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Article

Dynamic Subgroup Adaptive Secure Multi-Modal Heterogeneous Federated Learning (DSAS-MHFL)

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Abstract: Federated Learning (FL) enables remote clients to collaborate on model training while keeping their data private. They do this without sharing raw data. However, current FL systems have significant limitations in real-world scenarios. They assume data distributions are the same, that client participation is constant, and that aggregation algorithms are rigid. When clients have different types of data, such as medical images, financial transactions, retail data, and healthcare records, these limitations become even more serious. In this study, propose a framework for privacy-preserving collaborative intelligence in diverse distributed settings. This framework is called Dynamic Subgroup Adaptive Secure Multi-Modal Heterogeneous Federated Learning (DSAS-MHFL). DSAS-MHFL brings together several techniques within a single architecture. The proposed strategy is based on prototype-based few-shot learning, drift-aware federated aggregation, and adaptive Gaussian noise masking for differential privacy. It also uses Multi-Head Self-Attention to obtain semantic representations and adaptive feature-space alignment to create a shared 64-dimensional embedding space. We calculate client model drift in real time to improve convergence stability and reduce utility loss. This calculation guides both noise scaling and aggregate weighting. The Heart Disease UCI, Credit Card Fraud Detection, Online Shoppers' Intention, and Chest X-ray Pneumonia datasets are used to evaluate the system. The results show that DSAS-MHFL is a scalable foundation for diverse real-world federated intelligence. It achieves a classification accuracy of over 91%, maintains stable convergence in federated settings, supports efficient cross-modal semantic matching, and performs well in few-shot classification, even with limited labeled data.

Keywords: Federated Learning, Multi-Modal Learning, Semantic Embeddings, Few-Shot Learning, Heterogeneous Federated Learning, Drift-Aware Aggregation, Adaptive Security, Differential Privacy, Medical Imaging, Financial Fraud Detection.

I. INTRODUCTION

The demand for collaborative machine learning systems that protect privacy has grown rapidly as edge computing, IoT devices, distributed healthcare systems, and decentralized intelligent applications have advanced. Sensitive user data must be sent to centralized servers using traditional centralized machine learning techniques. This raises serious questions about data ownership, security, privacy, and regulatory compliance. These issues are addressed by Federated Learning (FL), developed by McMahan et al., which enables collaborative model training without sending raw data from participating clients. Clients train local models separately and provide only model parameters to a central server for aggregation, rather than exchanging local datasets. Applications of this decentralised learning paradigm in mobile intelligence, smart transportation, healthcare, finance, and recommendation systems have shown promise.[1]

The majority of the federated learning frameworks rely on several impractical presumptions, despite recent advancements. First, conventional FL systems often assume that all participating nodes use the same data formats and have comparable client characteristics. In practice, a variety of data types, such as financial transaction records, medical imaging, structured tabular data, and **behavioral** analytics, are often managed by remote clients. Second, real-world distributed systems deal with shifting client availability and varying subgroup participation; these frameworks typically assume continuous client participation throughout the training process. Third, most existing privacy-preserving aggregation techniques rely on predefined differential privacy mechanisms, which ignore model drift and client-specific behavioral changes. [2], [3]

This paper proposes a Dynamic Subgroup Adaptive Secure Multi-Modal Heterogeneous Federated Learning (DSAS-MHFL) framework that simultaneously handles federated learning, semantic representation alignment, heterogeneous modalities, and adaptive secure aggregation. Within a single optimization-federated learning architecture, the proposed system combines several structurally distinct modalities, such as healthcare data, financial transactions, retail analytics, and chest X-ray image features. To project diverse feature representations into a shared semantic embedding space, the framework introduces a Semantic Alignment Layer that employs Multi-Head Self-Attention. Additionally, during secure aggregation, client drift is dynamically calculated and used for both adaptive Gaussian noise masking and drift-aware aggregation weighting. Additionally, it facilitates dynamic client participation in subgroups, allowing for flexible and scalable deployment in heterogeneous, dispersed contexts.

II. LITERATURE REVIEW

Federated Learning was initially introduced by the Federated Averaging (FedAvg) algorithm proposed by McMahan et al.[4], which enables distributed collaborative training without centralized data sharing. Although FedAvg demonstrated strong communication efficiency, its performance significantly deteriorated under non-IID heterogeneous data distributions. Proximal regularization was proposed in FedProx [5]to reduce the discrepancy between local and global models. The goal of this strategy is to increase optimization stability in many scenarios. Then, during federated optimization, SCAFFOLD [6]employed control variates to reduce client drift. FedNova [7]Normalized local updates to improve convergence consistency. Federated convergence in dispersed learning environments was further enhanced by additional optimization methods, including FedOpt[8] and Mime[9].

Through semantic contrastive regularisation, model-contrastive federated learning techniques like MOON [10]Enhanced representation consistency. Client-specific adaptation in diverse distributed systems was further addressed by personalized federated learning techniques.[11] Existing federated learning methods primarily assume similar data distributions. They struggle to handle semantic inconsistencies across different data types, even with recent optimizations. HeteroFL [12] Provided diverse model structures for resource-constrained devices. FedBN [13]Used local batch normalization to improve the performance of federated learning in feature-shift, non-IID settings. Recent advances in medical federated learning have achieved great results for distributed healthcare intelligence and medical image classification [14], [15]. Harmony [16] Took this a step further by exploring heterogeneous multi-modal federated learning with modality-specific encoders.

In distributed intelligence systems, semantic representation learning has recently attracted attention. The Transformer architecture, which uses Multi-Head Self-Attention processes to learn contextual links among feature representations, was first introduced by Vaswani et al.[17].[18] Deep convolutional architectures such as ResNet [19] have also demonstrated strong feature-extraction capabilities for visual semantic learning and medical image analysis. The protection of privacy in federated learning has also been extensively studied. Differential privacy for deep learning with Gaussian noise injection was proposed by Abadi et al. [20]. Secure aggregation techniques that prohibit direct access to specific client updates were introduced by Bonawitz et al. [21].[22] The significance of privacy-preserving collaborative intelligence in distant medical systems has been emphasized by federated learning experiments in the healthcare domain [23]. Heterogeneity, communication efficiency, privacy preservation, semantic inconsistency, and optimization instability were recognized as significant open research concerns in distributed AI systems by large-scale surveys of federated learning [24].

III. PROBLEM FORMULATION

A. AA. System Model

Let

$$\boldsymbol{C}=\{\boldsymbol{c}_1,\boldsymbol{c}_2,\boldsymbol{c}_3,\boldsymbol{c}_4\} \qquad (1)$$

Represent the set of participating federated clients. Each client c_i possesses a local dataset

$$\boldsymbol{D_i}=\{(\boldsymbol{x}_j^{(i)},\boldsymbol{y}_j^{(i)})\}_{j=1}^{N_i} \qquad \textbf{(2)}$$

where:

- $x_j^{(i)}$ denotes the input sample,
- $y_j^{(i)}$ denotes the corresponding class label,
- N_i represents the number of samples available at client i.

The participating clients correspond to the Heart Disease, Credit Card Fraud Detection, Online Shoppers Intention, and Chest X-ray Pneumonia datasets. Since these datasets contain different feature dimensions and modalities, the resulting feature spaces are inherently heterogeneous.

B. Objective Function

The objective of the proposed framework is to learn a shared semantic representation function.

$$\boldsymbol{f_\theta}:\mathrm{R}^{d_i}\rightarrow\mathrm{R}^{64} \qquad (3)$$

where d_i denotes the original feature dimension of the client i64 represents the common semantic embedding dimension.

The federated optimization objective is defined as:

$$\min_{\theta}\sum_{i=1}^{K}\frac{N_i}{N_{total}}E_{(x,y)\sim P_i}[\boldsymbol{l}(\boldsymbol{g}_{\phi_i}(\boldsymbol{f_\theta}(\boldsymbol{x})),\boldsymbol{y})] \qquad (4)$$

where:

- K denotes the total number of participating clients,
- N_i denotes the number of local samples,
- $N_{total}=\sum_{i=1}^{K}N_i$,
- P_i denotes the local data distribution of the client i,
- $f_\theta(\cdot)$ represents the shared semantic encoder,
- $g_{\phi_i}(\cdot)$ denotes the client-specific classifier,
- $\mathrm{l}(\cdot)$ represents the weighted cross-entropy loss function.

This objective enables collaborative learning while preserving data privacy across heterogeneous federated clients.

C. Drift Computation

To quantify client heterogeneity during federated optimization, client drift between the local and global models is computed by the Euclidean distance:

$$\boldsymbol{\Delta_i=\|W_i\text{-}W_g\|_2} \qquad \textbf{(5)}$$

where:

- W_i denotes the local model parameters of the client i,
- W_g denotes the global federated model parameters,
- Δ_i represents the drift magnitude of the client i.

A lower drift value indicates greater consistency between local and global representations, whereas a higher drift value reflects greater divergence due to heterogeneous data distributions. The computed drift values are subsequently utilized for drift-aware aggregation and adaptive secure masking within the proposed framework.

IV. PROPOSED METHODOLOGY

The architecture of the suggested Dynamic Subgroup Adaptive Secure Multi-Modal Heterogeneous Federated Learning (DSAS-MHFL) framework is shown in Figure 1. The system is intended to support collaborative learning across diverse, distributed contexts with various data modalities while maintaining privacy. Heart disease prediction, credit card fraud detection, online shopper intention prediction, and chest X-ray pneumonia classification. These are the four federated clients that make up the architecture. Before federated training, each client performs independent local preprocessing and feature transformations because the datasets have varying feature dimensions and data modalities. To eliminate inconsistencies and improve the data quality, local data preparation is conducted first at each client. For medical imaging datasets, this step includes handling missing values, normalization, feature scaling, and image preprocessing. The adaptive feature alignment module then processes the data and converts features across different spaces into a common semantic representation.

A prototype-based few-shot learning module then leverages the generated semantic embeddings. In this phase, class prototypes are built in the embedding space from support samples, and query samples are categorized based on how closely they resemble the learned prototypes. This method improves generalization across heterogeneous datasets and allows strong learning with less labelled data.

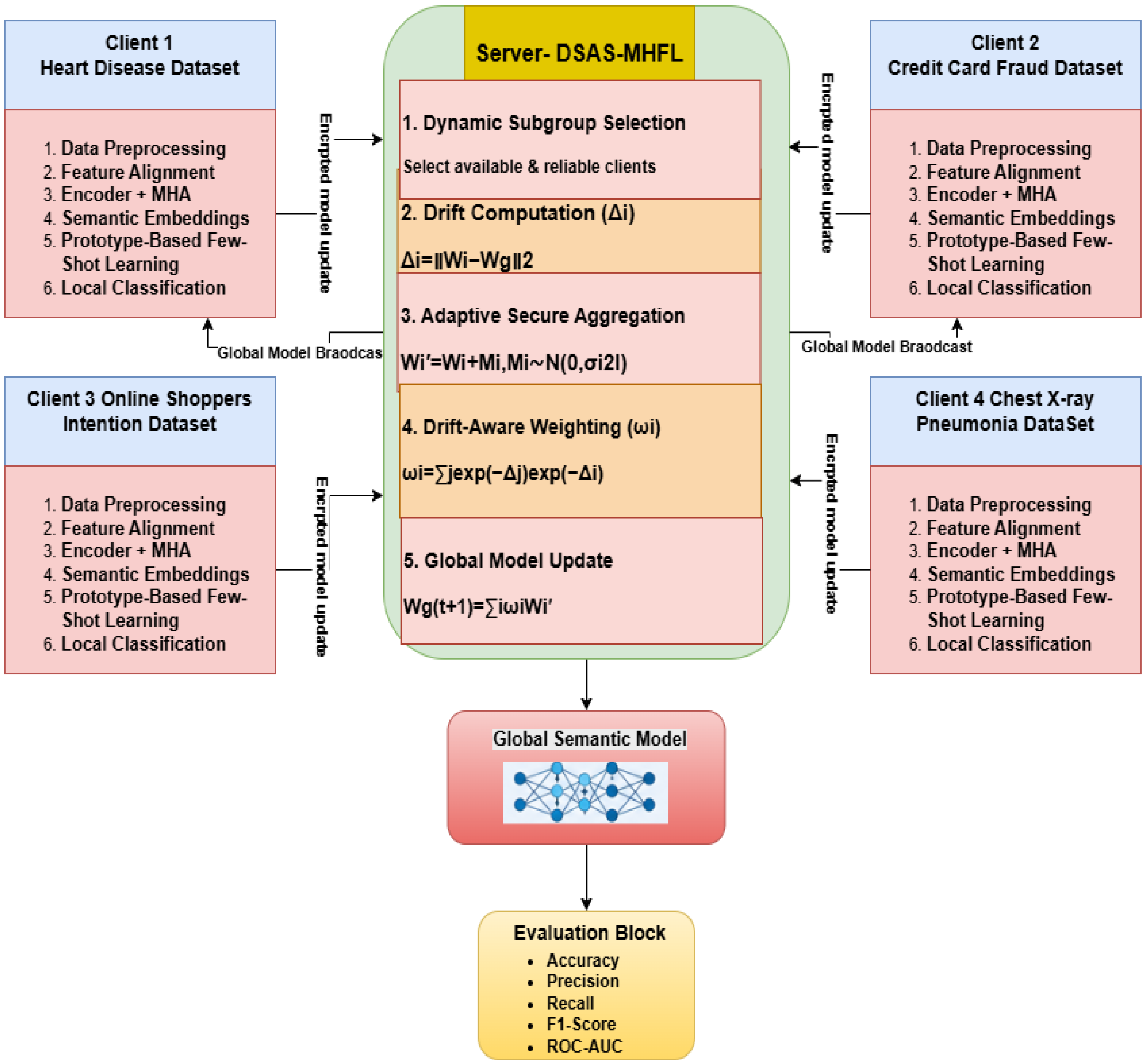

Fig.1. Proposed DSAS-MHFL Framework for Drift-Aware Secure Adaptive Semantic Multi-Head Federated Learning

After completing feature alignment, each client uses an encoder network and a Multi-Head Attention (MHA) mechanism to learn the relationships between contextual features and generate semantic embeddings. These embeddings provide modality-independent semantic representations that enable knowledge sharing across clients. A prototype-based few-shot learning module then uses the produced semantic embeddings. Support samples help develop class prototypes in the embedding space during this phase. By comparing query samples to the learned prototypes, they are categorized. This approach enhances the capacity to generalize across many datasets while enabling efficient learning even with less labeled data.

Local classification utilizes the generated semantic representation. This keeps data private while enabling each client to gain domain-specific knowledge. Only encrypted model changes are transmitted to the central federated server, rather than raw data. Dynamic subgroup selection on the server side identifies the most reliable and accessible clients to participate in the notification cycle. The server then uses the difference between local and global model parameters to calculate client drift values:

$$\Delta_i = \|W_i - Wg\|_2 \qquad (6)$$

W_i and Wg are the local and global model parameters, respectively. The computed drift values quantify the consistency of local learning relative to the global model. To protect privacy during communication, adaptive secure aggregation is employed before model fusion. Drift-aware stochastic masking adds adaptive Gaussian noise to local model updates. This reduces the risk of information leaks and attacks aimed at recreating the model. Next, drift-aware weighting assigns aggregation weights based on each client's reliability. This ensures that clients with less drift play a bigger role in updating the global model.

The model's weights and updates are aggregated to construct the global semantic model, which captures shared knowledge across all participating heterogeneous clients. The updated global model weights are communicated back to the selected clients for the next federated communication round, enabling iterative collaborative learning without exposing sensitive local datasets. Finally, the global semantic model is evaluated using standard classification metrics including Accuracy, Precision, Recall, F1-Score, and ROC-AUC. Through the integration of semantic representation learning, prototype-based few-shot learning, adaptive security mechanisms, and drift-aware federated optimization, the proposed DSAS-MHFL framework effectively addresses heterogeneity, privacy preservation, data scarcity, and federated convergence challenges within a unified distributed learning architecture, and the algorithm is given as

Algorithm: Dynamic Subgroup Adaptive Secure Multi-Modal Heterogeneous Federated Learning

(DSAS-MHFL)

Input:
$C=\{c_1,c_2,c_3,c_4\}$: Federated n clients

D={D1, D2, D3, D4) are local clients

T: Number of communication rounds

d = 64: Common embedding dimension

Output:

Global semantic model Wg

1. Initialize global model Wg
2. for each communication round t = 1 to T do
3. Perform Dynamic Subgroup Selection
4. Select active client subset Ct ⊆ C
5. for each client ci ∈ Ct do
6. Load local dataset Di
7. Perform Local Data Preprocessing, Missing values handling, Feature normalization, Label encoding
8. if Di is Chest X-ray Dataset, then
9. Extract image features using ResNet18
10. Apply PCA dimensionality reduction
11. end if
12. Perform Adaptive Feature Alignment
13. If Feature Dimension < 64 then
14. Apply Zero Padding
15. Else if Feature > 64 then
16. Apply Feature Truncation
17. end if
18. Obtain aligned feature vector Xi'
19. Generate Semantic Representations
20. Hi ← Encoder (Xi')
21. Ei ← Multi-Head Attention (Hi)
22. Perform Prototype-Based Few-Shot Learning
23. Generate support embeddings
24. Compute class prototypes
25. Classify query samples using prototype similarity
26. Train Local Classifier
27. Update local model Wi
28. Compute Client Drift

a. **$\Delta i = ||Wi - Wg||_2$**

29. Apply Adaptive Secure Aggregation
    a. **$\sigma i = \alpha + \beta\Delta i$**
    b. **$Mi \sim N(0, \sigma^2 i)$**
    c. **$W'i = Wi + Mi$**
30. Send secure update W'i to server
31. end for
32. Compute Drift-Aware Aggregation Weights
    a. exp(-Δi)
33. ωi = ------------
    a. Σk exp(-Δk)
34. Aggregate Secure Client Updates
35. Wg = Σi ωiW'i
36. Update Global Semantic Model
37. Broadcast updated model Wg to select clients
38. end for
39. Return final global semantic model Wg

V. RESULT DISCUSSION

The Heart Disease and Chest X-ray Pneumonia datasets were selected from four different datasets used in a heterogeneous federated setting to test the proposed DSAS-MHFL framework. The framework's ability to support collaborative learning across different types of data, such as tabular healthcare records and medical imaging, is demonstrated by selecting only these two types for the experiment.

A. Federated Training Convergence Analysis

Table 1 presents the drift values and average training loss obtained during the ten communication rounds. The results from Table 1 of the federated training process demonstrate a consistent reduction in client drift. From 5.7204 in the first communication cycle to 1.6699 in the final round, the heart disease client drift decreased by about 70.8%. Similarly, the client drift for chest X-rays decreased by almost 81.2%, from 4.7193 to 0.8868. The decreasing drift values indicate that local semantic representations progressively converge toward the global semantic model. This behaviour confirms the effectiveness of the proposed drift-aware aggregation mechanism in mitigating client divergence arising from heterogeneous data distributions. Furthermore, the average training loss decreased monotonically from **0.6724** to **0.2339**, representing a reduction of approximately **65.2%**. The smooth convergence observed in the federated loss curve demonstrates the stability of the adaptive secure aggregation and weighted federated optimization strategies.

TABLE 1: FEDERATED TRAINING CONVERGENCE RESULTS OF THE PROPOSED DSAS-MHFL FRAMEWORK

Round	Heart Disease Drift	Chest X-ray Drift	Average Loss
1	5.7204	4.7193	0.6724
2	4.3015	3.8755	0.6361
3	3.2085	2.7351	0.5794
4	2.5753	2.0053	0.5142
5	2.1802	1.3235	0.4630
6	2.0105	1.0200	0.4150
7	1.9096	0.8870	0.3632
8	1.8560	0.8150	0.3142

9	1.7913	0.8626	0.2633
10	1.6699	0.8868	0.2339

B. Heart Disease Dataset Performance

The proposed framework achieved the following performance on the heart disease dataset:

TABLE 2: PERFORMANCE OF DSAS-MHFL FOR HEART DISEASE DATASET

Metric	Value
Accuracy	85.93%
Precision	87.65%
Recall	79.78%
F1-Score	83.53%
AUC	93.19%

From Table 2, the high precision indicates that the framework effectively minimizes false-positive predictions. The obtained recall of **79.78%** demonstrates the model's ability to identify patients with heart disease despite the limited number of support samples used in prototype-based few-shot learning. The AUC value of **0.9319** indicates strong discriminative capability between normal and diseased patients

Confusion Matrix Analysis: The confusion matrix shows

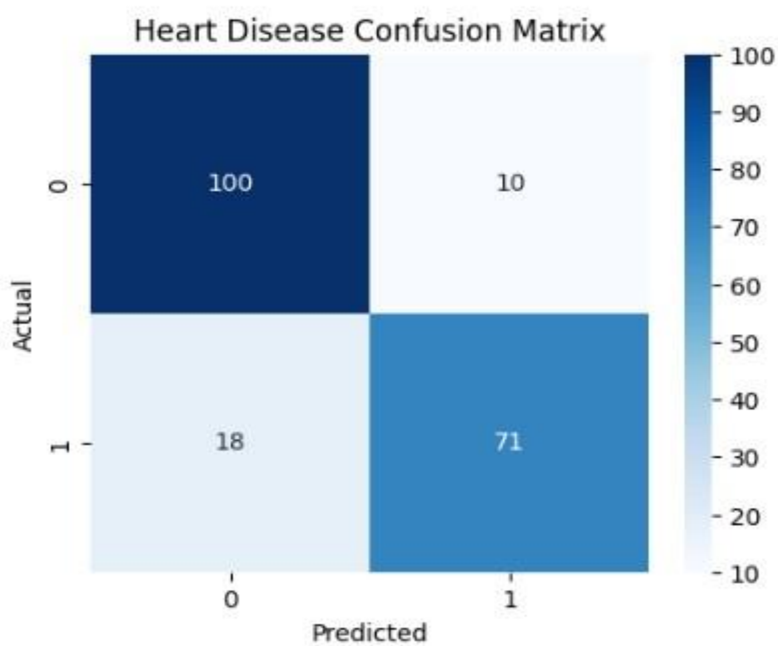

Fig.2. Heart Disease Confusion Matrix

From the confusion matrix, only **10 normal patients** were misclassified as diseased, while **18 diseased patients** were misclassified as normal. The higher number of false negatives suggests that future work should focus on improving disease sensitivity by enhancing prototype generation or adaptive threshold optimization.

C. Chest X-ray Pneumonia/Normal Performance

The proposed DSAS-MHFL framework achieved excellent performance on the Chest X-ray dataset.

TABLE 3: PERFORMANCE OF DSAS-MHFL FOR X-RAY DATASET

Metric	Value
Accuracy	94.55%
Precision	98.42%
Recall	94.18%
F1-Score	96.25%
AUC	98.92%

From Table 3, the extremely high precision value indicates that pneumonia predictions are highly reliable. The obtained recall demonstrates that most pneumonia cases were successfully identified. The AUC of 0.9892 approaches ideal classification performance, indicating that the semantic representations generated by the Encoder and Multi-Head Attention modules are highly separable.

Confusion Matrix Analysis

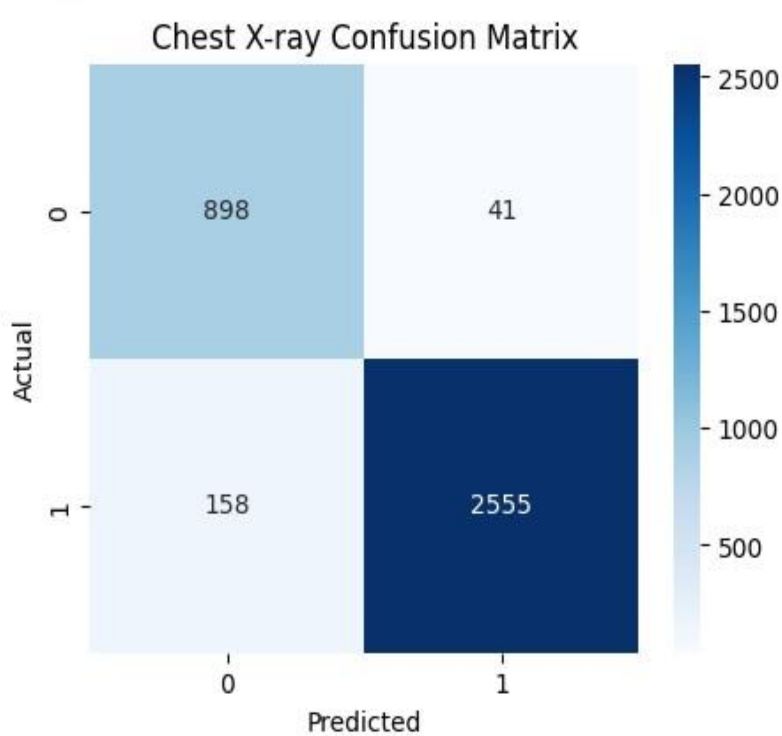

Fig.3. X-ray Confusion Matrix

From Figure 3, the framework correctly identified **2555 pneumonia cases** while misclassifying only **158 pneumonia samples**. Similarly, only **41 normal cases** were incorrectly predicted as pneumonia. As the results demonstrate, the proposed semantic representation learning strategy is robust for medical image analysis.

D. ***Federated Training Convergence Analysis***

As shown in Figure 4 below, the performance of the proposed DSAS-MHFL system over 10 federated communication rounds is presented. Average training loss reduces from 0.6724 (Round 1) to 0.2339 (Round 10). The loss decreases steadily, indicating that the local client models gradually converge to the global model during training. The proposed drift-aware aggregation method effectively reduces differences among clients and maintains the stability of federated learning by preserving a smooth convergence trend. In addition, the adaptive safe aggregation method enables cooperative model improvements without disrupting convergence. Such results indicate the framework's ability to facilitate effective prototype-based few-shot learning with privacy preservation in federated settings and to learn valuable semantic representations from heterogeneous data sources.

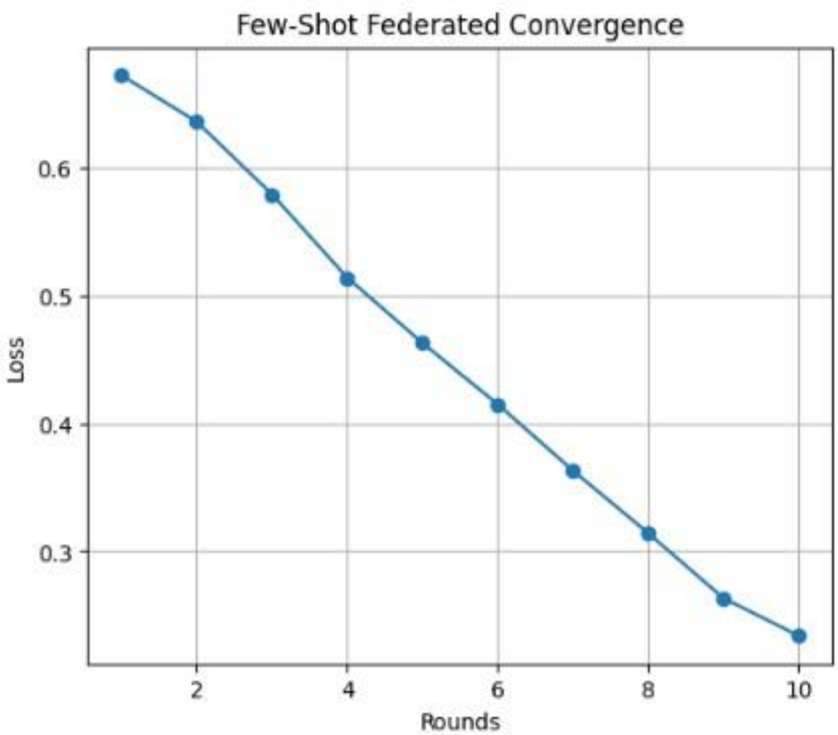

Fig.4. Few-shot federated learning convergence of the proposed DSAS-MHFL framework showing the reduction in average training loss over ten communication rounds.

E. ***Overall Discussion***

The performance of the proposed DSAS-MHFL system for 10 federated. The experimental results show that the proposed DSAS-MHFL framework successfully integrates semantic representation learning, prototype-based few-shot learning, adaptive secure aggregation, and drift-aware federated optimization within a unified heterogeneous federated learning environment. The reduced client drift, stable convergence behavior, and strong classification performance across both tabular and image modalities validate the effectiveness of the proposed architecture. The achieved performance further indicates that semantic embeddings generated by Multi-Head Attention facilitate cross-modal knowledge sharing, while prototype-based few-shot learning improves learning efficiency under limited data. Consequently, the proposed DSAS-MHFL framework provides an effective solution for privacy-preserving heterogeneous federated intelligence in healthcare-oriented distributed environments.

VI. CONCLUSION AND FUTURE SCOPE

This paper proposes a Dynamic Subgroup Adaptive Secure Multi-Modal Heterogeneous Federated Learning (DSAS-MHFL) framework that integrates semantic representation learning, prototype-based few-shot learning, adaptive secure aggregation, and drift-aware federated optimization within a privacy-preserving distributed environment. Experimental results demonstrated that the proposed framework effectively handles heterogeneous data modalities while achieving stable convergence and strong classification performance on heart disease and Chest X-ray datasets. The reduction in client drift and training loss across communication rounds validates the effectiveness of the proposed aggregation strategy. In future work, the framework can be extended by incorporating zero-shot learning, quantum-enhanced semantic representations, blockchain-based secure aggregation, and large-scale healthcare federated learning environments to further improve scalability, security, and predictive performance. The proposed approach, " Dynamic Subgroup Adaptive Secure Multi-Modal Heterogeneous Federated Learning (DSAS-MHFL)" framework, combines semantic representation learning, prototype-based few-shot learning, adaptive secure aggregation, and drift-aware federated optimization in a privacy-preserving distributed environment. Experimental results indicated that the proposed framework can process heterogeneous data modalities and achieve stable convergence and robust classification performance on heart disease and Chest X-ray datasets. The decrease in client drift and training loss across communication rounds shows the effectiveness of the proposed aggregation strategy. In future work, the approach can be extended to incorporate quantum-enhanced semantic representations, blockchain-based secure aggregation, and large-scale healthcare federated learning environments to improve scalability, security, and predictive performance.

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