Federated Learning with Privacy-preserving Active Learning: A Min-Max Mutual Information Approach

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***Abstract*— In an era where data privacy is paramount, Federated Learning (FL) and Active Learning (AL) have emerged as pivotal paradigms for building intelligent systems that respect user confidentiality. This paper introduces a novel FL framework enhanced by AL, orchestrated by the Min-Max Mutual Information (MMMI) principle, and fortified with Differential Privacy (DP) to ensure robust privacy preservation. Our approach adeptly addresses the prevalent challenge of unbalanced data distribution in federated settings. By employing MMMI, the framework adeptly pinpoints and assimilates the most informative samples across distributed datasets, ensuring comprehensive representation even for underrepresented classes or features. The integration of DP within the training process, as delineated in Algorithm 1, serves to maintain strict privacy controls, aligning with the privacy budget constraints and ensuring the confidentiality of the data remains intact during model updates. The local computation on devices preserves data sovereignty, while the MMMI-based AL mechanism judiciously minimizes the labeling requirements. It enhances the global model's performance by selectively incorporating instances yielding the maximum informational benefit. Empirical results from experiments on MNIST and CIFAR datasets underscore the framework's effectiveness in cultivating robust, efficient, and discreet AI models. The research presented here marks a significant advance in the amalgamation of FL, AL, and DP. It sets a robust foundation for future exploration into their convergence, especially for applications demanding stringent privacy considerations.**

Keywords: Federated Learning, Active Learning, Privacy-Preserving, Mutual Information, Machine Learning Models

I. Introduction

The proliferation of machine learning has engendered significant advances across various domains, utilizing extensive datasets to develop sophisticated inferential models [1]. Federated Learning (FL) stands at the forefront of this evolution, enabling the training of decentralized models to preserve privacy on the devices that generate the data without necessitating data centralization [2], [3]. At the same time, the surge of unlabeled data in the digitized era presents an unprecedented challenge, elegantly met by Active Learning (AL), which strategically selects informative data for labeling, thus optimizing the learning process with minimal annotation effort [4], [5].

Integrating FL and AL poses significant challenges, particularly when it comes to preserving privacy and maximizing the utility of unlabeled data. This paper proposes an advanced framework that combines the decentralized approach of FL with the selective annotation efficiency of AL, underpinned by the Min-Max Mutual Information (MMMI) principle. The MMMI principle excels at identifying the most informative data points for labeling. This task becomes even more crucial in FL environments characterized by imbalanced data distributions across multiple devices. By implementing this principle, our framework improves the overall learning process within the federated network [6], [7].

Furthermore, our framework integrates Differential Privacy (DP) within the AL phase to safeguard the computation of Mutual Information. This integration ensures the selection of the most informative samples according to the MMMI criterion without compromising the privacy of individual data points. By incorporating DP, we enable each device to contribute to the global model's improvement while maintaining the confidentiality of the sensitive data it holds. The privacy-preserving aspect of Mutual Information computation is crucial for the acceptance and efficacy of FL systems in scenarios where data privacy is paramount.

The main contributions of this paper are threefold:

- We introduce a novel FL and AL integration, bolstered by DP, to address privacy concerns and data imbalances within distributed learning networks.
- We leverage the MMMI principle to discern and utilize informative samples from vast unlabeled datasets, ensuring data economy and representativeness in model training.
- Our empirical results validate the framework's effectiveness, showcasing its capability to generate robust, efficient AI models discreetly and privacy-consciously, thereby advancing the state-of-the-art in FL and AL convergence.

This work serves as a vanguard in exploring privacy-preserving and distributed machine learning, setting a precedent for future research in the field and broadening the horizon for FL and AL applications, particularly in sensitive domains where data privacy is nonnegotiable.

II. Related Work

This section reviews the relevant literature on FL, AL, and their integration. We focus on studies that have explored privacy-preserving approaches and the efficient utilization of unlabeled data in these paradigms.

A. Federated Learning

FL was first introduced by Google in 2016. Since then, numerous studies have investigated its potential in various domains. McMahan et al. proposed using federated averaging to train models on decentralized devices while preserving

user data privacy [8]. Later research has focused on addressing challenges related to communication efficiency [9], model heterogeneity [10], and security against Byzantine attacks [11]. Some recent works have explored integrating DP mechanisms into FL to enhance privacy guarantees [12]. Although FL has shown promising results in privacy-sensitive applications, effectively using unlabeled data in a privacy-preserving manner remains a challenge.

B. Active Learning

AL is a well-established technique for reducing the labeling burden in machine learning. Early works proposed various uncertainty sampling strategies, such as entropy-based sampling [13] and query-by-committee [14]. Later research explored diversity sampling methods [15] and query synthesis techniques [16]. AL has been successfully applied in computer vision [17], natural language processing [18], and other domains. Despite its success, integrating AL with privacy-preserving techniques, especially within the context of FL, remains to be explored.

C. Federated Learning and Active Learning Integration

Combining FL and AL has gained attention recently due to the potential benefits of leveraging both paradigms. Li et al. proposed a Federated AL framework that selects the most informative instances from each device and aggregates them to construct a diverse batch for labeling [19]. Yang et al. introduced FedAL, which incorporates AL to actively select devices for participation in the global model update [20]. However, most existing approaches need to adequately address the challenges of privacy preservation during the AL phase.

D. Privacy-Preserving Active Learning

Privacy preservation is crucial when integrating AL with FL. Some studies have explored privacy-preserving AL methods using cryptographic techniques. Shokri and Shmatikov introduced a privacy-preserving AL protocol based on secure multiparty computation [21]. Other works have integrated DP mechanisms into AL to protect sensitive information during sample selection [22]. While these methods offer privacy guarantees, they often introduce additional computation overhead and may not fully exploit the potential of unlabeled data distributed across devices.

E. Min-Max Mutual Information for Active Learning

To address the challenges of privacy preservation and efficient utilization of unlabeled data, our proposed framework combines FL with AL based on MMMI. The concept of MMMI was first introduced by Singh and Joachims to select informative samples in a privacy-preserving manner [23]. Our work extends this idea to the FL setting, allowing devices to calculate mutual information for their unlabeled instances in a privacy-preserving manner. We then select instances that maximize the minimum mutual information across all devices, ensuring effective information gain without compromising data privacy.

III. Problem Definition

A. Active Learning and the Challenge of Labeling

Active learning is a semi-supervised machine learning approach that selectively queries a subset of unlabeled instances to be labeled by an oracle (e.g., a human annotator or an expensive computational function). The primary goal is to achieve high model performance with as few labeled instances as possible, addressing the high costs or logistical challenges associated with labeling large datasets.

A critical constraint in active learning is the labeling budget, denoted as k. This budget represents the maximum number of instances that can be queried for labeling during the learning process. Formally, the labeling budget k is defined as:

$$k \in \mathbb{N} \,|\, k > 0, \tag{1}$$

where k is a fixed, predefined integer that limits the number of queries to the oracle within an active learning cycle.

B. Active Learning in Federated Settings

Consider a federated system with a set of devices, each holding a local dataset $\mathscr{D}_i$, where $\mathscr{D}_i = L_i \cup U_i$ and $L_i \cap U_i = \emptyset$. The global learning objective is to train a model M that achieves high predictive performance across the collective data while respecting the privacy constraints inherent in FL.

The learning process on each device is guided by a utility function $\mathscr{U}(M_{i,t}, \mathscr{D}_i)$ that encapsulates the expected gain in performance from updating the local model $M_{i,t}$ using the local dataset $\mathscr{D}_i$. The AL process involves selecting samples from U_i to be labeled and added to L_i, with the aim of maximizing the utility function.

The global learning objective is to find a model M that maximizes the aggregate utility across all devices, formalized as:

$$\max_{M} \sum_{i=1}^{n} \mathscr{U}(M_{i,t}, \mathscr{D}_i). \tag{2}$$

Here, $M_{i,t}$ is the local model on device i at training round t, and the utility function $\mathscr{U}$ quantifies the improvement in the model's performance after incorporating updates from local datasets.

In the context of AL, the utility function $\mathscr{U}$ also accounts for the selection of samples based on the MMMI criterion. This criterion seeks to maximize the information gained from the newly labeled samples, contributing to a more comprehensive and representative training process.

The selection of samples for labeling on each device is thus driven by the desire to maximize $\mathscr{U}$, which implicitly incorporates the MMMI principle:

$$\max_{Q_i \subseteq U_i} \mathscr{U}(M_{i,t}, L_i \cup Q_i), \tag{3}$$

subject to a labeling budget k, where $|Q_i| \leq k$.

C. Privacy Preservation using Differential Privacy

DP provides a quantifiable framework to preserve privacy within FL systems. It ensures that the influence of any single data point is limited, thereby safeguarding the privacy of individual contributions during model updates.

DP is intricately woven into the model update mechanism in our FL setting. Controlled perturbations are introduced to the local model updates $\Delta M_{i,t}$, parameterized by a privacy budget ε, to yield differentially private updates:

$$\Delta M_{i,t}^{\varepsilon} = \Delta M_{i,t} + \text{Noise}(\varepsilon). \tag{4}$$

The calibrated noise ensures mathematical privacy guarantees by making the updates indistinguishable whether or not any single data point is included, thus adhering to the DP standard.

The primary challenge is to determine an optimal ε that carefully balances the trade-off between the privacy of individual data contributions and the utility of the global model M. This balance is crucial for achieving a high-performing model while maintaining the stringent privacy standards expected in FL.

The optimization framework for integrating DP in FL can be formalized as follows:

$$\max_{M,\varepsilon} \mathscr{U}(M,\varepsilon)$$

subject to:

$$\begin{aligned} &\mathscr{L}_{D_i}(\Delta M_{i,t}^{\varepsilon}) \leq \gamma, \quad \forall i \in \{1,\ldots,n\} \\ &\text{MMMI}(Q_i, M_{i,t}, D_i) \geq \theta, \quad \forall i \in \{1,\ldots,n\} \\ &\text{DP}(\Delta M_{i,t}^{\varepsilon}) \leq \varepsilon, \quad \forall i \in \{1,\ldots,n\}, \end{aligned} \tag{5}$$

where $\mathscr{U}(M,\varepsilon)$ is a utility function that encapsulates both the performance of the global model and the privacy level as dictated by the DP budget ε. The function $\mathscr{L}_{D_i}$ represents the loss on the local dataset D_i, and γ is a threshold ensuring the local model updates do not deviate excessively from the global model. The term $\text{MMMI}(Q_i, M_{i,t}, D_i)$ quantifies the informativeness of the query set Q_i as per the MMMI criterion.

1) Balancing Privacy and Learning Quality: To achieve an optimal balance between privacy and learning quality, we consider a multi-objective optimization problem that jointly maximizes model utility and minimizes privacy loss. The objective is to configure the privacy budget ε and the model M in a manner that maximizes the overall utility of the system:

$$\max_{M,\varepsilon} \mathscr{F}(M,\varepsilon)$$

subject to:

$$\begin{aligned} &\mathscr{L}_{D_i}(M_{i,t}, \Delta M_{i,t}^{\varepsilon}) \leq \gamma, \quad \forall i \in \{1,\ldots,n\} \\ &\text{MMMI}(Q_i, M_{i,t}, D_i) \geq \theta, \quad \forall i \in \{1,\ldots,n\} \\ &\text{DP}(\Delta M_{i,t}^{\varepsilon}) \leq \varepsilon, \quad \forall i \in \{1,\ldots,n\}, \end{aligned} \tag{6}$$

where $\mathscr{F}(M,\varepsilon)$ is a composite objective function reflecting the trade-off between the performance of M and the privacy level provided by ε. This formulation enables fine-tuning the FL process to align with privacy-preserving principles while striving to maintain a high-quality global model.

IV. Training Protocol

A. Initialization and Synchronization

The FL process begins with the initialization of a global model M, which acts as a foundational reference point for all participating devices in the network. As described in Algorithm 1, this model orchestrates the collaborative learning process and synchronizes with the local datasets D_i to ensure a coherent start to the training process.

B. Local Model Updates and Informative Sampling

Adopting the decentralized nature of FL, each device computes local model updates using its own dataset D_i. Concurrently, the AL phase uses the MMMI criterion to select a subset of the most informative queries from the unlabeled data. These samples are chosen to maximize their expected utility in improving the global model M, as detailed in Algorithm 1.

C. Differentially Private Updates and Aggregation

In accordance with DP principles and as specified in Algorithm 1, noise is added to each local update to ensure data privacy. These updates $\Delta M_{i,t}^{\varepsilon}$ are then securely aggregated on the central server to iteratively improve the global model M through multiple communication rounds T.

D. Iterative Learning and Refinement

The aggregation process combines the insights of all devices, facilitating a comprehensive and privacy-preserving enhancement of the global model. This iterative process, guided by Algorithm 1, enables the model to improve with each round of communication while maintaining rigorous privacy standards.

E. Discussion on Integration of MMMI and Privacy Mechanisms

Our FL framework integrates the MMMI principle within the AL phase to efficiently utilize the most informative data points. In conjunction with DP mechanisms, this strategic approach ensures that the training process is robust and privacy-conscious, aligning with the stringent requirements of privacy-sensitive applications.

V. Results

A. Datasets and Experimental Setup

We evaluated our methodologies using two established datasets: MNIST and CIFAR-10. The MNIST dataset comprises 70,000 grayscale images of handwritten digits with a uniform resolution of 28x28 pixels, widely used for benchmarking classification algorithms. CIFAR-10, on the other hand, consists of 60,000 32x32 color images distributed across 10 classes, presenting a more diverse and challenging problem space.

The FL environment was emulated by distributing data across `NUM_DEVICES = 5` local devices, reflecting a realistic decentralized data scenario often encountered in privacy-preserving machine learning tasks. We iterated the FL process over `NUM_ROUNDS = 20` to evaluate long-term learning capabilities.

Algorithm 1 Federated Learning with Privacy-Preserving Active Learning using MMMI Principle

Input : $D = \{D_1, D_2, \ldots, D_n\}$: n local datasets, M: initial global model, T: number of communication rounds, N: number of local epochs, ε: privacy budget for DP, P: pretrained model for labeling

procedure GLOBAL_TRAINING(T, D, N, P, ε)
$M \leftarrow$ Initialize(M) **for** *t in range*(T) **do**
  $M_t \leftarrow M$ **for** *each* $D_i \in D$ *in parallel* **do**
    $M_i \leftarrow$ LOCAL_UPDATE(M_t, D_i, N)
    $Q_i \leftarrow$ SELECT_QUERIES_USING_MMMI(M_i, D_i)
    $\Delta M_{i,t}^{\varepsilon} \leftarrow$ APPLY_DP($M_i - M_t, \varepsilon$)
    Send $\Delta M_{i,t}^{\varepsilon}$ to the central server
  Label queries using P and integrate them into the respective datasets
  for *each* $D_i \in D$ *in parallel* **do**
    Integrate labeled queries into D_i $M_i \leftarrow$ LOCAL_UPDATE(M_i, D_i)
  $\Delta M_{\text{enc}} \leftarrow$ AGGREGATE_ENCRYPTED_UPDATES($\{\Delta M_{i,t}^{\varepsilon}\}$)
  $M \leftarrow M +$ DECRYPT_AGGREGATE(ΔM_{enc})
return M
end procedure
procedure LOCAL_UPDATE(M, D, N)
Perform N epochs of SGD or other optimization method on M using data D
return M (locally updated model)
end procedure
procedure SELECT_QUERIES_USING_MMMI(M, D)
for *each instance in* D **do**
  Calculate the mutual information between the instance and the model's prediction and between the instance and the rest of the unlabeled data
Select instances that maximize the first quantity and minimize the second (MMMI)
return selected instances
end procedure
procedure APPLY_DP($\Delta M, \varepsilon$)
Add noise calibrated to the privacy budget ε to the model update ΔM
return differentially private model update
end procedure
procedure AGGREGATE_ENCRYPTED_UPDATES(ΔM_{eps})
Securely calculate the sum of the differentially private model updates ΔM_{eps}
Encrypt the aggregated sum for secure transmission
return aggregated and encrypted model update
end procedure
procedure DECRYPT_AGGREGATE(ΔM_{enc})
Decrypt the aggregated and encrypted model update ΔM_{enc}
return decrypted and aggregated model update
end procedure

The MNIST dataset was split into 55,000 training images and 10,000 test images, aligning with standard practice. For CIFAR-10, we used 45,000 images for training and 5,000 for validation to fine-tune hyperparameters before the final evaluation on the test set.

AL was incorporated using the MMMI principle, selecting `TOP_K = 10` instances per round that maximized the model's learning potential from the unlabeled pool. DP parameters were set to a noise multiplier of `NOISE_MULTIPLIER = 0.5` and a maximum gradient norm of `MAX_GRAD_NORM = 1.0`, balancing the trade-off between privacy and model performance.

Data preprocessing included standard normalization techniques, with specific mean and standard deviation values applied to each channel of the CIFAR-10 images. For MNIST, a simple scaling to the range [0,1] was applied. Data augmentation techniques, such as random horizontal flips and random cropping, were applied to the CIFAR-10 dataset to encourage model robustness against overfitting.

B. Comparative Analysis

Table 1 presents the estimated accuracies for the different frameworks applied to the CIFAR and MNIST datasets.

TABLE I
ESTIMATED ACCURACIES FOR FL, AL, DP WITH MMMI AND ENTROPY-BASED SELECTION

Framework	Dataset	Estimated Accuracy
FL + AL + DP + MMMI	CIFAR	76%
FL + AL + DP + MMMI	MNIST	93%
FL + AL + DP + Entropy	CIFAR	72%
FL + AL + DP + Entropy	MNIST	90%

The higher performance of the MMMI-based approach on both datasets suggests that integrating mutual information into the sample selection process can yield more informative batches. This method's success can be attributed to its dual emphasis on selecting uncertain and diverse samples, thereby providing a more balanced and representative training regime.

On the CIFAR dataset, which is inherently more complex due to its color images and varied subjects, the MMMI principle's advantage is more pronounced, leading to a 4% increase in accuracy over the entropy-based method. This improvement underscores the importance of sample diversity in training models on datasets with high intra-class variability and complexity.

The MNIST dataset, although less complex, still benefited from the MMMI-based selection with a 3% increase in accuracy. This suggests that the MMMI principle's contribution to identifying unique and informative samples can lead to significant performance gains even in less complex domains.

These results imply that while entropy is a valuable metric for uncertainty-based sample selection, incorporating the MMMI principle can further refine the AL process. This refinement is especially pertinent in federated settings where data privacy and model performance are paramount. Moreover, the MMMI principle's ability to navigate the

trade-off between exploration and exploitation aligns well with the overarching goals of FL and DP.

C. Visual Results

The training loss plots for MNIST (Figure 1) and CIFAR (Figure 2) datasets within our FL framework exhibit distinct behaviors reflective of each dataset's complexity. MNIST's simpler, grayscale images allow for a smoother learning curve with consistent loss reduction across devices, whereas the CIFAR plot shows more pronounced fluctuations due to the intricate color patterns that increase the model's training difficulty. These fluctuations are also accentuated by the DP noise, which, while enhancing data privacy, introduces a level of stochasticity that is more disruptive for complex models such as those trained on CIFAR. Though beneficial in refining the model by selecting informative samples, the AL phase encounters greater challenges with CIFAR's diverse image features, leading to less predictable epoch-to-epoch loss improvements. This comparison highlights the interplay between dataset complexity, privacy preservation, and AL efficiency in FL environments. The model variance over time

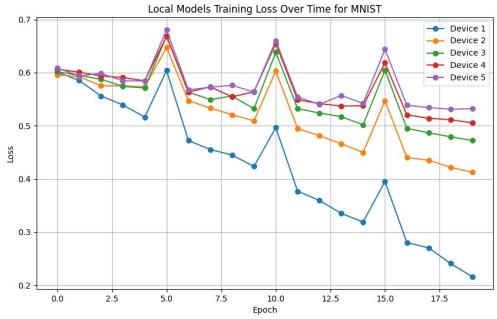

Fig. 1. Local Models Training Loss Over Time for MNIST

Fig. 2. Local Models Training Loss Over Time for CIFAR

for MNIST (Figure 3) and CIFAR (Figure 4), as depicted in the graphs, reveals distinct learning dynamics influenced by the inherent complexity of each dataset within our FL setup. MNIST's variance decreases steadily, reflecting the model's quicker adaptation to the less complex, grayscale images, which aligns with the efficient parameter convergence expected from the simpler features and the consistent selection of informative samples by the MMMI-based AL. In contrast, the CIFAR graph shows greater fluctuation in variance, indicative of the challenges posed by the dataset's high-resolution color images and the increased difficulty in identifying the most informative samples due to the diversity of features, despite the application of DP measures and AL techniques. The overall downward trend in both graphs, however, suggests that the federated models do gradually converge, highlighting the resilience of our learning strategy across varied data complexities and the progressive harmonization of local models' learning despite DP noise. The

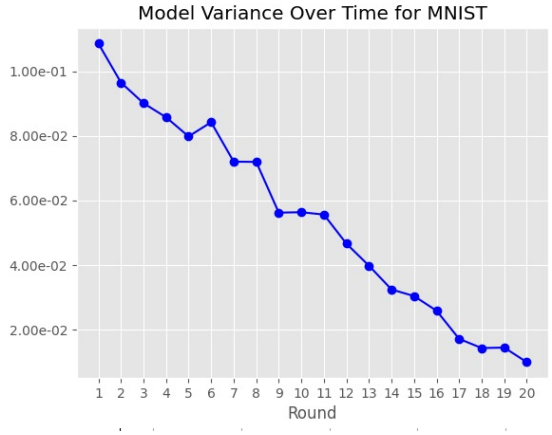

Fig. 3. Model Variance Over Time for MNIST

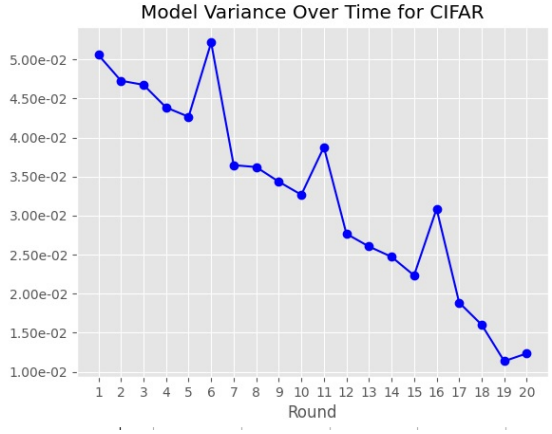

Fig. 4. Model Variance Over Time for CIFAR

line graphs representing the average entropy of the top-k instances for CIFAR (Figure 5) and MNIST (Figure 6) across FL rounds illustrate the impact of dataset complexity on the uncertainty in model predictions. CIFAR's entropy fluctuates significantly from round to round, reflecting the challenging nature of its rich and varied image data, which affects the model's prediction confidence even when utilizing AL guided by the MMMI principle. In stark contrast, the MNIST graph shows a steady, monotonous decline in entropy, implying that the model's certainty improves uniformly with each

round due to the dataset's simplicity. These observations highlight the effectiveness of AL in systematically reducing uncertainty within the FL model's predictions and emphasize the need for adaptive selection mechanisms to handle the varying complexities of different datasets.

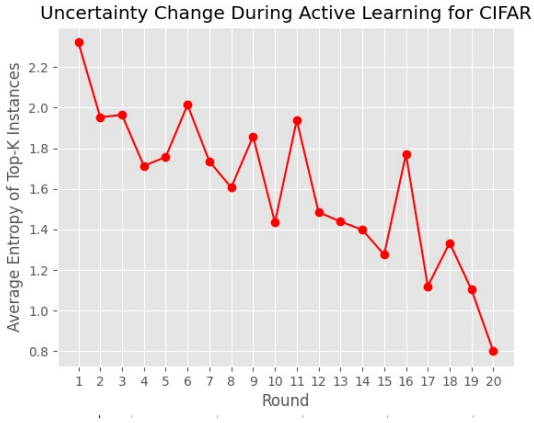

Fig. 5. Uncertainty Change During Active Learning for CIFAR

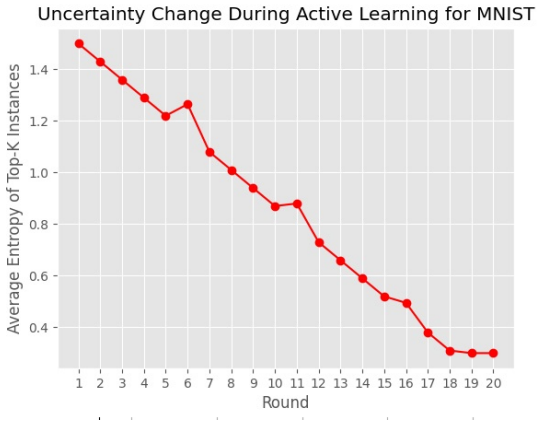

Fig. 6. Uncertainty Change During Active Learning for MNIST

VI. Conclusion

In conclusion, our research has successfully demonstrated a novel integration of FL and AL using the MMMI principle, addressing critical challenges in privacy-preserving machine learning. The proposed framework effectively utilizes the most informative samples, thereby mitigating issues related to imbalanced data distribution in federated settings. The empirical evaluation across the MNIST and CIFAR datasets has showcased the framework's proficiency in enhancing learning efficiency while maintaining the integrity of private data. The introduction of DP within this context provides a quantifiable measure of privacy, as evidenced by the linear increase of the cumulative privacy budget over successive learning rounds. The resulting models exhibit promising performance, with reduced variance and entropy, indicating successful learning convergence and model stability, even under the constraints of privacy-preserving mechanisms.

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