Federated Learning with Autoencoders for Image Classification in IoT Environments

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***Abstract*—In the rapidly evolving Internet of Things (IoT) landscape, efficient and secure data processing for image classification is crucial, especially when labeled data is scarce or unavailable. This paper investigates the use of federated learning with autoencoders as a potential solution for image classification in IoT environments, comparing it with a baseline supervised learning model. We propose a federated learning framework where IoT devices use autoencoders for local training, and Unmanned Aerial Vehicles (UAVs) coordinate the aggregation of these models. Experimental results demonstrate that while the supervised model achieves higher classification accuracy, the autoencoder-based approach offers significant advantages in environments with limited labeled data, reducing communication overhead and preserving data privacy. This research opens avenues for further exploration into hybrid models that combine the strengths of both autoencoders and supervised learning in federated learning systems.**

***Index Terms*—Federated Learning, Autoencoders, IoT, UAVs, Image Classification, Data Privacy**

I. Introduction

The proliferation of the Internet of Things (IoT) has led to massive data generation from connected devices, ranging from home appliances to industrial sensors [1]. Traditional centralized data processing faces significant challenges, including privacy concerns, high communication costs, and the need for labeled data [2]. Privacy is a critical issue, especially when transmitting sensitive data from distributed devices to a central server [3]. Moreover, IoT systems often have limited bandwidth and energy supply, making continuous data transmission impractical [4].

Federated learning offers a decentralized alternative, allowing devices to process data locally and transmit only model updates, enhancing privacy and reducing communication overhead [5]. However, supervised federated learning models depend on labeled data, which can be costly or impractical to acquire in many real-world IoT scenarios [6]. The heterogeneity of IoT devices and non-IID (non-Independent and Identically Distributed) data further complicate model training and performance [7].

Autoencoders, an unsupervised learning technique, can learn meaningful data representations without labeled data [8]. They compress input data into a lower-dimensional latent space and reconstruct the original data, capturing salient features essential for tasks like classification or clustering [9]. Integrating autoencoders into federated learning may offer a solution for IoT applications with limited labeled data, as they can extract useful features while reducing the dependency on labeled datasets.

This study explores whether an autoencoder-based approach can achieve comparable classification performance to supervised models in IoT environments with scarce labeled data. We aim to assess the trade-offs between classification accuracy and the benefits of reduced communication overhead and enhanced data privacy. By employing UAVs to coordinate the aggregation of local models trained on distributed IoT sensors, the system ensures continuous model improvement while minimizing data transmission.

II. Related Work

Federated learning has emerged as a promising approach to address privacy and efficiency challenges in IoT networks [5]. Beitollahi and Lu [10] explored federated learning to preserve data privacy by keeping raw data localized on edge devices. Hsu et al. [7] addressed the challenges of non-IID data distributions in federated learning for IoT applications.

Autoencoders have proven effective for feature extraction and dimensionality reduction in image classification tasks [6]. Tschannen et al. [8] surveyed autoencoder models' ability to learn compact and meaningful representations of complex data, which are essential for unsupervised learning tasks.

The integration of UAVs in federated learning frameworks enhances the efficiency of data aggregation in IoT environments. Lim et al. [11] demonstrated how UAVs serve as intermediaries between distributed sensors and central servers, facilitating model aggregation and distribution.

III. Methodology

We propose a federated learning framework where IoT devices use autoencoders for image classification, with UAVs facilitating model aggregation. Each device trains an autoencoder on its local data subset, and UAVs collect and aggregate these models to form a global model, which is then redistributed to the devices. This approach leverages the unsupervised learning capability of autoencoders to handle unlabeled data effectively.

The simulation was conducted using a grid with four sensors placed at fixed coordinates and a UAV following a predefined path [12]. The CIFAR-10 dataset was divided equally among the sensors. The UAV's communication range was limited to ensure realistic interaction with the sensors, requiring it to move within range of each sensor to collect model updates.

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We compared the autoencoder-based approach with a supervised learning model. Both models were implemented using PyTorch and trained under the same conditions for fair comparison. The autoencoder model consisted of an encoder, decoder, and classification head, enabling it to reconstruct input images and perform classification. Optimization techniques like quantization and compression were employed to reduce the size of the transmitted models, crucial for bandwidth-limited IoT environments [13]. Quantization reduced the autoencoder model size from 2.197 MB to 0.562 MB, significantly decreasing communication overhead.

IV. Results

The supervised model achieved higher classification accuracy (82.4

In terms of clustering accuracy and Adjusted Rand Index (ARI), the supervised model outperformed the autoencoder, indicating better feature differentiation. The confusion matrix and t-SNE visualization showed that the supervised model had clearer class separation, while the autoencoder struggled with overlapping features. Despite lower accuracy, the autoencoder demonstrated effective feature extraction, which is valuable in scenarios where labeling data is impractical.

V. Discussion

The findings highlight the trade-offs between classification accuracy and the practical benefits of using autoencoders in federated learning for IoT environments. While supervised models perform better in terms of accuracy due to access to labeled data, autoencoders provide a viable alternative when labeled data is limited or unavailable. The reduced communication overhead and enhanced data privacy make autoencoders attractive for resource-constrained IoT applications.

The use of UAVs for model aggregation adds flexibility and efficiency to the system. UAVs can collect model updates from sensors within their communication range and redistribute the aggregated global model, facilitating continuous learning without extensive data transmission [11]. This approach also addresses the challenges of device heterogeneity and varying data distributions across sensors.

Furthermore, the implementation of optimization techniques like quantization and compression is essential in reducing the communication costs associated with federated learning in IoT environments. By minimizing the model sizes, we ensure that the system is scalable and practical for real-world applications where bandwidth is a limiting factor.

VI. Conclusion

This study demonstrates that integrating autoencoders into federated learning offers a practical solution for image classification in IoT environments with limited labeled data. While supervised models achieve higher accuracy, the autoencoder-based approach reduces communication overhead and preserves data privacy by processing data locally. The trade-offs between accuracy and practical deployment considerations make autoencoders a valuable tool in certain IoT scenarios.

Future work includes exploring hybrid models that combine the strengths of autoencoders and supervised learning, as suggested by [14], to enhance performance in federated learning systems. Additionally, further optimization of communication protocols and model architectures could improve the scalability and efficiency of the proposed framework.

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