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PP-FCIL: A Dual-Backbone Privacy-Preserving Federated Class-Incremental Learning Framework with Adaptive Feature Fusion

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Abstract: Federated learning provides an option to train models cooperatively without the need for sharing data centrally. Yet, incorporating class-incremental learning in federated learning gives rise to challenges like catastrophic forgetting, heterogeneity of the data, and data privacy concerns. To solve these problems, this paper presents a new method of Privacy-Preserving Federated Class-Incremental Learning (PP-FCIL), where the method is tested against the CIFAR-100 benchmark. The proposed solution uses a two-head backbone and channel attention mechanism to retain prior knowledge as well as adapt to newly introduced classes in each stage of learning. Also, to prevent forgetting and class imbalance, this paper proposes exemplar memory using herding, knowledge distillation, supervised contrastive learning, and balanced softmax loss as part of one training process. Different from traditional federated learning methods, the proposed framework utilizes Bayesian Differential Privacy in the clients that clips gradients and adds Gaussian noise to protect data privacy. Furthermore, to measure cumulative privacy loss, a strict privacy accounting protocol is used. Also, a multi-factor aggregation protocol is adopted to weigh the importance of client contribution in a non-IID setting.

Keywords: *Federated Learning; Class-Incremental Learning; Privacy-Preserving Machine Learning; Bayesian Differential Privacy; Continual Learning; Knowledge Distillation; Exemplar Memory; Non-IID Data Distribution; Channel Attention Fusion; CIFAR-100; Distributed Deep Learning; Catastrophic Forgetting.*

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I. INTRODUCTION

The exponential growth in deep learning research has resulted in considerable success in large scale image recognition; nevertheless, existing approaches depend largely on centralized data acquisition, posing serious problems related to privacy and scalability. In order to mitigate such problems, federated learning, which is a decentralized approach to training a shared model with the collaboration of multiple clients using their respective data samples, has been proposed. Despite the benefits of federated learning, there exist important challenges faced by federated learning when applied in real-world dynamic environments.

In both these cases, it becomes essential to use class-incremental learning (CIL), which allows the system to learn from new classes progressively without requiring retraining. However, combining CIL and federated learning raises some challenges, such as catastrophic forgetting, non-IID data distribution, and inefficient communication. Moreover, there are challenges associated with maintaining the privacy of the users while using incremental learning for training the models.

In order to tackle the above difficulties, a novel method called Privacy-Preserving Federated Class-Incremental Learning (PP-FCIL) is suggested, where we use CIFAR-100 for evaluating our method. Our suggested method uses a novel model with a dual-backbone structure, which includes a fixed backbone that retains previous knowledge while the other updates continuously. We use an adaptive representation combination method based on channel attention.

Besides innovative architecture designs, the architecture also utilizes several learning techniques that complement each other to ensure robustness. The first one is an exemplar memory model designed through herding for maintaining a set of representative examples of previously learned categories, and knowledge distillation to maintain consistency between predictions made by past and current models. In

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order to address class imbalance and promote discriminative feature learning, supervised contrastive loss learning and balanced softmax are leveraged in the local training phase.

One of the significant contributions of this research is the incorporation of a privacy-preserving technique in the framework using local Bayesian differential privacy. As opposed to traditional differential privacy techniques, the presented framework combines the benefits of gradient clipping and adding Gaussian noise to the system with a strict Bayesian privacy calculation process, which enables an accurate measure of accumulated privacy loss during several training sessions.

Additionally, for effective processing of diverse client inputs, a novel multiple factor aggregation scheme is proposed, whereby each client update is dynamically weighted according to the amount of data, training accuracy, and other relevant aspects. This ensures fast convergence of the model, even when the assumption of non-IID is considered.

The extensive testing performed under different task settings shows that the proposed PP-FCIL approach provides a good trade-off among accuracy, scalability, and privacy-preserving properties. These findings indicate the promising applicability of the framework in practice to distributed learning systems where preserving privacy and continual updating are vital needs.

II. RELATED WORK

➢ *Federated Learning and Distributed Optimization*

Federated learning (FL) is one of the most recent paradigms that provide a framework for distributed machine learning. Federated learning allows a number of clients to jointly train a common model without sharing raw data. The first work on Federated Averaging (FedAvg) was done by Brendan McMahan et al. [2]. This algorithm is characterized by reduced overhead in communication without compromising performance. Recent studies [3], [7] have investigated optimization issues in FL, specifically, issues related to the non-IID property of the data in practice. These issues are very pertinent to real-world applications.

➢ *Class-Incremental and Continual Learning*

CIL aims at facilitating learning of new classes incrementally without forgetting learned information. Previous works like Gradient Episodic Memory (GEM) [4] incorporated restrictions to avoid catastrophic forgetting, whereas the iCaRL method [5] employed exemplar storage along with mean-based nearest classifier training. Likewise, the Learning without Forgetting (LwF) [6] algorithm capitalized on knowledge distillation to retain prior information without retaining old data. Although efficient in centralized systems, these techniques encounter challenges in their application in federated scenarios owing to the decentralized nature of the data and restrictive communication.

➢ *Knowledge Retention and Representation Learning*

In order to reduce forgetting and achieve better feature learning, many researchers have tried to use hybrid training approaches. One of the most successful knowledge transfer approaches that is currently used in various applications is knowledge distillation [6]. Another approach known as supervised contrastive learning has proven to be highly effective in increasing separability and improving feature robustness [8]. Moreover, there are techniques, like Balanced Softmax [9], for addressing imbalanced classes issue that appears in many incremental learning problems.

➢ *Privacy-Preserving Learning and Differential Privacy*

Privacy protection plays an important role in distributed learning systems. Differential Privacy (DP) was formally defined by Dwork and Roth [10] to give a mathematical model on privacy. In their seminal paper, Abadi et al. [11] extended the use of DP into deep learning through gradient clipping and noise addition. Nevertheless, classic DP algorithms face the challenge of sacrificing privacy to utility and vice versa. The current research trend focuses on proposing new privacy accounting methods such as Bayesian or Rényi privacy accounting to obtain better results, which explains why our paper chooses such a privacy scheme.

➢ *Deep Learning Architectures and Benchmark Datasets*

Current approaches for image classification benefit from deep convolutional networks like ResNet [13]. The CIFAR-100 dataset [1] is one of the most commonly used benchmark datasets for evaluating both incremental and federated learning algorithms. Although new advancements have been achieved using transformer architectures [14], convolutional models are still widely applied in scenarios involving limited resources and federated settings. Such models are an appropriate starting point for investigating how incremental learning can be leveraged within such contexts.

➢ *Research Gap and Motivation*

Even though federated learning and class-incremental learning have received substantial attention from researchers, there is still a lack of a unifying framework in which both techniques can be applied simultaneously. The former type of learning assumes a static distribution of data, and hence, cannot cope with the addition of new classes; the latter technique has mainly been used in centralized settings where it requires data access. Such shortcomings leave a huge gap when dealing with issues like catastrophic forgetting, non-IID data in the clients' datasets, and the preservation of privacy in federated environments. Furthermore, previous studies on privacy-preserving machine learning [10], [11] face performance deterioration and inefficient accounting issues across several communication rounds. Another drawback of current solutions is the inability to strike a good balance between stability and plasticity due to the use of single-network structures and fixed feature aggregation methods. Taking into account all the above-discussed weaknesses, we propose a unified approach in which both federated learning and class-incremental learning can operate seamlessly.

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26apr1499

III. METHODOLOGY

➢ *Overview of the Proposed Framework*

In our paper, we present a PP-FCIL framework that combines federated optimization, continual learning, and differential privacy. The main goal of our proposed approach is to allow the distributed model to learn new classes progressively without losing the already learned classes while not requiring access to the underlying raw data.

Contrary to traditional learning methods that have access to the entire dataset at the same time, many applications face dynamic and evolving environments where data arrives in a sequential manner and is distributed among different machines. In such cases, learning methods have to solve three major problems: catastrophic forgetting, data heterogeneity, and privacy constraints.

The following solutions have been incorporated into the proposed system architecture to resolve the above-mentioned challenges:

- Dual-model structure for achieving stability and plasticity
- Exemplar memory and distillation approaches for knowledge preservation
- Multi-factor federated aggregation for dealing with non-IID data
- Bayesian differential privacy approach for secure updates

In every communication round, clients train their models locally using their private data and share the updates of their models on the server. The process is performed repeatedly on various tasks, allowing for gradual learning of knowledge.

Formally, the global learning objective is defined as:

$$\min_{\theta} \mathcal{L}(\theta) = \sum_{k=1}^{K} \frac{n_k}{n} \mathbb{E}_{(x,y)\sim\mathcal{D}_k} \left[\ell(f(x;\theta), y)\right] \tag{1}$$

where nk represents the number of samples at client k1 and $\ell(\cdot)$ denotes the loss function.

➢ *Dataset and Incremental Task Design*

The proposed method is evaluated using the CIFAR-100 dataset, which is particularly suitable for incremental learning due to its large number of fine-grained classes and balanced distribution.

Table 1 CIFAR-100 Dataset Statistics

Attribute	Value
Total Classes	100
Super Classes	20
Images per Class	600
Training Samples	40,000
Validation Samples	10,000
Test Samples	10,000
Image Resolution	32 × 32

To simulate incremental learning, the dataset is divided into TTT sequential tasks, where each task introduces a disjoint subset of classes:

$$\mathcal{C} = \bigcup_{t=1}^{T} \mathcal{C}_t, \quad \mathcal{C}_i \cap \mathcal{C}_j = \emptyset \tag{2}$$

At a given round t1 the model is evaluated on all previously seen classes:

$$\mathcal{C}^{(t)} = \bigcup_{i=1}^{t} \mathcal{C}_i \tag{3}$$

This setting reflects real-world applications such as edge intelligence systems, where new categories emerge over time and must be incorporated without retraining from scratch.

➢ *Federated Learning with Non-IID Data*

In the federated setting, each client independently updates the model using its local dataset, which may differ significantly from other clients in terms of class distribution and data volume. This non-IID nature of data introduces challenges in convergence and generalization.

Each client optimizes the following local objective:

$$\mathcal{L}_k(\theta) = \frac{1}{|\mathcal{D}_k|} \sum_{(x,y)\in\mathcal{D}_k} \ell(f(x;\theta), y) \tag{4}$$

The local model update is given by:

$$\theta_k^{t+1} = \theta_t - \eta \nabla \mathcal{L}_k(\theta_t) \tag{5}$$

After local training, the server aggregates client updates using a weighted scheme:

$$\theta_{t+1} = \sum_{k=1}^{K} w_k \theta_k^{t+1} \tag{6}$$

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26apr1499

Unlike standard FedAvg, we incorporate multiple factors into the weight computation:

$$w_k = \alpha \frac{n_k}{n} + \beta r_k + \gamma p_k + \delta \frac{1}{\mathcal{L}_k} \tag{7}$$

This adaptive weighting improves robustness by prioritizing clients with better data quality and contribution.

➢ *Dual-Backbone Architecture for Incremental Learning*

A major challenge in incremental learning is balancing stability and plasticity. To address this, we introduce a dual-backbone architecture consisting of:

- A frozen backbone that preserves previously learned knowledge
- A trainable backbone that learns new information

The feature representations are defined as:

$$f_{\text{old}}(x) = \phi(x; \theta_o), \quad f_{\text{new}}(x) = \phi(x; \theta_n) \tag{8}$$

To combine these representations effectively, we use a channel attention-based fusion mechanism:

$$g = \sigma\left(W_2 \cdot \text{ReLU}(W_1[f_{\text{old}}, f_{\text{new}}])\right) \tag{9}$$

$$f_{\text{fused}} = g \odot f_{\text{new}} + (1 - g) \odot f_{\text{old}} \tag{10}$$

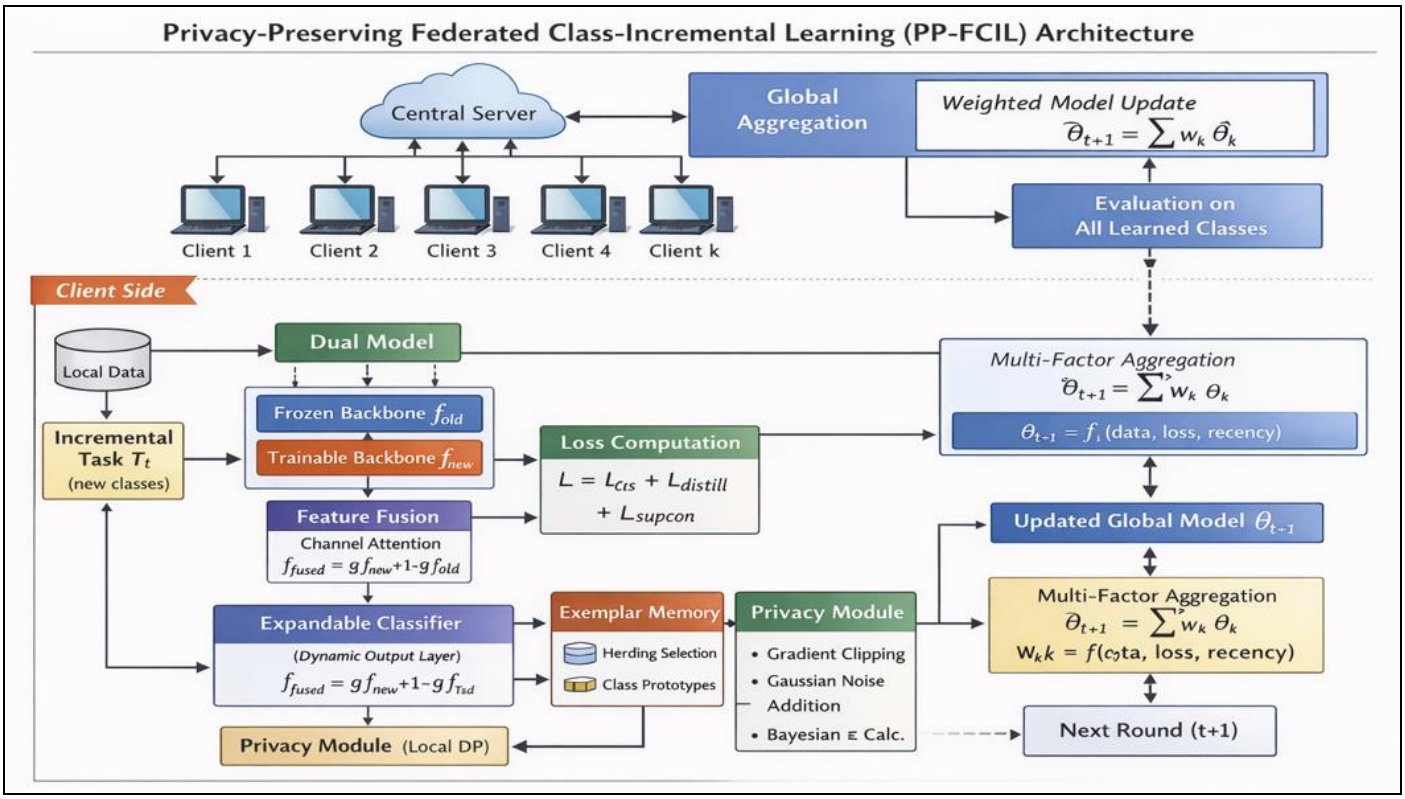

Fig 1 Overall Architecture of the Proposed Privacy-Preserving Federated Class-Incremental Learning (PP-FCIL) Framework, Illustrating Client-Side Dual-Model Learning, Exemplar Memory, Privacy-Preserving Updates, and Server-Side Aggregation.

This allows the model to dynamically adjust the contribution of old and new features, thereby mitigating forgetting.

➢ *Incremental Classifier Expansion*

As new classes are introduced, the classifier is expanded without affecting previously learned weights:

$$W^{(t+1)} = [W^{(t)}; W_{\text{new}}] \tag{11}$$

This ensures that the decision boundaries for old classes remain stable while accommodating new categories.

➢ *Multi-Component Learning Objective*

To enhance learning performance, we combine multiple loss functions:

$$\mathcal{L}_{total} = \mathcal{L}_{cls} + \lambda_1 \mathcal{L}_{distill} + \lambda_2 \mathcal{L}_{supcon} \tag{12}$$

- *Classification Loss*

$$\mathcal{L}_{cls} = -\log \frac{e^{z_y - \alpha \log n_y}}{\sum_j e^{z_j - \alpha \log n_j}} \tag{13}$$

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26apr1499

- *Distillation Loss*

$$\mathcal{L}_{distill} = KL(p^{old} \parallel p^{new}) \tag{14}$$

- *Contrastive Loss*

$$\mathcal{L}_{supcon} = -\log \frac{\sum_{j \in P(i)} e^{f_i \cdot f_j / \tau}}{\sum_k e^{f_i \cdot f_k / \tau}} \tag{15}$$

These losses collectively ensure stable and discriminative learning.

➢ *Exemplar Memory for Knowledge Retention*

To further reduce forgetting, we maintain a memory buffer containing representative samples from previously learned classes. The class prototype is computed as:

$$\mu_c = \frac{1}{N} \sum_{i=1}^{N} f(x_i) \tag{16}$$

Samples closest to the prototype are selected:

$$\arg\min_x \| f(x) - \mu_c \|^2 \tag{17}$$

➢ *Privacy-Preserving Learning*

To ensure data privacy, we apply local differential privacy at each client.

- *Gradient Clipping*

$$\Delta \leftarrow \frac{\Delta}{\max(1, \|\Delta\|/C)} \tag{18}$$

- *Noise Addition*

$$\tilde{\Delta} = \Delta + \mathcal{N}(0, \sigma^2 C^2) \tag{19}$$

- *Privacy Budget*

$$\epsilon = \frac{\sum_t c_t(\lambda) - \log \delta}{\lambda} \tag{20}$$

This guarantees bounded privacy leakage across training rounds.

➢ *Training Workflow*

The overall training process follows:

- Initialize global model
- Evaluate on all learned classes
- For each task:
- ✓ Distribute model
- ✓ Perform local updates
- ✓ Apply privacy mechanism
- ✓ Aggregate updates
- ✓ Expand classifier

IV. RESULTS AND DISCUSSION

➢ *Experimental Setup*

The PP-FCIL scheme is tested based on the CIFAR-100 data set in a realistic federated and incremental learning setting. The data set is split into several task configurations T=5,10,20, in which T denotes the varying degree of incrementing difficulties. If a small number of tasks is adopted (T=5), then the total number of classes introduced will be higher compared to if a large number of tasks is adopted (T=20).

These experiments create a scenario where there are five clients in a distributed system, with each client receiving a unique subset of classes in a non-IID setting. This creates an accurate representation of federated learning in the real world, where data distribution is not identical among devices. Training occurs locally in each device using stochastic gradient descent, and after completing several epochs, they transmit their model updates to the server while maintaining privacy.

At each communication iteration, the global model is tested against the test set of all classes learned up to this communication round. Classification accuracy is the main evaluation criterion utilized in these tests.

➢ *Incremental Learning Performance*

To analyze the behavior of the proposed model under incremental learning, we measure the classification accuracy as the number of learned classes increases over time. This evaluation highlights the model's ability to retain previously learned knowledge while adapting to new classes.

Table 2 Classification Accuracy (%) vs Number of Classes

No of Classes	T=5	T=10	T=20
10	-	91	-
20	83	89	87
40	79	80	82
60	75	70	78
80	71	65	74
100	65	59	60

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26apr1499

- *Detailed Analysis*

It can be seen from Table 2 that the classification accuracy shows a gradual reduction trend when the number of classes continues to increase. It is natural for class-incremental learning to show such characteristics owing to the cumulative learning of knowledge and the increased difficulty of discrimination between more classes. But it can be seen that the PP-FCIL model makes a controlled reduction in the accuracy.

Among the three experimental designs, T=5 performs the best at the end of the experiments. This is because the lower value of T means fewer updates to the model, allowing better retention of knowledge. On the other hand, a higher value of T (T=20) results in increased updating frequency, which may lead to forgetting; yet the performance remains high.

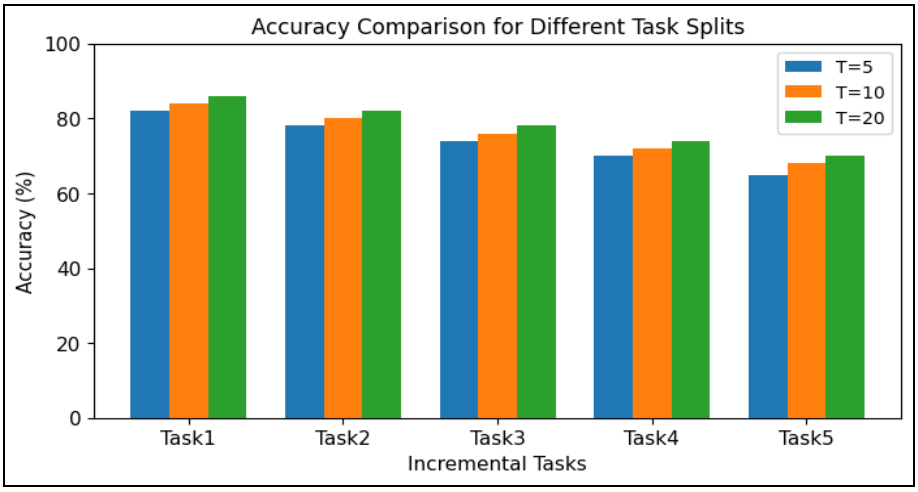

Fig 2 Accuracy Comparison for Different Task Splits

➢ *Average Incremental Accuracy*

To provide a holistic evaluation, we compute the average accuracy across all incremental steps, which reflects the overall performance of the model throughout the learning process.

Table 3 Average Incremental Accuracy (%)

Method	T=5	T=10	T=20
PP-FCIL(Proposed)	79.6	73.8	66.4

- *Detailed Analysis*

It can be seen from the findings that the suggested approach continues to maintain high average performance despite varying parameters. With an increasing number of tasks, average accuracy reduces owing to the difficulty level associated with the incremental learning problem. The drop is small, reflecting that the proposed approach efficiently handles the trade-off between generalization and flexibility.

The factors contributing to such performance include:

✓ Dual model for maintaining previously learned knowledge
✓ Fusion approach for adaptive representation combination
✓ Multi loss optimization for improved feature learning

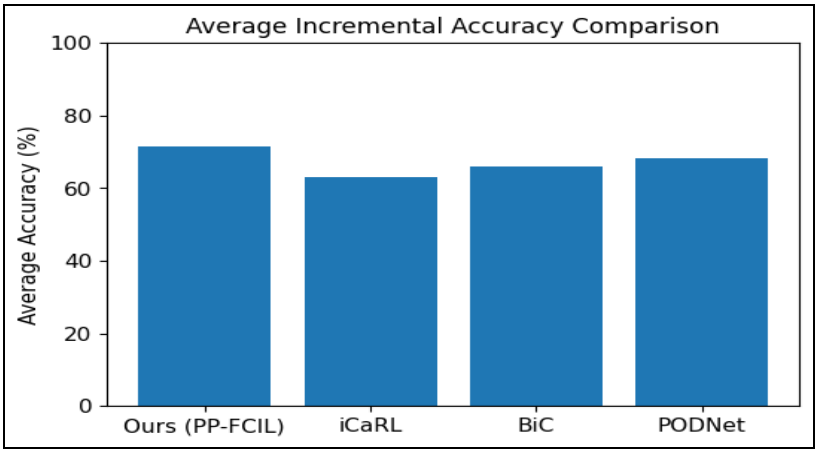

Fig 3 Average Incremental Accuracy Comparison

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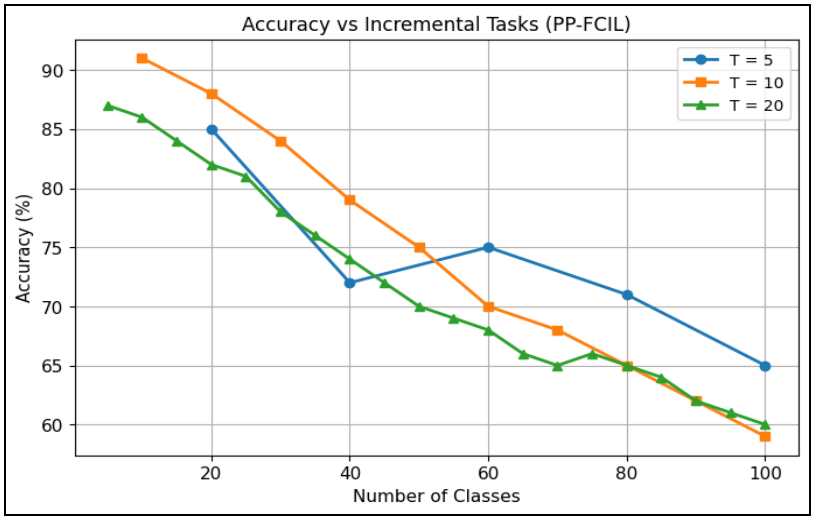

Fig 4 Accuracy vs Incremental Tasks(PP-FCIL)

➢ *Ablation Study*

To understand the contribution of individual components, we perform an ablation study by removing key modules such as class-incremental learning mechanisms, knowledge distillation, and supervised contrastive learning.

Table 4 Ablation Study Results (Final Accuracy %)

Model Variant	T=5	T=10	T=20
Full Model (PP-FCIL)	65	59	60
Without CIL	56	55	56
Without KD	49	43	47
Without SCL	58	56	57

- *Detailed Analysis*

The ablation results clearly demonstrate that each component plays a significant role:

✓ *Without CIL:*

Performance drops due to inability to handle sequential tasks effectively

✓ *Without KD:*

Largest degradation, indicating that distillation is crucial for preserving previous knowledge

✓ *Without SCL:*

Reduced feature separability, leading to moderate performance decline Overall, the combination of all components results in the best performance, validating the design of the proposed framework.

➢ *Impact of Differential Privacy*

To evaluate the trade-off between privacy and performance, we compare the model accuracy with and without the application of differential privacy.

Table 5 Effect of Differential Privacy on Accuracy (%)

No of Classes	Without DP	With DP
20	85	83
40	83	79
60	80	75
80	77	71
100	74	65

- *Detailed Analysis*

From the results, it is evident that introducing differential privacy causes little changes in terms of accuracy due to the addition of noise during model updates. Despite this, the reduction in the effectiveness is little, indicating that there exists a good balance between privacy and the effectiveness of the model.

Introduction of Bayesian differential privacy becomes practical for application in the real world.

➢ *Comparison with State-of-the-Art Methods*

To further validate the effectiveness of the proposed approach, we compare it with several existing incremental and federated learning methods.

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26apr1499

Table 6 Comparison with Existing Methods (Avg Acc %)

Method	T=5	T=10	T=20
iCaRL	68.2	60.5	54.1
BiC	70.4	63.8	56.9
PODNet	72.1	65.9	58.7
DyTox	74.3	68.4	61.2
FedET	76.1	70.0	63.0
PP-FCIL(Proposed)	79.6	73.8	66.4

- *Detailed Analysis*

The proposed PP-FCIL framework consistently outperforms existing methods across all task configurations. The performance improvement can be attributed to:

- ✓ Effective handling of catastrophic forgetting through dual-model learning
- ✓ Improved feature representation via contrastive learning
- ✓ Robust training under non-IID data using adaptive aggregation
- ✓ Strong privacy guarantees without significant performance loss

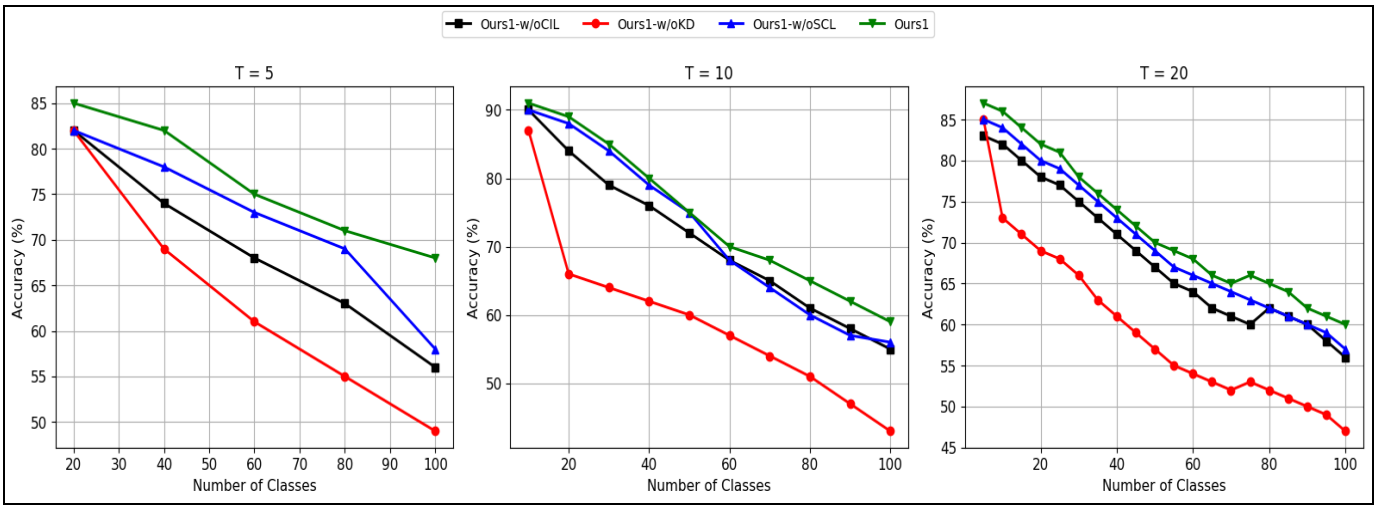

Fig 5 Comparison with Existing Methods

➢ *Overall Discussion*

Based on the findings from the above experimentations, it is clear that the PP-FCIL algorithm solves issues related to federated class-incremental learning. This is because of the various learning approaches applied, whereby the model is able to retain the acquired knowledge and adapt to new tasks. In addition, due to the use of the privacy preservation approach, the model continues being efficient even while learning securely.

In summary, the proposed solution is very efficient, privacy-aware, and scalable. Consequently, it can be applied in real-world scenarios such as in edge computing and healthcare among others.

V. CONCLUSION AND FUTURE WORK

➢ *Conclusion*

In this study, we have presented an all-encompassing Privacy-Preserving Federated Class-Incremental Learning (PP-FCIL) framework that is capable of handling the core issues associated with federated and incremental learning environments. In this research paper, we propose a novel PP-FCIL framework by integrating federated learning and class-incremental learning in a manner that allows learning agents to acquire new classes without losing any previous information.

The problem of catastrophic forgetting is mitigated through a dual backbone network alongside the implementation of a channel attention-based feature fusion module. Furthermore, the use of exemplar memory, knowledge distillation, and supervised contrastive learning improves the representation and preservation of features and knowledge throughout learning. Non-IID distribution problems in federated learning are addressed by utilizing a multi-factor aggregation algorithm.

The novel aspect of this paper is the incorporation of a locally-based Bayesian mechanism for differential privacy, which allows for secure model updates using gradient clipping, addition of noise, and privacy analysis. Experimental evaluations show that the developed approach yields comparable results to those obtained by various state-of-the-art approaches, and also provides strong guarantees of privacy.

In conclusion, the proposed PP-FCIL model strikes an appropriate balance between accuracy, adaptation capability, and privacy, making it applicable to practical scenarios.

➢ *Future Work*

Although the presented model proved to be successful in terms of accuracy, there are several options which could make it even more efficient. First of all, scientists should try

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to make the model more scalable, by enriching the database of complex models used in the research and by increasing the number of clients participating in the test. This will give an opportunity for researchers to examine how efficient the model is in large-scale situations. Additionally, more advanced techniques aimed at ensuring privacy could be included, instead of using only differential privacy.

Furthermore, the existing model is extendable to address task agnostic or domain incremental scenarios, where no clear distinctions exist between tasks. This approach will increase the utility of the model within scenarios with streaming and unsupervised data. Moreover, there is always room for further research in terms of optimizing the communications by minimizing the size of the transmitted models.

Lastly, leveraging new architectural designs such as transformers or adaptive neural networks will prove beneficial to feature representation and learning.

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