round.

2) Scenario 2. Heterogeneous Feature Distribution: Individual datasets comprise diverse attributes, including signal characteristics and corresponding feature distributions unique to each user. These distinctions evolve over time, influenced by various attributes like lifestyle, individual health conditions, environmental factors, and their dynamic changes. Using the very data from individual subjects in Ninapro DB6 fulfills this scenario, which encapsulates unique physical attributes (*e.g.*, age, height, and weight), personal experiences, and lifestyle choices specific to each individual.

3) Scenario 3. Heterogeneous Dataset Volume: While FL assigns uniform time frames to local participants until transmitting models are synchronized, the volume of local datasets may differ based on individual user engagement with prosthetic devices. This variability results in unequal training and test data distribution for edge models, consequently impacting their learning capabilities. To simulate this scenario, we randomly remove data points from the local dataset with a probability range randomly assigned between 10 to 90% across all subjects and global rounds.

C. Compared Models

The experimental investigation involved a comparative analysis of the performance of multiple learning paradigms in the three non-IID scenarios. Across all experiments, the experimental protocols, including test datasets, hyperparameter configurations, and model structure, are uniform. We compare four major learning paradigms, including Integrated Learning (IL), Centralized Learning (CL), Distributed Learning (DL), and FL-based models.

1) Integrated Learning: Integrated Learning (IL) represents a conventional machine learning training approach wherein all training datasets are merged in a single server and processed in batches. In this setting, the following two training strategies are introduced.

- *Combined-subject approach*: It consolidates datasets from all subjects, constructing a training dataset comprising repetitions 1 to 11, with repetition 12 serving as the test dataset.
- *Cross-subject approach*: It involves training distinct models for each subject using individual datasets encompassing data collected at various time intervals. Likewise, the training dataset comprises repetitions 1 to 11, utilizing repetition 12 for the test dataset.

2) Centralized Learning: Centralized Learning (CL) [11] adheres to an identical data distribution scheme using the same dataset. The key distinction lies in transmitting local datasets to a central server, where data transmission is synchronized across subjects. Subsequently, the global model is trained on this combined dataset in each global round on the server.

3) Distributed Learning: Distributed Learning (DL) [11] adopts a sequential dataset-feeding approach during each global iteration round. Using the Ninapro DB6 dataset, the DL framework comprised 10 consecutive global rounds, synchronized with 10 data acquisitions occurring over 5 days, involving 2 data acquisitions per day. Within each round, the training dataset comprised repetitions 1 to 11, while the 12th repetition served as the test dataset for each subject. In each global round, the local model is iteratively trained in each local, without the aggregation process in a central server.

4) FL-based variation models: Our experiment compared various Federated Learning (FL) models, including FedAvg [5], FedSGD [5], FedProx [12], FedHealth [13], FedMA [14], FedMix [15], FedBN [16], and FedMD [17], under the premise of not exchanging personalized information among clients. We maintained a standardized data distribution protocol similar to that in the DL setting.

D. Feature Extraction

EMG data analysis necessitates manual feature engineering to condense dimensionality, thereby economizing computational resources and empowering the model to effectively encapsulate pertinent features that enhance training performance. In our experiments, we adopt the feature extraction methodology proposed by Phinyomark *et al.* [18], an 11 window-based time and frequency domain features, including Mean Absolute Value (MAV), Waveform Length (WL), Willison Amplitude (WAMP), Zero Crossing (ZC), MAV Slope (MAVS), four Auto-Regressive (AR) coefficients, Median Frequency (MNF), and Power Spectral Ratio (PSR).

E. Model Architecture

For the design of the classification model architecture, we adopted the Single View-Convolution Neural Network architecture [9] as the baseline model. As briefly illustrated in Fig. 1, this architecture consists of a sequence of layers organized as follows: Batch Normalization (BN), Convolutional 2D (Conv2D) with 64 filters, BN, Conv2D (64), BN, Locally Connected 2D (LC2D) with 64 filters, BN, LC2D (64), BN, Dropout (30%), Flattening, Fully Connected (FC) with 512 units, Dropout (50%), FC (512), Dropout (50%), and a final FC layer with a variable number of classes (*classes*).

F. Training Settings

All experiments were carried out with a batch size of 512, ReLU activation, and the Adam optimizer. We employed a learning rate decay strategy: starting at 0.001, we decreased it to 0.005, 0.001, 0.0005, and 0.0001 at the 50th, 100th, 150th, and 200th epochs, respectively. Each model was trained for 250 epochs. The experiments were performed on an RTX 3080Ti GPU with 16GB of VRAM.

TABLE I
COMPARISON OF MODEL PERFORMANCES ACROSS THREE NON-IID SCENARIOS.

	Non-IID Scenario 1	**Non-IID Scenario 2**	**Non-IID Scenario 3**
IL-Combined Subject	29.04%	40.87%	35.54%
IL-Cross Subject	43.26%	64.06%	42.40%
CL [11]	47.16%	57.30%	42.58%
DL [11]	47.75%	67.96%	57.96%
FedSGD [5]	14.84%	14.91%	14.25%
FedAvg [5]	52.73%	72.60%	60.13%
FedProx [12]	55.23%	72.85%	52.13%
FedHealth [13]	51.85%	72.39%	60.02%
FedMA [14]	51.16%	68.17%	60.83%
FedMix [15]	56.08%	73.90%	62.41%
FedBN [16]	50.42%	73.82%	53.37%
FedMD [17]	42.38%	66.33%	53.44%
FedAssist (Ours)	**62.01%**	**77.18%**	**64.67%**

G. Results and Discussion

In Table I, the comparative analysis illustrates the superior performance of our FedAssist in all non-IID scenarios compared to other learning paradigms and variations of FL models. Our findings consistently indicate that FL models outperform other learning paradigms, highlighting the efficacy of the FL approach in coordinating distributed multi-user models for gesture classification. Fig. 3 illustrates the maximum test accuracy and synchronized loss across each global iteration. The results for IL models are denoted as dotted lines, reflecting training executed solely once, devoid of subsequent global rounds for aggregation. Notably, in contrast to FedAssist, existing models exhibit limited success in achieving stable learning trajectories. Several models display stagnant learning effects attributed to non-IID characteristics, evident in scenarios 1 and 3. Furthermore, in scenarios 1 and 3, most models exhibited notably reduced performance compared to scenario 2 due to the introduction of higher levels of non-IID attributes, resulting in a plateaued learning effect. Nonetheless, our FedAssist consistently demonstrated improved performance compared to other models in every scenario.

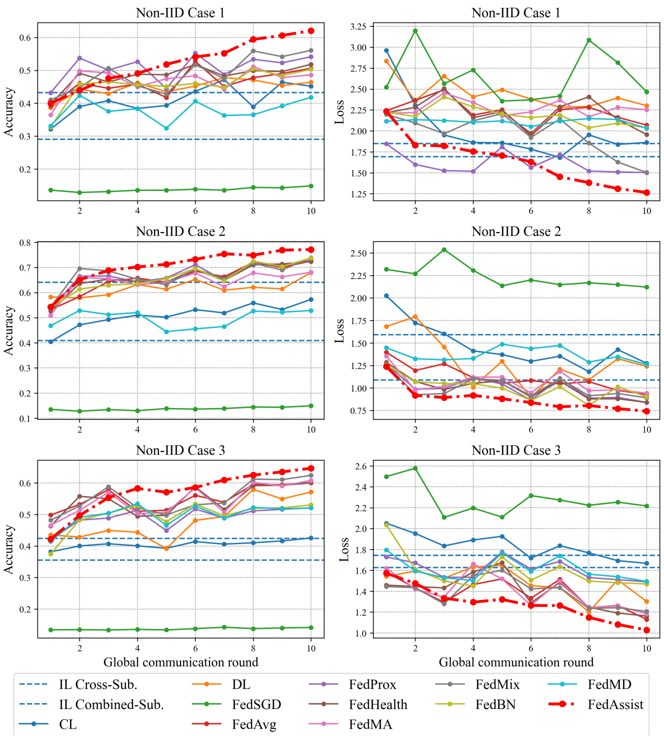

Fig. 3. Test accuracy and loss results of 13 different models across three non-IID scenarios.

Despite diverse non-IID attributes inherent in all scenarios, our FedAssist framework mitigated the impact of such factors, achieving the highest performance levels among diverse learning paradigms and FL variant models. This outcome can be attributed to the inclusion of supplemented IID datasets and subsequent model fine-tuning, effectively reducing the disparity among edge models trained on non-IID datasets. Moreover, this emphasizes how the combined application of local and global-level measures greatly assists in surpassing other FL models in combating the inherent non-IID effects within EMG datasets sourced from multiple users.

IV. Conclusion

In this study, we have introduced *FedAssist*, a novel federated learning framework that facilitates decentralized collaborative modeling of sEMG-based AI-powered prosthetics. Specifically tailored to handle the non-IID nature of decentralized sEMG datasets, FedAssist incorporates supplemented IID datasets and subsequent model fine-tuning. Through rigorous experimentation across three distinct non-IID scenarios, FedAssist consistently demonstrates its effectiveness in managing distributed non-IID EMG data from multiple users. This study underscores the significance of employing FL technology to ensure the sustainability and generalizability of integrating collective data among diverse user populations, highlighting strategies for effectively leveraging heterogeneous knowledge. Overall, this research marks a significant step forward in the application of federated learning to address crucial challenges in the field of sEMG, paving the way for more personalized and secure AI-controlled prosthetics and rehabilitation solutions.

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References

[1] R. Pilkar, K. Momeni, A. Ramanujam, M. Ravi, E. Garbarini, and G. F. Forrest, "Use of surface emg in clinical rehabilitation of individuals with sci: barriers and future considerations," *Frontiers in neurology*, vol. 11, p. 578559, 2020.

[2] M. C. Tosin, J. C. Machado, and A. Balbinot, "Semg-based upper limb movement classifier: Current scenario and upcoming challenges," *Journal of Artificial Intelligence Research*, vol. 75, pp. 83–127, 2022.

[3] H. Zhou and G. Alici, "Non-invasive human-machine interface (hmi) systems with hybrid on-body sensors for controlling upper-limb prosthesis: A review," *IEEE Sensors Journal*, vol. 22, no. 11, pp. 10 292–10 307, 2022.

[4] Fact.MR. (Mar. 2022) Artificial limbs market analysis report by product (upper extremity, lower extremity, sockets, liners), by technology (cosmetic prosthetics, cable-operated/battery-powered prosthetics, electrically-powered/myoelectric prosthetics), by region-global forecast 2019-2025. FACT4359MR. [Online]. Available: https://www.factmr.com/report/4359/artificial-limbs-market

[5] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-efficient learning of deep networks from decentralized data," in *Artificial intelligence and statistics*. PMLR, 2017, pp. 1273–1282.

[6] N. Rieke, J. Hancox, W. Li, F. Milletari, H. R. Roth, S. Albarqouni, S. Bakas, M. N. Galtier, B. A. Landman, K. Maier-Hein *et al.*, "The future of digital health with federated learning," *NPJ digital medicine*, vol. 3, no. 1, p. 119, 2020.

[7] H. Zhu, J. Xu, S. Liu, and Y. Jin, "Federated learning on non-iid data: A survey," *Neurocomputing*, vol. 465, pp. 371–390, 2021.

[8] F. Palermo, M. Cognolato, A. Gijsberts, H. Müller, B. Caputo, and M. Atzori, "Repeatability of grasp recognition for robotic hand prosthesis control based on semg data," in *2017 International Conference on Rehabilitation Robotics (ICORR)*. IEEE, 2017, pp. 1154–1159.

[9] W. Wei, Q. Dai, Y. Wong, Y. Hu, M. Kankanhalli, and W. Geng, "Surface-electromyography-based gesture recognition by multi-view deep learning," *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 10, pp. 2964–2973, 2019.

[10] P. Kairouz, H. B. McMahan, B. Avent, A. Bellet, M. Bennis, A. N. Bhagoji, K. Bonawitz, Z. Charles, G. Cormode, R. Cummings *et al.*, "Advances and open problems in federated learning," *Foundations and Trends® in Machine Learning*, vol. 14, no. 1-2, pp. 1–210, 2021.

[11] M. Asad, A. Moustafa, and T. Ito, "Federated learning versus classical machine learning: A convergence comparison," *arXiv preprint arXiv:2107.10976*, 2021.

[12] T. Li, A. K. Sahu, M. Zaheer, M. Sanjabi, A. Talwalkar, and V. Smith, "Federated optimization in heterogeneous networks," *Proceedings of Machine learning and systems*, vol. 2, pp. 429–450, 2020.

[13] Y. Chen, X. Qin, J. Wang, C. Yu, and W. Gao, "Fedhealth: A federated transfer learning framework for wearable healthcare," *IEEE Intelligent Systems*, vol. 35, no. 4, pp. 83–93, 2020.

[14] H. Wang, M. Yurochkin, Y. Sun, D. Papailiopoulos, and Y. Khazaeni, "Federated learning with matched averaging," *arXiv preprint arXiv:2002.06440*, 2020.

[15] T. Yoon, S. Shin, S. J. Hwang, and E. Yang, "Fedmix: Approximation of mixup under mean augmented federated learning," *arXiv preprint arXiv:2107.00233*, 2021.

[16] X. Li, M. Jiang, X. Zhang, M. Kamp, and Q. Dou, "Fedbn: Federated learning on non-iid features via local batch normalization," *arXiv preprint arXiv:2102.07623*, 2021.

[17] D. Li and J. Wang, "Fedmd: Heterogenous federated learning via model distillation," *arXiv preprint arXiv:1910.03581*, 2019.

[18] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for emg signal classification," *Expert systems with applications*, vol. 39, no. 8, pp. 7420–7431, 2012.