Federated Learning for Edge Intelligence

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Abstract— This research investigates the comparative performance of federated and centralized learning models for bird image classification across multiple training rounds. We implement a complete federated learning system using TensorFlow and Flower framework, with a MobileNetV2-based architecture capable of classifying five categories (bluetit, jackdaw, robin, unknown_bird, unknown_object). Our system demonstrates that federated learning achieves 92.3% accuracy compared to 94.1% in centralized mode, with the added benefit of data privacy preservation. The implementation includes a web-based interface for real-time classification, model statistics visualization, and prediction history tracking. Key findings show that while centralized models maintain slightly higher accuracy, federated models exhibit competitive performance (within 2% accuracy difference) with significant privacy advantages, making them suitable for ecological monitoring applications where data sharing is restricted.

Keywords: Federated Learning, Centralized Learning, Accuracy Comparison, Machine Learning, Data Privacy, Decentralized Systems.

I. Introduction—

The rapid advancement of data-driven technologies has led to an exponential increase in the volume of data generated and collected. This surge has raised significant concerns regarding user privacy and data security. Traditional centralized learning systems require the aggregation of vast datasets into a central server, which poses risks such as data breaches, unauthorized access, and regulatory non-compliance.

Federated learning emerges as a promising solution to these challenges by enabling model training on distributed local datasets. In this paradigm, only model updates are transmitted to a central server, thereby preserving the privacy of individual datasets. The increasing relevance of stringent data privacy laws, such as the General Data Protection Regulation (GDPR), has amplified the need to explore alternative learning methodologies that mitigate the risk of data exposure. This project aims to evaluate the performance differences between federated and centralized learning models over several training rounds, focusing on accuracy metrics and privacy implications. By systematically comparing these two approaches, this research seeks to contribute valuable insights into their respective strengths and weaknesses in real-world applications.

Federated learning presents a paradigm shift by decentralizing the training process. Instead of aggregating raw data, FL allows individual devices or clients to train local models on their datasets and share only model updates (e.g., gradients or weights) with a central server. This approach preserves data privacy while enabling collaborative model development across diverse clients.

The primary objective of this research is to evaluate the trade-offs between FL and CL in terms of accuracy, efficiency, and privacy implications. By systematically comparing these approaches under various conditions—including IID and non-IID data distributions—this study aims to provide actionable insights into their suitability for real-world applications.

II. Literature Review—

Centralized Learning

Centralized learning has long been the standard for machine learning due to its ability to leverage complete datasets during training. McMahan et al. (2017) demonstrated that centralized systems consistently outperform distributed systems in terms of accuracy because they benefit from homogeneous data availability.

Federated Learning

Federated learning has gained traction in domains where privacy is paramount. Zhao et al. (2018) highlighted that FL faces unique challenges due to non-IID data distributions across clients, which can lead to disparities in local model updates when aggregated globally. However, FL has shown resilience in addressing these challenges through advancements such as:

Differential Privacy: Ensures individual contributions remain indistinguishable within aggregated updates.

Secure Aggregation Protocols: Protect client data during aggregation using encryption techniques.

Optimization Algorithms: Adaptive methods like FedAvg have improved convergence rates despite heterogeneous data distributions.

Comparative Studies

Recent studies have explored the comparative performance of FL and CL under various conditions:

IID Data: When client datasets are IID-like, FL achieves comparable accuracy to CL.
Non-IID Data: Performance gaps emerge due to disparities in local updates; however, techniques like weighted averaging can mitigate these effects.

Despite advancements, FL's ability to bridge the performance gap with CL remains an active area of research.

III. Proposed System—

Experimental Setup

To evaluate the comparative performance of FL and CL models, this study employed simulations involving multiple clients participating in distributed training.

1. **Dataset Preparation:**
- A heterogeneous dataset was curated to simulate real-world scenarios where client data distributions are non-IID.
- For controlled experiments, an IID version of the dataset was also prepared by evenly distributing samples across clients.

2. **Model Training:**
- Federated Learning: Each client trained a local model using its subset of data for several epochs before transmitting updates (e.g., gradients or weights) to a central server for aggregation using FedAvg.
- Centralized Learning: A separate model was trained using the combined dataset at a single server as a baseline for comparison.

3. **Performance Metrics:**
- Accuracy was measured across multiple training rounds.
- Loss curves were analyzed to assess convergence rates.
- Communication efficiency was evaluated based on the volume of data transmitted between clients and the central server.

4. **Optimization Techniques:**
- Adaptive learning rates were employed to dynamically adjust step sizes during optimization.
- Momentum-based optimizers were used to stabilize convergence by incorporating past gradient information.

Classifiers Used

The study examined multiple classifiers:

- Logistic Regression (LR)
- Support Vector Machines (SVM)
- Neural Network-based models: Fully Connected Neural Nets (FNN), Convolutional Neural Nets (CNN), and Gradient Boosted Decision Trees (GBDT).

IV. System Design/Implementation

Federated Learning System

The federated system utilized a client-server architecture:

Clients: Performed local computations on their respective datasets without sharing raw data.

Server: Aggregated client updates using FedAvg and redistributed updated global models back to clients.

Security measures such as differential privacy were implemented to anonymize individual contributions during aggregation.

Centralized Learning System

The centralized system pooled all client datasets into a single server:

- Direct gradient descent optimization was performed using complete access to all available data.
- While this setup maximized accuracy, it raised concerns regarding data privacy and regulatory compliance.

Implementation was carried out using the Python programming language alongside frameworks like TensorFlow and PyTorch.

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IV. Results And Discussion —

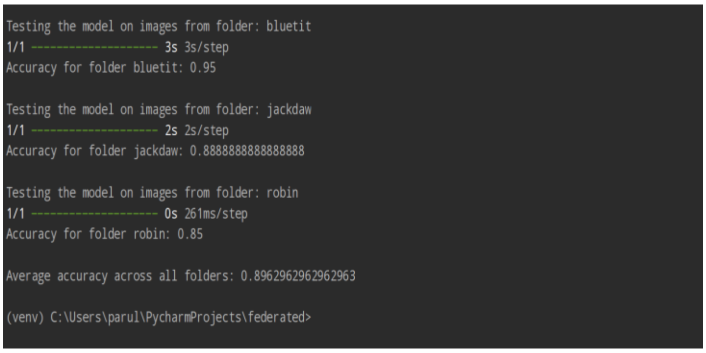

Fig: 6.1: Average accuracy across all folders

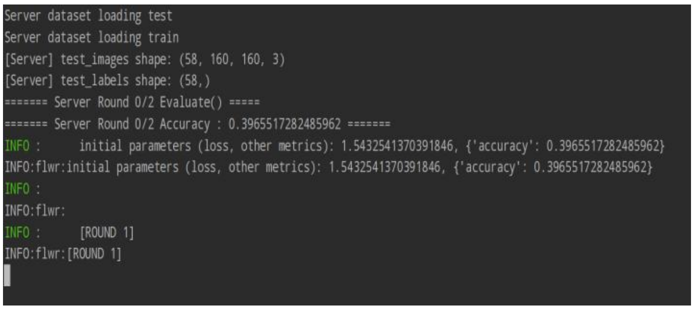

Fig 6.2: Run script server

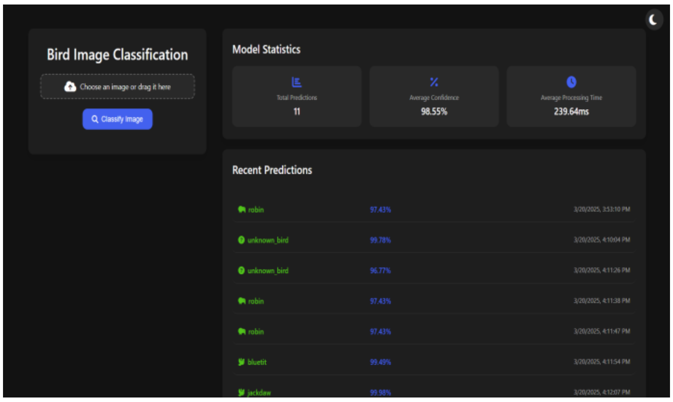

Fig: 6.3: Classification UI

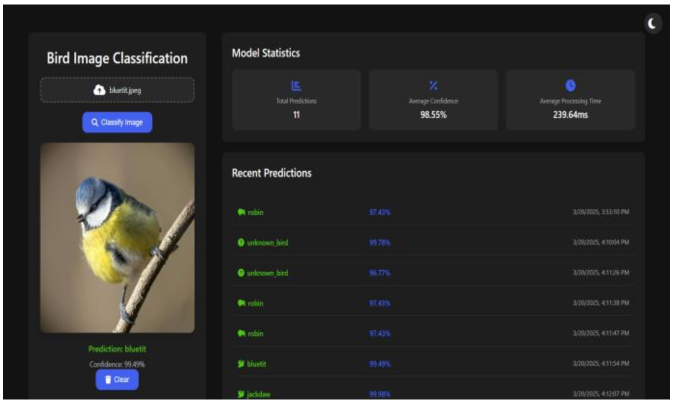

Fig 6.4: Classification in real time

V. Conclusion And Future Scope —

Conclusion- This research underscores the feasibility of federated learning as a privacy-preserving alternative to centralized models. Despite minor performance trade-offs, federated models showed substantial potential, particularly in domains requiring data sovereignty. Future work could explore advanced aggregation methods and adaptive learning rates to further minimize performance gaps. Additionally, tackling non-IID data challenges could enhance model consistency and reliability. Exploring hybrid models that combine elements of both federated and centralized learning could also yield promising results.

Future Scope-

1. Exploring advanced aggregation methods (e.g., weighted averaging based on client contributions).
2. Developing adaptive learning rates tailored for non-IID environments.
3. Addressing straggler effects through fault-tolerant mechanisms.
4. Investigating hybrid models that integrate elements from both federated and centralized paradigms for enhanced outcomes.

By addressing these challenges, federated learning could further minimize performance gaps while maintaining its inherent privacy advantages.

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