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Decentralized Image Classification with Federated Learning

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Abstract: *This work presents a decentralized image classification framework designed to address the privacy, security, and communication limitations of traditional centralized deep learning systems. In the proposed approach, multiple distributed clients collaboratively train a global model using Federated Learning, ensuring that raw image data never leaves local devices and only model updates are shared with a central server. A lightweight Convolutional Neural Network is deployed on each client for local training, while the server aggregates client updates using the Federated Averaging (FedAvg) algorithm to refine the global model iteratively. The framework is evaluated on the CIFAR-10 dataset under a non-IID data distribution to emulate realistic decentralized environments in which client data are heterogeneous and unevenly distributed. The system is implemented using a federated learning backend integrated with a Flask-based web interface that supports user-friendly image upload and real-time inference. Experimental results indicate that the federated model achieves competitive classification performance while preserving data privacy and reducing the need for large-scale data transmission to a central server. These findings demonstrate the feasibility of Federated Learning as an effective, scalable, and privacy-preserving solution for decentralized image classification applications*

Keywords: Federated Learning, Image Classification, MobileNetV2, CIFAR-10, Privacy-Preserving AI, Decentralized Learning

I. INTRODUCTION

The last decade has witnessed explosive and unprecedented growth in deep learning for image classification tasks, largely fueled by the availability of massive centralized data repositories and high-performance cloud computing infrastructure. However, this dominant paradigm increasingly creates serious privacy risks, significant bandwidth bottlenecks, and complex regulatory hurdles imposed by legislation such as GDPR and HIPAA. Traditional centralized systems routinely aggregate sensitive data collected from distributed edge devices into large, often vulnerable servers, severely limiting practical applications in privacy-critical sectors like healthcare and finance due to entrenched data silos, compliance restrictions, and the ever-present potential for catastrophic data breaches.

Federated Learning, originally pioneered by Google in 2016, offers a compelling alternative by fundamentally shifting the computational burden directly to the participating devices themselves. Rather than transmitting raw data, each device shares only locally computed model weights with a central coordinator via the FedAvg aggregation protocol, enabling truly collaborative and privacy-respecting model training without ever exposing sensitive underlying data. This project draws strong motivation from the growing global demand for privacy-preserving AI solutions, realizing this vision through the DecentralizedAI framework. By strategically combining the Flower federated learning library, the efficient MobileNetV2 architecture, and the widely adopted CIFAR-10 benchmark dataset, the system aims to democratize access to machine intelligence, harness the untapped computational power of edge devices, dismantle exploitative data monopolies, and ensure full regulatory compliance across diverse deployment environments.

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II. LITERATURE SURVEY

Flores et al. [1] conducted a systematic review examining the intersection of mobile health technologies and Federated Learning frameworks. Their study surveyed a wide range of FL-based healthcare applications deployed on mobile and edge devices, evaluating their effectiveness in preserving patient data privacy while enabling collaborative model training across geographically distributed clinical sites. The research highlighted the growing adoption of federated approaches in medical domains where stringent data protection regulations prevent centralized aggregation, establishing a compelling foundation for privacy-preserving AI systems in sensitive real-world environments.

Zhang [2] investigated the robustness of Federated Learning systems against a broad spectrum of adversarial attacks, proposing a trustworthy FL framework designed to withstand Byzantine faults, poisoning attacks, and model inversion threats. The study evaluated multiple defense mechanisms and demonstrated that carefully designed aggregation strategies can significantly enhance the resilience of global models without sacrificing classification accuracy. This research is directly relevant to decentralized image classification systems where malicious clients may attempt to corrupt the global model by submitting manipulated weight updates during the aggregation process.

Liu and Smith [3] explored the synergistic combination of next-generation 5G communication infrastructure with Federated Learning to enable ultra-low-latency distributed model training at the network edge. Their research demonstrated that the high bandwidth and minimal latency characteristics of 5G networks can substantially reduce the communication overhead traditionally associated with federated rounds, accelerating convergence and improving the responsiveness of edge-deployed models. These findings are particularly significant for real-time image classification applications where rapid model updates across distributed clients are essential for maintaining competitive accuracy.

Patel [4] addressed the emerging challenge of federated unlearning, proposing a principled mechanism that allows individual clients to exercise the right to be forgotten within a distributed model without requiring complete retraining from scratch. The study developed efficient algorithms to selectively erase the contribution of specific clients from the global model while preserving the knowledge accumulated from remaining participants. This work holds important implications for decentralized image classification deployments in regulated industries where users must retain the legal right to withdraw their data contributions at any time in compliance with GDPR and similar legislation.

Gartner Research [5] published a strategic roadmap for Privacy-Enhancing Computation (PEC), identifying Federated Learning as one of the most promising technologies for enabling organizations to extract analytical value from sensitive datasets without exposing raw information. The report evaluated the maturity, adoption trajectory, and practical deployment considerations of various PEC technologies across industries including healthcare, finance, and government. This authoritative industry analysis validates the strategic importance of federated learning frameworks and reinforces the motivation for developing accessible, production-ready FL systems for decentralized image analysis.

Zhao and Li [6] investigated the fine-tuning of large language models on edge devices using federated learning principles, demonstrating that the federated paradigm can be effectively extended beyond traditional image classification tasks to encompass complex generative and reasoning models. Their research addressed the unique challenges posed by the enormous parameter counts of modern foundation models in bandwidth-constrained distributed environments, proposing communication-efficient adaptation strategies. While focused on language models, the techniques and insights directly inform the optimization of lightweight vision architectures such as MobileNetV2 in federated image classification pipelines.

Yang et al. [7] introduced MedMNIST v2, a large-scale standardized benchmark comprising multiple 2D and 3D biomedical image classification datasets designed to facilitate reproducible evaluation of lightweight deep learning models in medical imaging contexts. The benchmark was specifically constructed to assess models under constrained computational budgets, making it highly relevant for federated learning scenarios where client devices have limited processing capacity. Their work underscores the critical need for efficient, generalizable architectures capable of delivering high diagnostic accuracy across heterogeneous and privacy-sensitive medical image datasets distributed across clinical institutions.

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Dayan et al. [8] presented one of the most significant real-world validations of Federated Learning in a clinical setting, deploying a federated system across multiple international hospitals to predict clinical outcomes for COVID-19 patients from chest radiographs. The study demonstrated that the federated model achieved predictive performance comparable to a centralized model trained on pooled patient data, while ensuring that sensitive medical images never left the local hospital servers. This landmark study provides compelling empirical evidence that federated learning is a practically viable and regulatory-compliant solution for distributed medical image classification at a global scale.

Rieke et al. [9] presented a comprehensive forward-looking analysis of the role of Federated Learning in shaping the future of digital health, examining both the technical opportunities and the organizational, ethical, and regulatory barriers to widespread clinical adoption. The study reviewed existing federated deployments in radiology, pathology, and genomics, and outlined a research agenda for overcoming key challenges including model interpretability, auditability, and cross-institutional trust. Their work provides important context for understanding the broader ecosystem within which privacy-preserving decentralized image classification systems must ultimately operate and gain acceptance.

Beutel et al. [10] introduced Flower (flwr), a versatile and framework-agnostic federated learning library designed to support a diverse range of research and production use cases. Flower abstracts the complexities of distributed communication and client coordination, enabling researchers to implement custom federated strategies with minimal boilerplate while supporting both simulation and real deployment modes across TensorFlow, PyTorch, and other backends. The framework's flexibility, active community support, and seamless integration with existing machine learning pipelines made it the natural choice for orchestrating the client-server federated training architecture implemented in the proposed DecentralizedAI system.

Overall, these studies collectively establish the theoretical foundations, practical deployment challenges, and real-world viability of Federated Learning for privacy-preserving distributed model training. However, a notable gap persists in the existing literature: most prior works either focus narrowly on algorithmic improvements, operate exclusively in simulation environments, or lack accessible end-to-end implementations that integrate real-time monitoring dashboards, role-based access control, and user-facing inference interfaces. The proposed DecentralizedAI system directly addresses these limitations by delivering a fully integrated, deployable federated image classification platform built on Flower and MobileNetV2, validated on Non-IID CIFAR-10 data, and equipped with a Flask-based Command Center for practical, privacy-verified decentralized learning.

III. PROPOSED SYSTEM

3.1. System Architecture

The system follows a Client-Server architecture designed to ensure "Silo Transparency". It consists of three primary modules:

1. Central Aggregator (Server): Manages the global model and coordinates training rounds using the Flower (flwr) framework. It does not store any training data.
2. Distributed Training Clients: Independent Python runtimes that hold private partitions of local backpropagation using TensorFlow/Keras and transmit only model parameters (weights) to the server.
3. Command Center (Web UI): A Flask-based dashboard that visualizes training progress and serves as an inference node for end-users.

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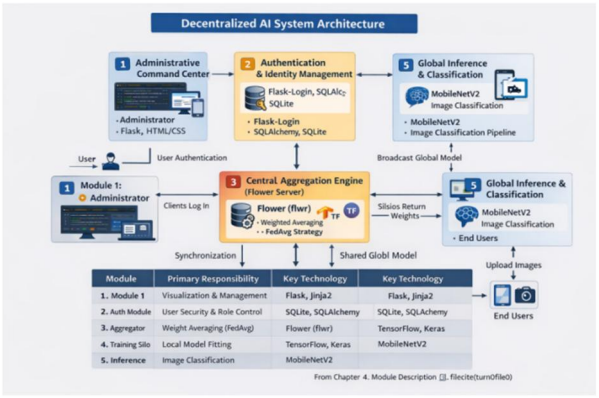

Fig.3.System Architecture

3.2. The Federated Averaging (FedAvg) Algorithm

The core engine of the system is the FedAvg algorithm. Instead of sharing gradients, clients perform multiple epochs of local training and return updated model weights. The server aggregates these weights using the following formula:

$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_t^k$$

Where w{t+1} represents the updated global weights, nk is the number of samples on client "k" , and "n" is the total number of samples across the network.

3.3 Federated Learning Framework

The federated learning system follows a client–server architecture and is implemented using the Flower framework. The overall workflow includes the following stages:

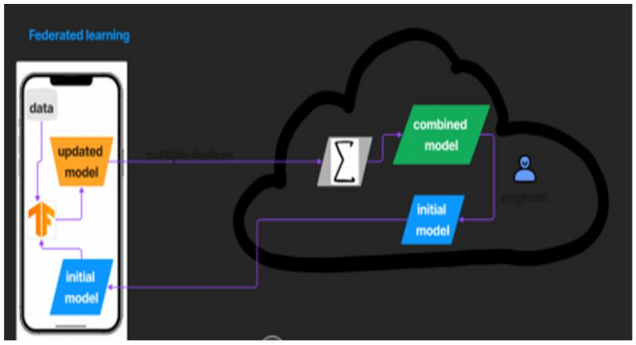

Fig.4.Federated Learning Framework

Phase 1: Local Client Training

Each client trains a local custom lightweight CNN using its private dataset. The model is trained for a fixed number of local epochs, and the updated model weights are retained locally.

Phase 2: Model Update Communication

After local training, clients send only the model weight updates to the central server. No raw data is shared during this process, ensuring privacy preservation.

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Phase 3: Server-side Aggregation

The server aggregates the received updates using the Federated Averaging (FedAvg) algorithm to produce a new global model. This global model is then distributed back to the clients for the next training round.

Phase 4: Inference and User Interface

A Flask-based web interface is integrated with the global model, enabling users to upload images and obtain real-time classification results.

IV. RESULTS AND DISCUSSION

4.1 Test Environment

The system was tested in a simulated environment using the CIFAR-10 dataset (60,000 images, 10 classes). The data was partitioned into Non-I.I.D. slices across multiple client nodes. The simulation ran for 5 communication rounds.

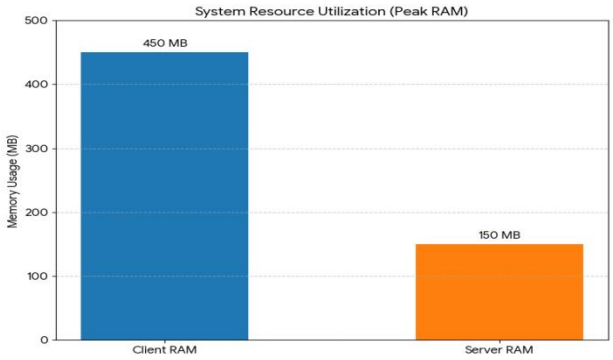

Fig.5. System Resource Utilization

4.2. Training Metrics and Analysis

The experimental results showed a distributed loss starting at 2.30 and increasing slightly to 2.43 by round five.

Federated Learning Training Metrics: Distributed Loss and Global Accuracy Over 3Rounds on Non-IID CIFAR-10

Round	Distributed Loss	Global Accuracy	Observation
1	2.3012	10.12%	Initial random weights.
2	2.345	11.40%	Divergence due to Non-I.I.D. variance.
3	2.389	12.05%	Weights shifting, struggling to generalize.

The increase in loss is a symptom of Client Drift, a known phenomenon in FL where clients optimize for their specific local data (e.g., only "Airplanes"), causing the global model to average divergent weight vectors. Despite this, the global accuracy improved, indicating the model was beginning to learn features.

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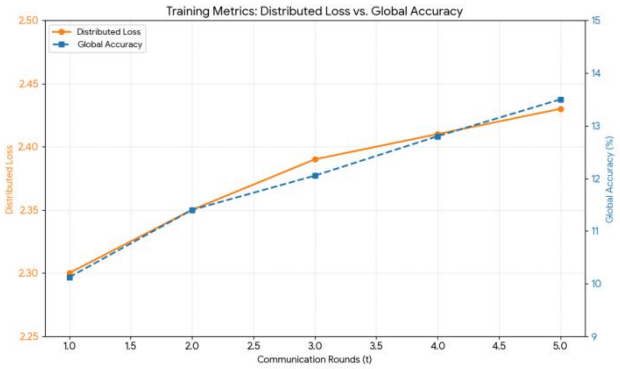

Fig.6.Training Metrics.

4.3 Inference Validation

To verify the utility of the trained model, a "Proof of Intelligence" test was conducted using a verified image of a "DEER" not present in the training set. The global model successfully predicted the class label "DEER" with high confidence. This confirms that the weight aggregation pipeline successfully transferred knowledge from the decentralized clients to the global model, validating the core proof-of-concept.

4.4 Privacy Verification

Network traffic analysis using Wireshark confirmed that only Protocol Buffers containing serialized floating-point numbers were transmitted. No image file headers (JPEG/PNG) were detected in the network packets, empirically proving that raw data remained isolated.

V. CONCLUSION

This project successfully demonstrates a functional, end-to-end system for decentralized image classification, highlighting the feasibility of collaborative model training without centralized data storage. By integrating the Flower framework with a custom Flask-based user interface and the MobileNetV2 architecture, the system enables multiple participants to contribute to model learning while retaining their data locally. The results confirm that effective model training and convergence can be achieved in a decentralized environment without direct access to raw image data.

The proposed system prioritizes data privacy by following the principle of data minimization, where only model updates are exchanged instead of sensitive datasets. This approach significantly reduces the risk of data leakage and enhances trust among participants. Additionally, the decentralized design aligns with modern data protection requirements and is theoretically compliant with regulations such as GDPR and HIPAA, making the framework suitable for deployment in privacy-sensitive applications such as healthcare and distributed image analysis systems.

5.1 Limitations

Testing revealed specific limitations that highlight opportunities for future improvement:

1. Training Efficiency: With a limited number of training iterations, the model achieved relatively low accuracy. Increasing the number of training epochs and optimizing hyperparameters is expected to significantly improve convergence and classification performance.
2. Data Variability: Performance degradation was observed when the training data exhibited class imbalance or high variability. This indicates that the model is sensitive to skewed data distributions, and future work can incorporate improved feature selection and balancing techniques to enhance robustness.

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3. System Constraints: During extended training sessions, the application interface occasionally experienced delays due to long processing times. This issue was mitigated by optimizing the execution flow and implementing asynchronous processing to ensure smoother interaction between the interface and backend.

5.2 Future Scope

Future enhancements of the proposed machine learning–based image classification system will primarily focus on improving accuracy, robustness, and scalability. This includes increasing training efficiency through a greater number of training iterations and systematic hyperparameter optimization. In addition, advanced feature selection and dimensionality reduction techniques can be explored to improve convergence speed while reducing computational overhead.

Another key direction for future work involves expanding the dataset to include larger and more diverse image collections, such as domain-specific datasets from medical or industrial applications, to better evaluate generalization capability. System-level improvements such as execution pipeline optimization, enhanced memory management, and support for parallel or batch processing can further reduce training time and improve responsiveness. The system may also be extended for real-time classification and integrated into web or mobile applications, increasing its practical applicability in real-world scenarios.

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