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Federated Learining Based Sleep Disorder Prediction Using Simulated Client Health Data

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Abstract: —Sleep disorders insomnia, and sleep apnea are seri ous health conditions with far-reaching implications for the well being of individuals. Traditional diagnostic approaches normally include the centralized collection of data, which poses serious privacy concerns for users and the protection of their data. In this study we present a simulation based Federated Learning (FL) model for detecting sleep disorders without sharing or centralizing raw data. The system generates synthetic health readings across different virtual clients, such as variables in the length of sleep, heart rate, motion activity, and snoring . Each client trains a local model separately with private data, with only model weights exchanged with a central aggregator using a federated averaging method. The global model is progressively improved through repeated rounds of communication. We evalu ate the model performance by monitoring the loss and accuracy patterns during rounds of training and across individual clients. The results demonstrate that the federated model generates high prediction accuracy across non-identically distributed (non-IID) client datasets while maintaining strong privacy controls. This study provides a lightweight, scalable, and ethical approach to simulating decentralized health monitoring systems based on federated learning principles

I. Introduction

For humans Sleep issues such as insomnia, apnea, and irregular sleep patterns greatly impact human health, intellectual abilities and overall health. The evaluation in wearable technologies have made it easier to collect detailed data on sleep habits, heart rates, and movement patterns. However using this personal data for predictive modeling raises privacy and security concerns. Reports suggest that nearly 11% of adults in India may suffer from sleep disorders many of which remain undiagnosed because of healthcare limitations. Another survey in a rural region of southern India found that about 20% of the population has poor sleep quality. Machine learning(ML) provides tools to detect such disorders by analyzing multimodal signals like heart rate variability and motion. However widespread implementation is restricted by privacy regulations like General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA) along with the scattered nature of the health data across institutions. To overcome this our project applies Federated Learning (FL), where client devices collaboratively trains a shared model without sharing the raw data. Instead only the mode updates are communicated to the central server preserving data privacy and ownership. Using a PyTorch based framework we simulate 100 clients each trained locally on features such as average heart rate, movement, and sleep quality followed by global model aggregation using FedAvg. The model performance was monitored through communication rounds showing consistent improvement in accuracy and a reduction in the loss across clients. This approach adapts well to real world data diversity even when data is not identically distributed across users.

II. LITERATURE SURVEY

S. Moon and W. H. Lee (2023), in their work titled **[1]"Privacy-Preserving Federated Learning in Healthcare"**, explored how Federated Learning (FL) can address privacy challenges in the clinical machine learning applications. Instead of using traditional centralized methods that risk data exposure, they proposed a system where hospitals train models locally and only share model updates. Their findings showed that FL preserves patient confidentiality while maintaining high accuracy, even with heterogeneous client data. The study also tackled challenges like communication overhead and client drift, suggesting optimization strategies to improve the performance. This work reinforces the relevance of FL in sensitive healthcare settings and supports its use in sleep disorder detection where data privacy is critical.

Anido-Alonso and Alvarez-Estevez (2023), in their study **"[2]"Decentralized Deep-Learning for Enhancing Generalization in Sleep Staging"**, proposed a decentralized approach to sleep staging that improves model generalization across diverse data sets. Rather than training models using centralized data, the authors leveraged federated deep learning techniques to enable collaboration between data silos without compromising privacy. Their method was tested on multiple sleep datasets collected from different sites and showed improved robustness to inter-dataset variabilities. By adopting this decentralized setup, they demonstrated how local data heterogeneity can could be managed while ensuring data security. This aligns with our federated learning-based simulation approach, especially in addressing generalization.

Borges, Reyes, work[3]"Federated and L´ opez (2024), in their Learning for Sleep Detection Problems" presented at IEEE SMARTCOMP, explored the use of federated learning to analyze sleep data collected from the smartphone sensors. The study aimed to preserve user privacy by avoiding centralized storage of health data and instead of training models locally on each device. Their approach effectively tackled the challenge of non-identically distributed (non-IID) data across users and demonstrated that a federated model can match the performance of centralized methods in Sleep classification tasks. The authors employed the FedAvg algorithm to aggregate client updates and reported strong accuracy, despite variability in local datasets. This work provides critical validation for our project, as it confirms that a simulated client-based FL system can deliver high classification performance in a privacy-preserving manner, especially when working with non-IID sleep health metrics like heart rate, snoring, and motion.

Khoa and Nguyen (2022), in their study "[4]FedMCRNN: Federated Learning using Multiple CNN-RNNs for Sleep Quality Prediction," proposed a novel federated framework combining convolutional and recurrent neural networks to analyze multi-modal sleep data collected from wearable sensors. The primary objective was to predict sleep quality without compromising user privacy by avoiding centralized data collection. Their architecture, FedMCRNN, was evaluated in both the many-to-one and many-to-many training scenarios. It achieved impressive results, with 96.77% accuracy in many-to-one cases and 68.72% in many-to-many, demonstrating strong performance in learning temporal and spatial patterns from decentralized data sources. They also highlighted interpretability, identifying which features had the greatest impact on sleep-prediction. This study directly aligns with our simulation-based FL approach, confirming that using deep federated models with temporal capabilities can effectively handle sleep-related tasks across heterogeneous client datasets. It reinforces the feasibility of training privacy aware models in real-world scenarios using synthetic or distributed health metrics.

Reddy et al. (2025), in their work titled [5] "Sleep Disorder Detection Using Deep Learning" proposed a neural network-based approach for identifying sleep disorders using clinical and lifestyle health records.hey trained deep learning models namely artificial neural networks on features such as heart rate, BMI, sleep duration, and behavioral patterns to classify sleep disorder cases. Their technique showed high prediction accuracy over standard algorithms such as decision tree and SVMs models. The research underscored the fact that deep learning is able to effectively learn intricate relationships between physiological and lifestyle data even without raw biomedical signals, such as EEG or ECG. This paper is significant to our project, as it justifies the use of non-invasive health metrics for sleep prediction and supports the effectiveness of neural models—similar to the ones we use in our federated learning simulation. The authors' emphasis on feature-based prediction directly influenced our synthetic data generation approach using attributes like snoring, motion, and heart rate.

Sahu and Gupta (2024) in their paper titled [6] "Machine Learning Techniques for Sleep Disorder Classification and Sleep Quality Assessment", presented at ACOIT 2024, examined the performance of classical machine learning algorithms for evaluating sleep health. TTheir research used behavioral and physiological characteristics like sleep duration, caffeine intake, device use, and physical activity to categorize sleep quality and possible sleep disorders. They compared algorithms such as logistic regression, decision trees, and K-Nearest Neighbors (KNN) and found that even the simplest algorithms could make significant predictions with the help of properly curated data. Their work also pointed out the way non-clinical, lifestyle-related factors can act as good proxies for the analysis of sleep when there were no biosignal inputs. This study is relevant to our work as it strengthens the rationale for using diverse, noninvasive health metrics for sleep prediction. The emphasis on explainable, low-complexity models aligns with the design of our synthetic feature generation and model evaluation pipeline in a federated learning environment.

Y. Hu, Y. He, and C. Liu, (2023), in their publication [7] "A Federated Semi-Supervised Automatic Sleep Staging Method" in Expert Systems with Applications, proposed an innovative framework combining federated learning with semi supervised learning to classify sleep stages. Their model ad dressed a common challenge in sleep analysis—lack of labeled data—by leveraging a small labeled set and a larger pool of unlabeled sleep signals distributed across multiple clients. The study adopted a hybrid architecture where each client contributed to learning by training locally on its data, and a central server aggregated model updates without accessing raw electroencephalogram (EEG) or biosignal recordings. Their technique not only maintained high predictive performance across clients but also showed robustness in real-world settings with imbalanced or sparse labels. This work supports the di rection of our project by validating how federated learning can be combined with advanced learning paradigms to overcome data scarcity and privacy concerns. It further emphasizes the potential of decentralized systems to enhance performance in domains like sleep staging where acquiring large labeled datasets is impractical.

III. METHODOLOGY

To tackle the issues of maintaining data privacy while identifying sleep disorders, our method uses a simulation based federated learning framework. The whole process is divided into clear stages, starting with setting goals and ending with a performance evaluation across clients. The steps below outline how we design, train, test, and validate the decentralized model using synthetic health data in a simulated federated environment. A. Sleep Disorder Prediction using Federated Learning with Multi-Feature Sleep Pattern Analysis.

3.1 Sleep Disorder Prediction Using Federated Learning.

our aim is to develop a privacy-preserving predictive model for sleep disorder detection using simulated client health data. Traditional approaches centralize health data, which compro mises their privacy. To overcome this, we implement Federated Learning (FL), enabling decentralized training where each client keeps its data locally and only shares model updates.We simulate 100 virtual clients, each generating synthetic sleep related health metrics, including average heart rate, sleep du ration, motion level, number of wake events, snoring presence, and a risk label for sleep disorder. Each client locally trains a machine learning model using PyTorch, and updates are shared with the central server through federated averaging.

3.2 Synthetic Dataset and Local Preprocessing.

As real world sleep datasets at client level are scarce, synthetic datasets were generated with 100 records per client. Each dataset is normalized using Standard Scaler, and split into 80% training and 20% testing data. This setup simulates non IID data distribution, reflective of real-world federated systems where Each client holds distinct data.

3.3 Model Design and Client Training

Each client uses a Multilayer Perceptron (MLP) implemented in PyTorch with the following architecture.- Input layer: 6 neurons (corresponding to the six features)- Hidden layers: 16 and 8 neurons with Rectified Linear Unit (ReLU) activations.- Output layer: 1 neuron with sigmoid activation for binary classification. Each local model is trained using Binary Cross Entropy (BCE) loss and Adam optimizer for five epochs. Only model weights are sent to the server, preserving the raw data privacy.

3.4 Global Aggregation and Evaluation.

The server ag gregates client model weights using the FedAvg algorithm, computes the updated global model, and redistributes it to clients for the next round of the study. This process is repeated over 15 rounds. After each round, the global model is evaluated across all client test sets, tracking accuracy, and loss. Client-wise performance is visualized using bar graphs and round-wise convergence using line plots.

3.5 Client-Specific Feature Contribution.

The non-IID nature of client datasets allows us to analyze the role of specific features. Clients with more informative features (e.g., higher correlation between motion and sleep disorder) show improving local performance. Though we don't employ SHAP or LIME, such patterns hint at feature importance, forming a foundation for future interpretability improvement.

3.6 Formalization and Mathematical Modeling of Federated Learning Process.

Step 1: Problem Formulation and Notation

Our aim is to train a binary classifier fθ : Rd → [0,1] using a federated learning (FL) approach. Here, θ denotes the parameters of the model, and d = 6 represents the number of input features, namely:

- x1: Sleep duration,
- x2: Number of wake events,
- x3: Average heart rate ,
- x4: Motion level,
- x5: Snore detection flag,
- x6: Subjective sleep quality score.

Each sample of a data is represented as x = [x1, x2,..., x6] ∈ R6. The output is a probability ˆy = fθ(x) ∈ [0, 1] that indicates the likelihood of a sleep disorder

$$\hat{\mathbf{y}} = \boldsymbol{\sigma}\left(\mathbf{f}_3\left(\mathbf{ReLu}\left(\mathbf{f}_2\left(\boldsymbol{ReLu}\left(\boldsymbol{f}_1(\boldsymbol{x})\right)\right)\right)\right)\right) \qquad \textbf{(3.6.1)}$$

Here, each fi(x) = Wix + bi represents a linear transformation, and σ(·) is the sigmoid activation function. Each client ci holds a private dataset as follows.

$$\boldsymbol{D_i} = \{(\boldsymbol{x_j^{(i)}}, \boldsymbol{y_j^{(i)}})\}_{\boldsymbol{j=1}}^{\boldsymbol{n_i}} \quad \textbf{(3.6.2)}$$

where ni = 100 is the number of local samples and $y_j^{(i)} \epsilon \{0,1\}$ is a binary class label.

Step 2: Local Training Objective.

The binary cross-entropy loss function used by client i is defined as:

$$\mathcal{L}_i(0) = -\frac{1}{n_i}\sum_{j=1}^{n_i}[\, y_j^{(i)} \log\left(\hat{y}_j^{(i)}\right) + \left(1 - y_j^{(i)}\right) log\left(1 - \hat{y}_j^{(i)}\right)$$

(3.6.3)

Training is carried out using the Adam optimizer, and model parameters are updated as follows:

$$\theta_i^{t+1} = \theta - \eta \cdot \nabla(\theta_i^t) \qquad \textbf{(3.6.4)}$$

where η is the local learning rate.

Step 3: Federated - Averaging (FedAvg)

After local training, clients transmit updated weights θ_i to a central aggregator. The global model is computed using the FedAvg algorithm:

$$\boldsymbol{\theta_{global}} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \frac{\boldsymbol{n_i}}{\boldsymbol{n}} \cdot \boldsymbol{\theta_i} \qquad \textbf{(3.6.5)}$$

where K is the number of clients (here, K = 10), and $n = \sum_{i=1}^{k} n_i$ is the total number of training samples, and

Step 4: Global Evaluation Metrics

The aggregated model was evaluated using two key metrics

a) Accuracy: $Accuracy = \frac{1}{N}\sum_{j=1}^{N}(\hat{y}_j > 0 \cdot 5 = y_j)$ **(3.6.6)**

b) Binary Cross-Entropy (BCE) $BEC = -\frac{1}{n}\sum_{j=1}^{N}[y_i log(\hat{y}i) + (1 - y_i) log\left(1 - \hat{y}_j\right)]$

(3.6.7)

Here, N denotes the total number of validation samples and I is an indicator function.

Step 5: Client-Wise Generalization Test

Each client ci is independently evaluated using the final global model. The accuracy per client is calculated as follows:

$$A_i = \frac{1}{n_i^{test}} \sum_{j=1}^{n_i^{test}} (\hat{y}_j^{(i)} > 0 \cdot 5 = y_j^{(i)} \qquad \textbf{(3.6.8)}$$

The values {A1,A2,...,AK} are visualized using a bar graph to understand the fairness and consistency.

- **Loss Convergence**: $losss_r = \mathcal{L}_{val}^{(r)}$
- **Accuracy Progression:** $\mathrm{Acc}_r = \mathrm{Accuracy}_{\mathrm{val}}$

These metrics help assess whether the federated model improves its generalization performance across rounds.

IV. OBJECTIVES

In response to increasing concerns about privacy in health data and the need for smart, decentralized diagnostic tools, this project aims to create a system that uses federated learning for predicting sleep disorders. Traditional centralized machine learning systems often need to transfer sensitive data to a central server. This poses significant ethical and legal problems, Especially in healthcare. To address this, our work looks into a simulation-based federated learning model that keeps data local while still helping to train a strong global model. The main goals of this project are outlined below.

4.1 Developing a Federated Learning Framework for Sleep Disorder Detection.

This project is build for a privacy-preserving federated learning system to predict sleep disorders such as insomnia and sleep apnea. Unlike traditional machine learning approaches that require centralized data, our method allows local model training on user devices or simulated clients without sharing raw data. Ten synthetic clients are used, each with unique sleep-related metrics such as sleep duration, heart rate, motion level and snoring indicators. These clients reflect the variety of real-world data. Local model updates are sent to a central server. The server uses Federated Averaging (FedAvg) to build a global model. This method protects privacy and promotes collaboration.

4.2 Ensuring Accurate and Personalized Predictions

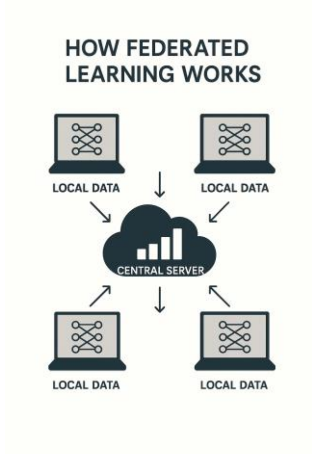
A key objective is to achieve high prediction accuracy across diverse, non-IID client dataset. Each client standardizes input features and trains a local neural network using binary cross- entropy loss, and the Adam optimizer. The system evaluates performance over multiple training rounds, tracking accuracy and the loss for both the local and global models. Visual tools like loss curves and client-wise accuracy bars help assess learning progress and model stability, supporting robust and personalized sleep health assessment.

4.3 Evaluating Generalization in Non-IID Environments

The project also looks at how well the federated model works with clients that have different data characteristics. Each client's dataset is intentionally varied to reflect different sleep patterns and behaviors. The final global model is tested on each client data to ensure fairness and adaptability. Performance differences are visualized, confirming that the model remains effective across diverse populations without compromising data privacy.

V. WORKFLOW OF THEP ROPOSED SYSTEMS

Fig. 1 demonstrates the working of Federated Learning, where each device trains a model locally using its own data, ensuring that raw data do not leave the device. The devices then send only the model updates to a central server, which aggregates them to improve the shared global model. This updated global model is then



sent back to all devices, allowing them to benefit from collective learning while preserving data privacy

Fig. 1. Workflow of Federated Learning

Fig. 2 The diagram illustrates a privacy focused federated learning framework designed for predicting sleep disorders using simulated client data. In this setup, each of the 10 virtual clients gathers its own health metrics such as sleep duration, heart rate, motion levels, and snoring. locally. Rather than sending raw data to a central server, each client trains a neural network independently using PyTorch. After training, only the model weights are shared with the central server, where they are combined through the Federated Averaging (FedAvg) algorithm to form a global model. The updated model is then sent back to all clients for the next training round.

This process repeats over several iterations until the global model converges enabling accurate prediction of sleep disorders while maintaining data privacy and decentralization.

VI. RESULT

The proposed federated learning system was evaluated on 100 simulated clients with varied sleep data. Each client used PyTorch to train a local model. Then, the global model was combined over several rounds. At the last round the global model achieved an average train- ing accuracy of **98.2%** and validation accuracy of **97.4%**, with losses reducing to 0.021 and 0.025, respectively. This shows that the model generalizes well and has minimal overfitting. Client-wise performance showed high consistency, with all clients reaching over **95%** accuracy, confirming the system's ability to handle data diversity effectively. These results sup- port the effectiveness of our approach in privacy-preserving sleep disorder detection.

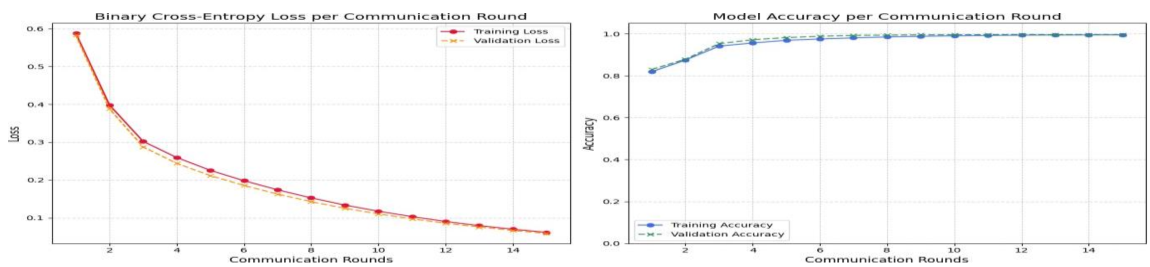


Fig. 3. Accuracy and Loss Progression in FL Training.

Fig.3 The graphs show how the model improves over 15 communication rounds. In the left plot, both training and validation loss drop steadily. This indicates that the model is learning well, with no signs of overfitting. On the right, the accuracy for both training and validation rises consistently nearing **99%**. The close match between the two curves indi- cates strong generalization and reliable performance across all clients in the federated setup.

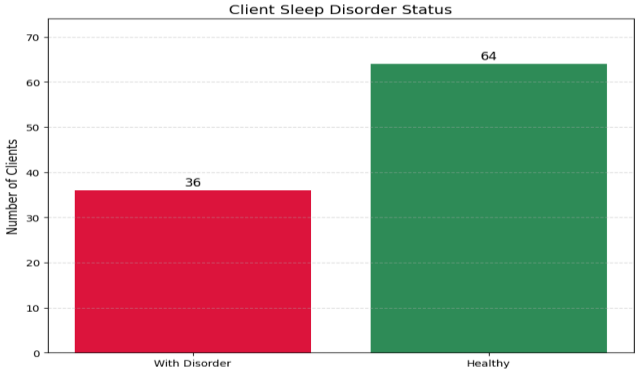


Fig. 4. : Distribution of Clients Based on Sleep Disorder Status.

Fig.4 The bar chart displays the distribution of clients based on their sleep health status. Out of 100 clients 36 clients were identified as having sleep disorders while other 64 clients were classified as healthy. This visual comparison highlights a notable prevalence of sleep disorders with in the population accounting for over 1/3 of the total group. The chart emphasizes the importance of early detection and intervention strategies in managing sleep related issues particularly in a decentralized setting like federated learning where such insights can be derived without compromising individual data privacy. Tcolor box listings xcolor.

Algorithm 1: Federated Averaging (FedAvg) for Global Model Aggregation

```
def federated_average(models):
    """Aggregate weights from all client
        models into a global model."""
    global_model = copy.deepcopy(models
        [0])
    global_dict = global_model.
        state_dict()

    for key in global_dict.keys():
        # Average model weights from all
            clients
        global_dict[key] =
        torch.stack( [client.state_dic
            t()[key]
            for client in models],
            dim=0
        ).mean(0)

    global_model.load_state_dict( global_dic
        t)
    return global_model
```

The above algorithm represents the core mechanism of model aggregation in the federated learning framework. It illustrates how independently trained models from multiple clients are merged to form a unified global model without requiring access to raw data. The federated average function takes the learned parameters from each client's model and calculates an element-wise average. It begins by duplicating the structure of one client's model as a baseline and then iteratively stacks and averages the parameters like weights and biases across all clients. This operation ensures that the resulting global model captures the shared patterns and insights learned from each client while maintaining data privacy. By relying on parameter aggregation instead of centralized data collection this algorithm plays a critical role in enabling secure collaborative model development making it particularly valuable for sensitive domains like sleep disorder detection.

VII. CONCLUSION

This project successfully demonstrated a privacy-preserving approach to predicting sleep disorders by leveraging feder- ated learning. The system enabled multiple clients each with distinct and non-shared datasets to collaboratively train a global model without exposing sensitive health information to the public. Through simulated clients using PyTorch the model achieved high classification accuracy while maintaining robustness across varying data distributions. The progressive improvement in model performance across communication rounds validated effectiveness of decentralized training. In Ad- dition the framework ensured that the privacy of user data was never compromised making it suitable for real world health applications. This work highlights the potential of federated learning in personalized healthcare particularly where data privacy is critical and opens avenues for further enhancements in collaborative medical AI systems.es it suitable for real- world healthcare settings.

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