BLOCKCHAIN AND FEDERATED LEARNING

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ABSTRACT

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1 MOTIVATION

2 BLOCKCHAIN-BASED FEDERATED LEARNING

Although Federated Learning allows for participants to contribute their local data without it being revealed, it faces issues in data security and in accurately paying participants for quality data contributions. (Martinez et al.) propose an EOS Blockchain design and workflow to establish data security, a novel validation error based metric upon which (Martinez et al.) qualify gradient uploads for payment, and implement a small example of the blockchain Federated Learning model to analyze its performance. (Awan et al., 2019) propose a blockchain-based privacy-preserving federated learning (BC-based PPFL) framework, which leverages the immutability and decentralized trust properties of blockchain to provide provenance of model updates. (Korkmaz et al., 2020) propose a decentralized federated learning approach named Chain FL that makes use of the blockchain to delegate the responsibility of storing the model to the nodes on the network instead of a centralized server. (Sharma et al., 2020) propose a distributed computing defence framework for sustainable society using the features of blockchain technology and federated learning. In the work (Li et al., 2020) propose a crowdsourcing framework named CrowdSFL, that users can implement crowdsourcing with less overhead and higher security. This paper (Chen et al., 2020) propose a distributed computing architecture, the federated Learning based on the consortium blockchain. (Kumar et al., 2021) propose a framework that collects a small amount of data from different sources (various hospitals) and trains a global deep learning model using blockchain based federated learning. Additionally (Kumar et al., 2021) collect real-life COVID-19 patients data, which is, open to the research community. The security of local parameters, the learning quality, and the varying computing and communication resources, are crucial issues that remain unexplored in federated learning schemes. (Guo et al., 2020) propose a data sharing mechanism that combines blockchain and federated learning over smart city. The security of local parameters, the learning quality, and the varying computing and communication resources, are crucial issues that remain unexplored in federated learning schemes. (Lu et al., 2021b) present its potential application scenarios in beyond 5G. (Ma et al., 2021) propose a blockchain-based federated learning framework and a protocol to transparently evaluate each participant's contribution. The framework protects all parties' privacy in the model building phase and transparently evaluates contributions based on the model updates. Collaborative model development and privacy protection are critical considerations while training a global deep learning model. To address these challenges (Durga & Poovammal, 2022) propose a novel framework based on blockchain and the federated learning model. Other influential work includes (Lu et al., 2020a), (Lee & Kim, 2021).

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3 RESEARCH LINES

3.1 Security issues: privacy

There are many security problems neglected in federated learning, for example, the participants may behave incorrectly in gradient collecting or parameter updating, and the server may be malicious as well. (Weng et al., 2021) present a distributed, secure, and fair deep learning framework named *DeepChain* to solve these problems. (Nguyen et al., 2020) provide a state-of-art survey on the integration of blockchain with 5G networks and beyond. (Kumar et al., 2020) introduce a secure and decentralized training for distributed data. (Lu et al., 2020b) propose a new architecture based on federated learning to relieve transmission load and address privacy concerns of providers. (Otoum et al., 2020) introduce a solution that integrates both federated learning and blockchain to ensure both data privacy and network security. The security of federated learning is increasingly

being questioned, due to the malicious clients or central servers' constant attack to the global model or user privacy data. To address these security issues (Li et al., 2021) propose a decentralized federated learning framework based on blockchain, i.e., a Blockchain-based Federated Learning framework with Committee consensus (BFLC). (Liu et al., 2020b) propose a blockchain-based secure FL framework to create smart contracts and prevent malicious or unreliable participants from involving in FL. (Lu et al., 2021a) introduce the digital twin wireless networks (DTWN) by incorporating digital twins into wireless networks, to migrate real-time data processing and computation to the edge plane. In further (Xu et al., 2021) propose the concept of device's score and use entropy weight method to measure the quality of model update. Other influential work includes (Lu et al., 2020a).

3.2 Quality management: incentive

There are many security problems neglected in federated learning, for example, the participants may behave incorrectly in gradient collecting or parameter updating, and the server may be malicious as well. (Weng et al., 2021) present a distributed, secure, and fair deep learning framework named *DeepChain* to solve these problems. This technique provides a promising privacy preservation for mobile devices while simultaneously ensuring high learning performance (Kang et al., 2019). (Liu et al., 2020a) propose FedCoin, a blockchain-based peer-to-peer payment system for FL to enable a feasible SV based profit distribution. (Lin et al., 2022) propose a novel Wirelessly Powered Edge intelliGence (WPEG) framework, which aims to achieve a stable, robust, and sustainable edge intelligence by energy harvesting (EH) methods. (Wang et al., 2021) propose SFAC, a secure federated learning framework for UAV-assisted MCS. A new ecosystem of ML model trading over a trusted Blockchain-based network is proposed (Nguyen et al., 2021). Problems, however, can arise if there is a lack of quality data for AI-model training, scalability, and maintenance. (Chaabene et al., 2022) propose a data-centric federated learning architecture leveraged by a public blockchain and smart contracts to overcome this significant issue. The proposed approach employs privacy-preserving bidirectional long-short term memory (BiLSTM) and augments the security through the integration of Blockchain technology based on Ethereum smart contract environment (Rahmadika et al., 2022). While several works focus on strategic incentive designs and client selection to overcome this problem, there is a major knowledge gap in terms of an overall design tailored to the foreseen digital economy, including Web 3.0, while simultaneously meeting the learning objectives. To address this gap (Pandey et al., 2022) propose a contribution-based tokenized incentive scheme, namely `FedToken`, backed by blockchain technology that ensures fair allocation of tokens amongst the clients that corresponds to the valuation of their data during model training. Other influential work includes (Lu et al., 2020a).

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Do not include acknowledgements in the initial version of the paper submitted for blind review.

If a paper is accepted, the final camera-ready version can (and probably should) include acknowledgements. In this case, please place such acknowledgements in an unnumbered section at the end of the paper. Typically, this will include thanks to reviewers who gave useful comments, to colleagues who contributed to the ideas, and to funding agencies and corporate sponsors that provided financial support.

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A PLEASE ADD SUPPLEMENTAL MATERIAL AS APPENDIX HERE

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