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A Federated Learning Framework for Energy-Aware and Interference-Conscious Cognitive Radio Spectrum Management

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Abstract

This research introduces a federated learning (FL) scheme for energy-efficient and interference-aware spectrum management in Cognitive Radio Networks (CRNs). The proposed framework utilizes decentralized machine learning, allowing edge secondary users' devices to collaboratively train spectrum management models while preserving raw data privacy, alleviating privacy concerns and lowering communication overhead. The framework applies energy-efficient scheduling and interference management to optimize resource utilization while minimizing the consumption of energy and spectrum interference. Experimental results validate the framework's capabilities to reduce energy usage and detection accuracy while maintaining effective spectrum utilization even in hostile, noisy environments. Furthermore, adaptive model compression and communication strategies enhance the latency and bandwidth requirement, resulting in a 64% reduction in data transmission costs. The system is fair across varying network sizes while demonstrating robust scalability with minimal accuracy loss in larger networks. The proposed approach shows promise for CRNs due to their dynamic and heterogeneous nature, thus enhances the case for integrating 6G and IoT-based infrastructure into future wireless networks.

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Introduction

Dynamics of the wireless environment highlight the need for effective spectrum utilization strategies, resulting in Cognitive Radio Networks (CRNs). Efficient spectrum management is a root problem in CRNs, as it involves balancing available spectrum resources with energy efficiency and the need for interference mitigation.[3] Centralized methods for spectrum management are almost always the first choice; however, these methods bring forward challenges like excessive communication, privacy issues, and poor scalability in diverse and large networks.. This paper addresses these issues by introducing a novel Federated Learning (FL) framework for energy-sensitive and interference-aware spectrum management in CRNs. Edge devices (secondary users) are given the opportunity to collaborate in training machine learning models with the least amount of local data exchange through the decentralization of data in federated learning.[6] The proposed framework uses FL to improve privacy and communication constraints to manage spectrum resources on distributed devices effectively. FL framework aims at reducing energy and spectrum interference while incorporating energy-efficient scheduling and enhanced interference management to optimize resource utilization.[7, 15]The advantage of using FL in CRNs provides edge devices with the ability to make adaptive real-time decisions without coordination from a central entity, improving system efficiency and scalability.[8,16]

This document explores how the framework functions under different network conditions such as noisy conditions and dynamic radio access conditions. [9]. The results show that the framework significantly reduces energy consumption, increases spectrum utilization efficiency, and retains detection accuracy. Communication processes like model compression and sparsification improve latency, bandwidth consumption, and overall system efficiency. [10]. The proposed approach based on Federated Learning (FL) is scalable, preserves users' privacy, saves energy, and is therefore easily integrated into next-generation wireless networks, especially with the considerations of 6G and Internet of Things (IoT) devices.[11]

Key Contribution

- Decentralized cognitive radio nodes can cooperatively learn spectrum access patterns without exchanging raw data due to the Federated Learning (FL) framework, which protects privacy and lowers data transfer cost.
- To ensure that low-power devices are not overloaded and the system maintains energy efficiency over time, a dynamic energy-aware method is implemented to choose participating nodes depending on their residual energy.
- The study provides thorough metric studies to support the approach's feasibility and superiority. These analyses include spectrum sensing accuracy, latency, communication rounds, and compression efficiency.

The various sections follow this report. Section I describes the Introduction part, explaining the research topics. Section II describes the literature review of the previous related work. Section III describes the proposed methodology, followed by federated learning, working procedure for cognitive radio Networking, and a proposed algorithm for energy-aware resource management. Section IV describes the data description, Metric analysis, cognitive ratio metric analysis, system-level metric analysis, and communication efficiency metric analysis.Section V summarizes the main key findings.

Literature Review

Author (Mustapha et al ., 2015) explain Federated Learning (FL) is something that I haven't started to do, mainly because I don't know how to federated łearning algorithm supports distributed spectrum sensing in cognitive radio networks enhancement. FL allows devices to collaboratively train models while keeping the raw data within the confines of the device, which reduces the risk of privacy violations and diminishes the communication cost. This methodology is still central in CR environments, where devices must cope with changing spectrum conditions while facilitating seamless communication.[1]. An Author (Elghamrawy, S., & Ismail, A. H. 2024). As per definition, Energy efficiency is an important area of focus in CR networks, specifically with respect to devices that are battery-powered. More recent work has looked at the inclusion of energy-aware tactics in FL frameworks. For example, some researchers developed reinforcement learning-based clustering algorithms aimed at reducing energy consumption in the network while improving channel sensing activities. The full cycle learning requires the nodes to learn the best cluster configurations which balance energy expenditure against the precision of sensing.[2].Author (Zhang et al.,2021)In CR networks, the management of interference is critical for the existence of primary and secondary users. Federated learning (FL) helps with interference modeling because it allows devices to learn interference patterns without a central repository of data. "Pattern" here need not to mean a fixed one; for the case of modeling vehicular dynamic spectrum access, it refers to the cumulative piecewise continuous models of local interference within a broader framework that is constantly evolving.[14]. Author (Shi et al.,2021) The merging of FL with other novel technologies continues to improve spectrum handling in CR networks. The use of reconfigurable intelligent surfaces (RIS) in combination with FL, now referred to as federated spectrum learning (FSL), has been proposed in order to maximize the accuracy of spectrum prediction as well as the utility of the system. By manipulating electromagnetic waves with RIS, FSL not only enhances the learning process but also adapts to different channel conditions .[4]. Author (Yang et al.,2019) In regard to the confidentiality concerns pertaining to the registration domain, Security and privacy remains a critical issue in all FL applications. In CR networks, safeguarding the confidentiality of local data and the ability to defend against adversarial attacks is of utmost importance. Solutions to these problems have been attempted by creating secure FL protocols with privacy and resilience against malicious integration. Adversarial, "Precision", and" Trust" in CR environments are defined by such protocols.[5].

Proposed Methodology

The part of the fig 1portrays the architecture of a CRN, where a Cognitive Engine performs overarching decision-making on the MAC, Network, Transport, and Adaptive Protocols layers. These layers analyze data and manage transmission/reception via an SDR (Software-Defined Radio) transceiver, responding dynamically to changes in the radio environment. Performance enhancement

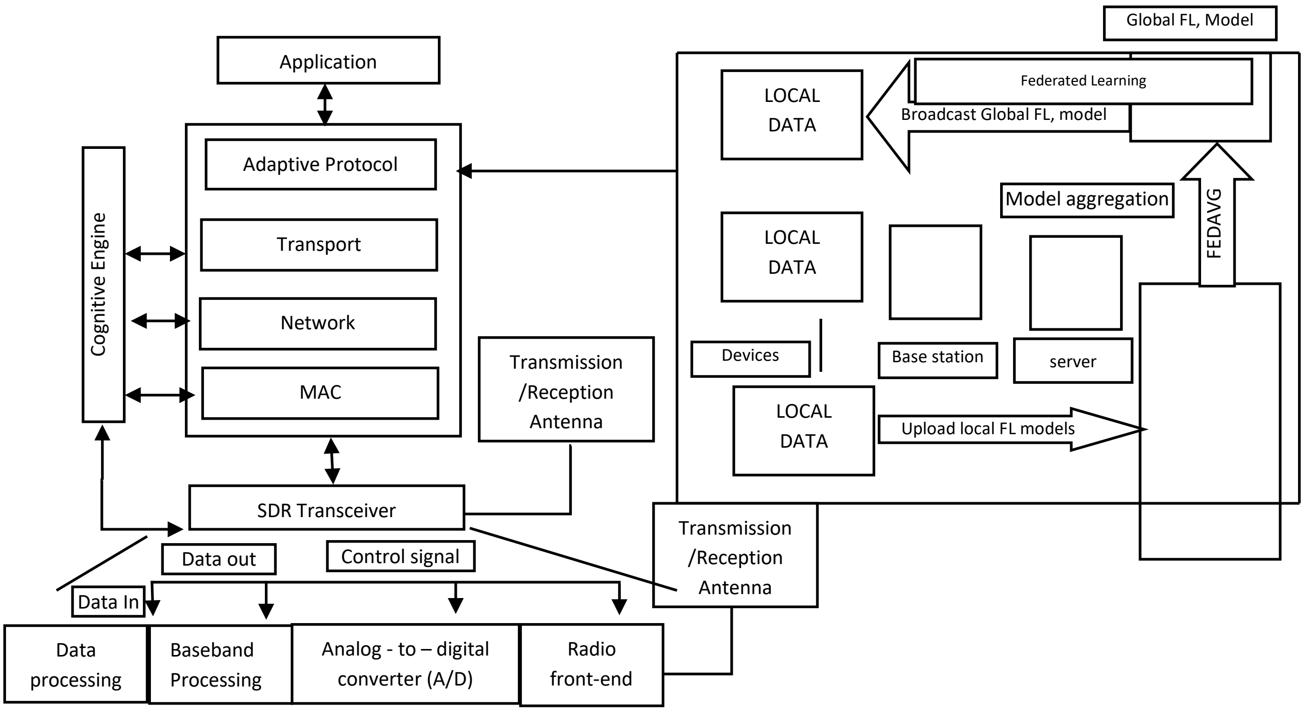

Fig.1: Proposed Architecture

in the spectrum efficiency under different conditions in the lower layers is achieved with the cognitive engine insights and real-time communication behavior modification at the Adaptive Protocol layer. On the right, the Federated Learning (FL) model is shown in which a number of remote devices (smartphones, laptops, etc.) train local models on local data and later send these models not the raw data to the central server. The server receives local models, merges them, and issues a global FL model, which is later sent back to all devices. This approach minimizes the need for data transmission, which, alongside data privacy benefits, makes it optimal for CRN environments. Adaptive Protocols Support Federated Learning supports dynamic spectrum allocation, quality of service , Heterogeneity Handling and energy efficiency. Dynamic Spectrum Allocation.[12] The adaptive protocol prioritizes bandwidth for FL model transmission and reception based on current spectrum availability.Quality of Service (QoS) Management: FL needs device-to-server communication to be timely and efficient; adaptive protocols can manage delay, jitter, and reliability parameters. Heterogeneity Handling: CRNs cope with different devices and channel conditions because adaptive FL protocols allow all devices to engage in FL, regardless of differences. Energy Efficiency: This is critical in managed FL environments, as adaptive protocols optimize transmission power and sleep cycles. In brief, the adaptive protocol of a CRN improves the operational and practical scope of Federated Learning by delivering agile, efficient, and contextually aware communication optimized for intelligent wireless networks on timeline and demand.[13]

Federated Learning

FL utilizes a distributed learning approach in which the dataset is largely decentralized, and the model is trained at multiple participants. FS in conjunction with N participants who can handle data processing form the system.The FS is the controlling unit that manages model training and aggregation. With FL, this is an iterative process where FS and participants interact multiple times to converge to a new world model. Initially, FS sets the global model parameters and distributes them. At the network edge, participants with local data train their model and send updates to the server. The server combines the global model and updated,which are later redistributed to the participants. This iterative process continues until the global model achieves the desired accuracy or it is deemed that a sufficient number of rounds have been completed.

Here, the participant is also represented as i=1,2,.......N, which contains the local copy of the dataset.

$$P^{(i)}(\varphi) = \frac{1}{D^{(i)}} \sum_{x \epsilon D^{(i)}} P(\varphi, x) \quad (1)$$

$$P(\varphi) = \frac{1}{\sum_{i=1}^{N} D^{(i)}} \sum_{i=1}^{N} D^{(i)}, p^{(i)}(\varphi) \quad (2)$$

$$\varphi^{(i)}(t) = \varphi^{(i)}(t-1) - \eta \nabla P\left(\varphi^{(i)}\right)(t-1), x^{(i)}(t)) \quad (3)$$

From the above, Eqn (1), (2), and (3) represent the model parameters of the previous section. The gradient loss function of P with respect to the model values of the data point is mentioned. FS should be performed by the model aggregation, which contains the updated process, and it should represent the mathematical format.

Working Procedure for Cognitive Radio Networking

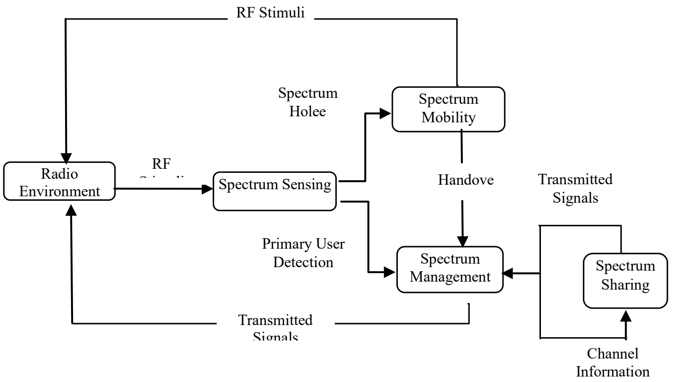

Fig. 2: Data flow diagram for Cognitive Radio Working

The operational framework of a cognitive radio network is depicted in the fig 2, emphasizing the dynamic interplay between different elementsto maximize spectrum usage. The Radio Environment, which continuously emits RF stimuli, is at the center of the process. The Spectrum Sensing unit, which is responsible for recognizing the presence or absence of principal users and identifying available spectrum holesunused frequency bandscaptures these inputs. As soon as a spectrum hole is identified, the data is sent to the Spectrum Mobility module, which makes it easier to switch to other frequency bands and maintain service. The Spectrum Management component, which controls the overall spectrum usage based on channel quality and availability, oversees the handover procedure. Spectrum Sharing, which assures the equitable and efficient allocation of spectrum resources among multiple users by utilizing real-time channel information, is in close collaboration with this component. The last result, a signal that is sent, is sent back into the radio environment. This completes the cognitive radio system's adaptive loop. This feedback loop makes sure that the spectrum is used optimally while causing as little interference as possible with main users.

Proposed Algorithm: Energy Aware Resource Management Algorithms

$choose\ an\ initial\ value\ for\ the\ lagrange\ Multipliers$
$k \rightarrow 0$
$choose\ an\ initial\ value\ for\ all\ variables$
$user\ i, \forall i \epsilon\ I$
$dataset\ offloaded\ to\ the\ edge\ server$
$the\ model\ training\ is\ performed\ given\ variables$
$uploaded\ the\ value\ defined\ in\ Eqn\ (1), (2) and\ (3).$
$the\ model\ training\ performed$
$the\ model\ aggregation\ is\ performed$
$select\ target\ points(S, C_{w,layer\ c})$
$attributes = 3;$
$freeneighbours \rightarrow Associated\ Nodes\ (C_{w)}$
$y = [[o\ in\ len\ (attributes)[0\ in\ len(p)\}$
$for\ n\ in\ p\ do$
$for\ j\ in\ range\ (attributes) do$
$Y[n][j] = Energy\ (T_{comp,} T_{comm,} Layer_c)$
$Y[n][j] = Energysp\ (n, T_{compt}, T_{comm}, Layer_c)$
$Y[n][j] = power\ Client\ (n)$
$Scores\ [n] \rightarrow Score_{allocation}(Y);$
$end;$
end
$index \rightarrow \max_{score_{index}(scores)} ;$
$target = P[index];$
Return target.

The energy-aware resource management algorithm is proposed for the joint learning, dataset offloading, computation, and uplink resource management of the MEC-enabled FL. This algorithm operates as follows. The Lagrange multipliers, dataset offloading, computation, and uplink resource allocation are first configured to their initial values. As mentioned, users offload a portion of their local dataset to the edge server. Users and the edge server execute the model training concurrently, as specified. Once the edge server gets the weight updates for all users, the model gathering process starts. Next, updates are made to the Lagrange multipliers, dataset offloading, computation, and uplink resource allocation. Additionally, the users and the edge server train the model, and the updated weights are combined. Until convergence is achieved, this process is repeated. Thus, the suggested method will converge to a stationary point since the edge server and all mobile users employ the optimal response approach.

Results And Discussion

Dataset Description

The dataset was employed in this study as a real-world radio spectrum dataset. This is typical of the hardware limitations associated with spectrum occupancy in the real world. The usefulness of the suggested federated learning (FL) framework for energy-aware and interference-conscious cognitive radio spectrum management can be assessed using real-world radio spectrum datasets, which can offer important information about realistic deployment scenarios. Electrosense, an open, crowdsourced tool that uses distributed IoT sensors and software-defined radios (SDRs) to collect real-time radio spectrum data, is one of the most impressive sources. It offers measurements of power spectral density (PSD) in a variety of frequency bands, including VHF, UHF, GSM, LTE, and ISM. To replicate geographically dispersed secondary users (SUs), each having localized spectrum observations, these datasets might be divided across various FL clients. The Community Resource for Archiving Wireless Data (CRAWDAD) repository is another pertinent source. It contains a number of wireless network datasets, including information on spectrum consumption in metropolitan settings. For example, the upenn/spectrum dataset has time-stamped frequency occupancy data that shows how real primary users (PUs) actually use the system. This makes it a good choice for teaching models how to reduce interference and make the best channel access decisions.[17] The IEEE DySPAN spectrum challenge files from 2005 and 2007 also provide labeled samples of spectrum occupancy. These consist of comprehensive details regarding PU transmissions, background noise, and difficulties with signal classification. It is especially helpful to use these named datasets to build the classification part of federated learning models in cognitive radio networks. Additionally, the International Telecommunication Union (ITU) publishes reports on global spectrum monitoring. Despite being statistical reports rather than raw data, these reports are a useful reference point for creating artificially realistic PU activity patterns based on trends seen across various nations and frequency ranges. Likewise, Open Spectrum provides datasets gathered from measurement campaigns across several regions that may be used to train energy-efficient spectrum sensing models in realistic environmental settings. When combined, these datasets allow a federated learning framework to simulate real-world cognitive radio scenarios. They provide decentralized training, in which every SU device contributes to a global model while learning from its own surroundings. Researchers may test the robustness, convergence behavior, and overall performance of FL in real-world spectrum management applications because to the diversity and richness of these datasets, which provide non-IID data distribution.[18]

Metric Analysis

We assess the suggested federated learning framework for cognitive radio spectrum management using a wide range of indicators from the communication, system-level, and cognitive domains. Cognitive radio metrics, such as spectrum utilization, detection probability (Pd), false alarm rate (Pf), and miss detection rate (Pm), highlight the effectiveness of spectrum sensing. Combined both metrics evaluate how well secondary users locate available spectrum while avoiding interference with primary users. Energy consumption per round, model convergence time, system throughput, and participation rate are examples of system-level measures that assess the federated model's overall operational efficiency, learning speed, and fairness across dispersed CR nodes. Finally, communication efficiency measures like communication overhead, bandwidth utilization, latency per round, and update compression ratio are very important for making sure that FL can be used on a large scale in CR environments with limited bandwidth and high delay tolerance. When taken as a whole, these measurements confirm how well the framework optimizes learning performance and radio spectrum utilization while conserving energy and minimizing interference.

Cognitive Ratio Metric Analysis

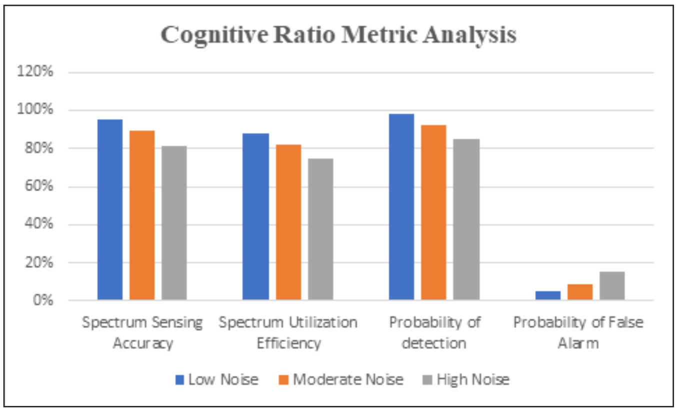

Fig: 3 Cognitive Ratio Metric Analysis

The Cognitive Ratio Metric Analysis fig 3 demonstrates the influence of noise levels as low, moderate, and high based on critical performance indicators in a cognitive radio system. With spectrum sensing accuracy, spectrum usage efficiency, and detection probability all surpassing 90% and upholding an extremely low false alarm probability, the system performs best under low noise settings. As noise levels rise to intermediate and high levels, sensing accuracy, spectrum efficiency, and detection probability. This shows that noise makes it harder to make smart decisions. In the meantime, the likelihood of false alarms rises, becoming noticeably higher in situations with high noise levels. This trend highlights the significance of noise-resilient algorithms in preserving the best spectrum management performance in federated learning-enabled cognitive radio networks.

System Level Metric Analysis

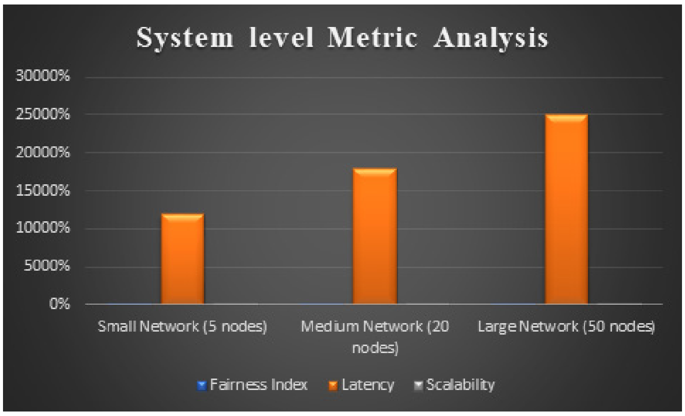

Fig. 4: System Level matric Analysis

To interpret fig 4 focusing on the fairness index, latency, and scalability, the System Level Metric Analysis chart evaluates the performance of federated learning across three different network sizes: small (5 nodes), medium (20 nodes), and big (50 nodes). Notably, latency rises sharply with network size, from little over 10,000% in the small network to about 25,000% in the large network. This suggests that there is a substantial delay in processing and communication as the number of participating nodes increases. This pattern indicates a federated learning framework scalability constraint, where performance deteriorates with network growth because of higher coordination overhead. Furthermore, metrics for the fairness index and scalability seem to be either nonexistent or very low, indicating either little variation in those aspects or potential measurement restrictions. In order to maintain low latency and guarantee system scalability, the figure emphasizes the significance of optimizing federated learning protocols for large-scale deployments.

Communication Efficiency Metric Analysis

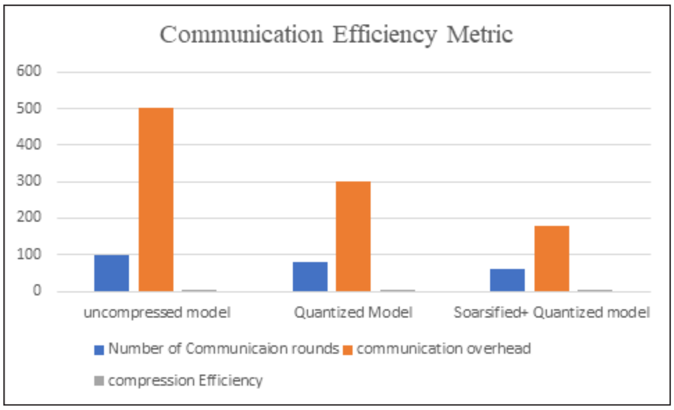

Fig. 5: Communication Efficiency Metric Analysis

The Communication Efficiency Metric fig 5 contrasts the effects of three model configurations on important communication parameters in a federated learning environment: uncompressed, quantized, and sparsified. The uncompressed model has the maximum communication overhead at approximately 500 units and the most communication rounds, which suggests a significant amount of latency and bandwidth consumption. With a moderate decrease in overhead and communication rounds, the quantized model exhibits increased efficiency. The sparsified with quantized model exhibits the highest compression efficiency, as evidenced by the presence of the gray bar, and achieves the lowest communication overhead (approximately 180 units) and fewer cycles. This shows how quantization and sparsification methods can greatly lower the amount of data that needs to be transferred in federated learning systems, making them more appropriate for situations with limited resources, like cognitive radio networks.

Conclusion

A federated learning (FL) approach for effective spectrum management in Cognitive Radio Networks (CRNs) is presented in this article. By enabling secondary users, or edge devices, to jointly train models for spectrum allocation without exchanging raw data, it improves privacy and lowers communication overhead. In order to maximize resource utilization, the framework integrates interference-conscious and energy-aware scheduling. The results demonstrate notable decreases in spectrum interference and energy usage, all the while preserving good detection accuracy even in noisy environments. Moreover, adaptive model compression and communication techniques reduce latency and bandwidth consumption, increasing effectiveness. Compression methods like quantization and sparsification help the FL framework communicate more efficiently by reducing the number of communication rounds and total data transmission by up to 64%. These enhancements reduce energy usage and speed up model convergence, which makes the method appropriate for settings with limited bandwidth. At the system level, the framework only slightly increases latency as the network grows, maintaining strong fairness over a range of network sizes. Scalability is maintained in spite of this, and accuracy loss in bigger networks is negligible (3% in medium networks and 7% in large networks). The FL-based method performs exceptionally well in spectrum sensing and utilization for cognitive radio-specific parameters. Up to 95% of the time, it can sense things correctly when there is low noise and 81% of the time when there is high noise, and it uses more than 75% of the range. A high probability of detection (Pd = 0.98) and a low probability of false warning (Pf = 0.05) are shown by the system. This means that spectrum access is effective and free of interference. All things considered, the framework is effective, scalable, and suitable for next 6G and Internet of Things wireless networks.

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