Quantum-Enhanced Federated Learning for Malware Detection in Heterogeneous IoT Networks

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: How does the integration of quantum-enhanced federated learning affect the accuracy and convergence rate of malware detection models compared to classical federated learning in heterogeneous IoT. This work investigates the possibilities enabled by federated learning concerning IoT malware detection and studies security issues inherent to this new learning paradigm. In this context, a framework that uses federated learning to detect malware affecting IoT devices is. 12 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.4/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Federated Learning for Malware Detection in IoT Devices. Research question: How does the integration of quantum-enhanced federated learning affect the accuracy and convergence rate of malware detection models compared to classical federated learning in heterogeneous IoT networks, measured by F1-score and round convergence time?.

2 Methodology

Systematic literature search across multiple databases yielded 11 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.4/10.

3 Results

11 papers retrieved. 12 claims extracted; 1 independently verified. Quality review score: 4.4/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
Federated Learning (FL) enables data privacy by design, as data is not shared with any external identity.	×	0.11
FL approaches lack the use of realistic datasets in the FL context, the analysis on adversarial impact, or the discussio	×	0.04
The proposed framework covers both anomaly detection and classification approaches using multi-client FL.	×	0.08
The use case presents a B5G scenario where there is a necessity of detecting cyberattacks affecting IoT devices, managin	×	0.08
The security framework uses FL to detect, in a privacy-preserving fashion, cyberattacks affecting IoT devices.	✓	0.18
The model training is performed in a decentralized manner by different nodes, or clients, that use local data.	×	0.06
Each decentralized node trains an individual model using its own data and shares the model parameters with the rest.	×	0.07
The exchange of the model parameters and their aggregation to create a unique and global model can be performed through	×	0.07
After several iterations, each client has a global model obtained as an aggregation of the individual model of each clie	×	0.06
The dataset is split into 79% for training, 1% unused, and 20% for known device test.	×	0.02
The dataset is split into 39.5% for training, 39.5% for threshold selection, 1% unused, and 20% for known device test.	×	0.01
The centralized model achieves 95% accuracy with a 7.8% benign rate and 7% benign rate for the federated model.	×	0.06

References

- `http://arxiv.org/abs/2104.09994v3`

- http://arxiv.org/abs/2112.09429v2
- http://arxiv.org/abs/2207.02337v1