Federated Learning Enhancement via Swarm Intelligence Algorithms

CS4099 Project Final Report

Submitted by

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CERTIFICATE

Certified that this is a bonafide record of the project work titled

FEDERATED LEARNING ENHANCEMENT VIA SWARM INTELLIGENCE ALGORITHMS

done by

Mathew Bino
Alvin Gigo

of eighth semester B. Tech in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering of the National Institute of Technology Calicut

Project Guide	**Head of Department**
Dr. Nirmal Kumar	Dr. Subashini R
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DECLARATION

We hereby declare that the project titled, **Federated Learning Enhancement via Swarm Intelligence Algorithms**, is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or any other institute of higher learning, except where due acknowledgement and reference has been made in the text.

Place : Calicut,Kerala,India
Date : 5/5/2025

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Abstract

Federated Learning (FL) enables decentralized model training across distributed edge devices while preserving data privacy by eliminating the need for direct data sharing. This project investigates the performance of two advanced federated optimization algorithms: **Federated Particle Swarm Optimization (FedPSO)** and **Federated Constrained Particle Swarm Optimization (FedCPSO)**. We address critical challenges in FL, including reduced network transmission costs, minimized on-device memory requirements for model storage, and statistical heterogeneity through non-IID data distributions. Through extensive experiments, we evaluate the convergence behavior and accuracy of FedPSO and FedCPSO under varying conditions, comparing them against baseline approaches such as Federated Averaging (FedAvg). Our results show that FedCPSO effectively handles non-IID data by adaptively balancing client contributions during aggregation, significantly outperforming standard approaches. Furthermore, we analyze the impact of optimization techniques on reducing communication overhead and shrinking model footprints while maintaining robustness, particularly in resource-constrained environments. Our results demonstrate significant reductions in bandwidth usage (51% lower) and local memory demands (70% smaller models), with only marginal trade-offs in accuracy , offering practical insights for deploying FL on edge devices with limited computational resources. The implementation leverages the `Flower` framework and is validated on benchmark datasets (e.g., CIFAR-10, MNIST), demonstrating the efficacy of the methods.