Blockchain-aided Decentralized Collaborative Automatic Modulation Classification for Next-Generation Wireless Networks

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***Abstract*—Automatic modulation classification (AMC) is essential to dynamic spectrum access in B5G and 6G networks for refarming the spectrum resources. However, the recent deep learning (DL)-based AMC framework has communication overhead, requires more computing resources, and poses security issues. Next-generation wireless networks allow distributed collaborative scenarios to provide ultra-reliable and low-latency communications (URLLC) services. This study proposes a blockchain-assisted decentralized collaborative AMC framework with a lightweight convolution neural network (CNN) model. The proposed system utilizes the federated learning (FL) technique to enable a privacy-preserving scheme by performing local training on edge and collaboratively producing a reliable model. A blockchain-based decentralized aggregation technique is implemented, using the Interplanetary File System (IPFS) as off-chain distributed storage for local and global models. This framework applied an improved accuracy-aware client selection mechanism (iACSM) to enhance the model performance and reduce communication overhead by selecting high-reputation authorized clients. Moreover, an ERC-20 token-based incentive mechanism has been developed to incentivize high-reputation selected clients. The proposed model measurement achieves high accuracy AMC with a low-complexity model structure in a trust-based decentralized learning scenario for constrained-resource wireless devices.**

***Index Terms*—automatic modulation classification (AMC), lightweight convolutional neural network (CNN), federated learning (FL), blockchain-based decentralized aggregation, client selection, incentive mechanism**

I. Introduction

The automatic modulation classification (AMC) framework is widely implemented for cognitive radio, signal detection, and spectrum utilization beyond 5G (B5G) and 6G networks. Recently, there has been extensive utilization of deep learning (DL) techniques for the development of advanced AMC with enhanced functionalities. The centralized DL-based AMC frameworks were proposed for the orthogonal frequency-division multiplexing (OFDM) systems [1], [2]. However, the centralized DL scenarios for the AMC applications have communication overhead and require more computing resources [3]. The constrained computing resource of wireless mobile devices makes it challenging to train and produce a reliable AMC model. Furthermore, the centralized DL-based AMC framework poses privacy issues by sending raw data to the cloud server for training processes [4]. As a solution, federated learning (FL) is implemented to address the issues and preserve the data privacy of each participant by performing local training on edge using their data [5]. The FL scenario allows the clients to collaboratively generate a robust model and reduce communication overhead [6]. The authors [5] implemented AMC frameworks with a decentralized learning technique using lightweight CNN to reduce the model complexity for constrained edge devices.

The vanilla FL system applied a centralized aggregation mechanism, which poses a single point of failure (SPoF) issue and is vulnerable to distributed denial-of-service (DDoS) attacks [6]. Moreover, unauthorized clients can perform a Byzantine attack by sending false data, resulting low-quality aggregated model. Implementing blockchain in the FL system offers advantages in terms of security, trustworthiness, transparency, data integrity, and provenance in a decentralized learning environment. Moreover, the blockchain can address the SPoF problem by performing a decentralized aggregation scheme in the FL system. In [7], the authors applied blockchain for training an ensemble federated AMC model using a simple majority voting method. A FLChain framework is developed to store local and global models in the blockchain during aggregation. In another study, the authors [8] implemented a blockchain-based federated learning (BFL)-based AMC framework with a validity evaluation mechanism. Therefore, the system can reduce the effect of malicious nodes with anti-attack capacities. However, in these approaches [7], [8], low-quality clients can contribute to the FL system, affecting the reliability of the aggregated model and inhibiting the convergence of the model. A client selection technique is required.

This study proposes a blockchain-assisted decentralized collaborative AMC framework with a lightweight convolution neural network (CNN) model. The proposed system imple-

TABLE I
COMPARISON BETWEEN PROPOSED SYSTEM AND EXISTING AMC FRAMEWORKS

Year	Technique	Ref	Method	Decentralized learning	Client selection	Decentralized aggregation	Lightweight model	Authorized technique	Incentive mechanism
2020	Centralized	[3]	IC-AMCNet	✗	✗	✗	✓	✗	✗
2022	Centralized	[2]	OFDMsym-Net	✗	✗	✗	✓	✗	✗
2023	Centralized	[1]	GGCNN	✗	✗	✗	✓	✗	✗
2020	Decentralized	[7]	CNN	✓	✗	✓	✗	✗	✗
2021	Decentralized	[4]	FedeAMC	✓	✗	✗	✓	✗	✗
2022	Decentralized	[8]	BFL-ResNet	✓	✗	✓	✗	✓	✗
2022	Decentralized	[5]	DecentAMC	✓	✗	✗	✓	✗	✗
2023	Decentralized	**Ours**	BCFedAMC	✓	✓	✓	✓	✓	✓

✓: Considered, ✗: Non-Considered

ments an improved accuracy-aware client selection mechanism (iACSM) to enhance the model performance and reduce communication overhead by selecting high-reputation authorized mobile device clients. A blockchain-based decentralized aggregation technique uses proof-of-authority (PoA) consensus and the Interplanetary File System (IPFS) as off-chain distributed storage for local and global models. The comparison between the proposed system and existing AMC frameworks is presented in Table I. The proposed system considers several advantages: decentralized collaborative learning, client selection, blockchain-based trusted decentralized aggregation, lightweight model for constrained mobile edge devices, authorized technique, and incentive mechanism. Therefore, the main contributions of this study are as follows:

1) We proposed a BFL-assisted AMC framework called BCFedAMC to provide a robust, trusted, and light communication overhead AMC technique with a low-complexity CNN-based AMC model.
2) We developed a lightweight CNN module utilizing a factorized convolution structure and grouped convolution configuration. Moreover, a residual connection configuration was implemented to address the gradient vanishing issue and improve learning efficiency.
3) We utilized iACSM to select the potential clients to contribute to the FL environment and collaborated to provide reliable aggregated model performance. The proposed client selection technique effectively reduces the low-quality clients' effect on the model's reliability.
4) A blockchain-based trusted decentralized aggregation mechanism is implemented using PoA consensus and IPFS as off-chain distributed storage for local and global models.
5) We introduced a fairness blockchain-based ERC-20 token incentive mechanism to incentivize the selected FL clients for motivating client contributions.

The remaining sections of this study is structured as follows: Section II presents the decentralized collaborative AMC framework for next-generation wireless networks, followed by the BLF-based AMC with trust-decentralized aggregation and incentive mechanisms in Section III. Simulations and discussions are carried out in Section IV, and Section V provides this study's conclusion and future works.

II. DECENTRALIZED COLLABORATIVE AMC FOR NEXT-GENERATION WIRELESS NETWORKS

A. Problem Formulation

The recent DL-based AMC frameworks use centralized DL scenarios [1]–[3] to train the data on the cloud server. However, this technique has communication overhead, requires more computing resources, and poses security issues. To overcome the centralized DL-based AMC issues, FL-based AMC frameworks were applied to enable privacy-preserving learning techniques on mobile edge devices [4]. However, a vanilla FL technique uses a centralized aggregation, is vulnerable to DoS/DDoS attacks, and poses a SPoF issue. Implementing blockchain in the decentralized collaborative AMC [7], [8] tries to address these issues. Blockchain provides security, trustworthiness, and transparency capabilities through a decentralized aggregation. Therefore, the BFL-based AMC with a lightweight model can enable a trusted AMC framework for constrained-resource wireless devices in decentralized environments. Moreover, the integration client selection technique and incentive mechanism to motivate potential clients to contribute to the FL system is still subject to be addressed.

B. Proposed Blockchain-assisted Decentralized Collaborative AMC

This study proposes a blockchain-assisted decentralized collaborative AMC framework to address security, SPoF, and vulnerability of DoS/DDoS issues for centralized aggregation scenarios in the recent decentralized AMC environments. The proposed system provides robust client selection, blockchain-based trusted decentralized aggregation, and a fairness ERC-20 token-based incentive mechanism in decentralized collaborative AMC for next-generation networks. The detail of the proposed system is presented in Fig. 1. Mobile devices register to the blockchain network and perform local training using local datasets. The aggregation server aggregates the local model from the mobile devices and calculates the global model. A smart contract is developed to store and access the models in or from the off-chain and on-chain.

C. Signal Modeling for AMC

AMC is performed in the receiver to identify the modulation type of received signals in software-defined radio (SDR)-based

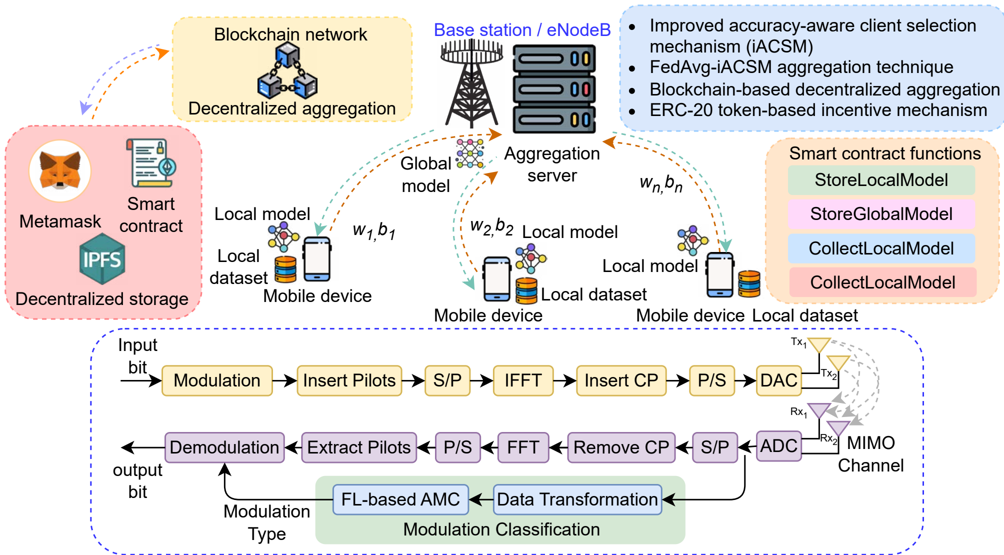


Fig. 1. Blockchain-asssited Decentralized Collaborative AMC Framework in Massive MIMO-OFDM System for Next-Generation Networks

communications. The received signal is modeled with a time-varying carrier phase offset (CPO) and additive white Gaussian noise (AWGN), expressed as

$$q(r) = \alpha e^{j\theta_c} p(r) + n(r), r \in [0, R-1], \tag{1}$$

where $[p(r)]_{r=0}^{R-1}$ denotes the transmitted signal, $[q(r)]_{r=0}^{R-1}$ represents the received signal, and $[n(r)]_{r=0}^{R-1}$ expresses the AWGN as the complex-valued signals. Moreover, α and θ_c represent the channel gain and the CPO, respectively. The channel gain α follows a Rayleigh distribution within the range of [0, 1]. Concerning the signal model mentioned earlier, the received signal can be separated into its real and imaginary components, which can be written as

$$I = [real\,(q(0))\,, real\,(q(1))\,, .., real\,(q(R-1))]\,, \tag{2}$$

$$Q = [imag\,(q(0))\,, imag\,(q(1))\,, .., imag\,(q(R-1))]\,, \tag{3}$$

Here, the in-phase and quadrature parts are represented by I and Q, respectively. The training or testing samples consist of I and Q, denoted as $R = [I; Q]$, commonly referred to as the IQ sample.

D. Decentralized Collaborative AMC with Client Selection

The proposed decentralized collaborative AMC framework comprises computing nodes and the aggregation coordinator. The computing nodes are wireless mobile devices that act as FL clients, denoted as $C = \{C_1, C_2, C_3, ...C_N\}$, where $C_i\,(i = 1, 2, 3, ...N)$ are the $i-$th wireless devices. The computing nodes C_i handle the local training using local data D_i, where D_i represents the local data wireless device C_i and $|D_i| = N_i$. Based on the value of $\left[\delta_i = \frac{d_i}{d_1+d_2+d_{3,..}+d_n}\right]$, where d_i is data size of resources D_i. The aggregation coordinator A_c collects the updated local model ω_i^r from D_i to perform a client selection mechanism and aggregation process to calculate the global model using a particular aggregation algorithm. This system applied an iACSM technique to select high-reputation clients with high-accuracy histories. Subsequently, only the local model parameters from the selected clients will be calculated for the aggregation process. The A_c performs an average aggregation algorithm and generate a global model $\omega_{g_{t+1}}^r$ with selected clients (FedAvg-iACSM), expressed as

$$\omega_{g_{(selected,t+1)}}^r = \sum_{i=1}^{N} \frac{d_i}{d} \omega_{i_{t+1}}^l. \tag{4}$$

The iACSM technique considers the reevaluation mechanism to enhance the federated AMC model performance with maximized model generalization. The reevaluation process is periodically performed by conducting local training for all available clients, including selected clients. This mechanism enhances our previous client selection technique [9], which has limitations for model generalization issues.

E. Lightweight Federated CNN-based AMC Model

This study proposes a lightweight CNN-based AMC model in the FL environment, as shown in Fig 2. The proposed model is conducted by composite group convolution (CGC) and deep composite group convolution (DCGC) modules to extract the features. These modules utilize a factorized convolution configuration, residual connection, and grouped convolution to generate more deep features and provide low computational complexity. The normalized IQ samples need to be reshaped into $\mathbf{I} \in \mathbb{N}^{2 \times 128 \times 1}$ dimension as the input feature of the model. Subsequently, the feature is fed into the stacked (1×3) and (3×1) composite convolution layers, each utilizing 8 kernels. The composite convolution process involves convolution, batch normalization, and ReLU activation layers. After ReLU activation, a (2×2) max pooling layer is used to reduce the feature dimensions. Furthermore, a residual connection with (1×1) composite convolution of 8 kernels is used to

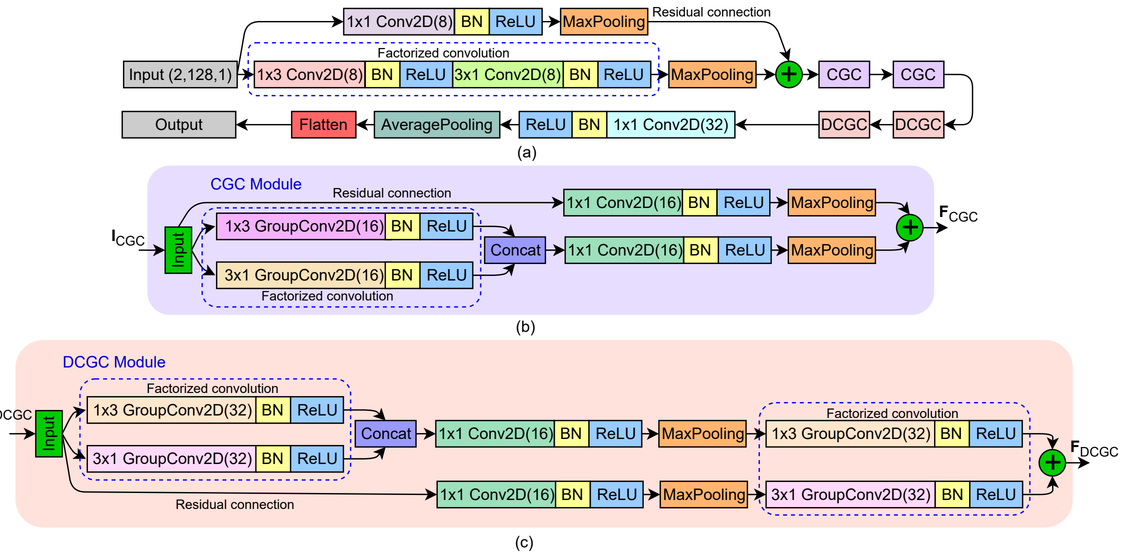


Fig. 2. Proposed lightweight CNN-based model for decentralized AMC framework: (a) main proposed model, (b) CGC module, and (c) DCGC module

resist the network model from vanishing gradient issues and enhance learning efficiency. The additional operation between stacked convolution and residual connection can be presented as follows:

$$F^{C}_{add} = F^{C}_{(3\times1)}\left(F^{C}_{(1\times3)}\left(I\right)\right) + F^{C}_{(1\times1)}\left(I\right), \qquad (5)$$

where I, F^{C}_{add}, $F^{C}_{(3\times1)}\left(F^{C}_{(1\times3)}\left(I\right)\right)$, and $F^{C}_{(1\times1)}\left(I\right)$ denote as the input of the model, output of the additional operation, stacked composited convolution, and (1×1) kernels of residual connection, respectively.

Afterward, the output of F^{C}_{add} feature is performed to the CGC module that consists of two flows (1×3) and (3×1) composite grouped convolution of 16 kernels. These convolutions are divided into four groups to extract more deep features. A concatenate layer combines all the features and enhances feature diversity. The concatenated feature maps can be presented as:

$$F^{GC}_{concat} = \chi\left(F^{GC}_{(3\times1)}\left(F^{C}_{add}\right), F^{GC}_{(1\times3)}\left(F^{C}_{add}\right)\right), \qquad (6)$$

here, χ represents concatenate, $F^{GC}_{(3\times1)}\left(F^{C}_{add}\right)$ detonates (3×1) grouped composite convolution and $F^{GC}_{(1\times3)}\left(F^{C}_{add}\right)$ presents (1×3) grouped composite convolution operations. Following the concatenation, the expanded feature fed to (1×1) composite convolution, (2×2) max pooling, and residual connection. This model consists of two CGC modules, and the second CGC module's output F^{CGC2}_{out} can be presented as:

$$F^{CGC2}_{out} = F_{CGC2}\left(F^{C}_{(1\times1)}\left(F^{GC}_{concat}\right) + F^{C}_{(1\times1)}\right), \qquad (7)$$

where $F^{C}_{(1\times1)}\left(F^{GC}_{concat}\right) + F^{C}_{(1\times1)}$ presents the output of first CGC module. Subsequently, the extracted feature is fed to the DCGC modules. The proposed model consists of two DCGC modules that are employed by (1×3) and (3×1) grouped composite convolution with 32 kernels, (1×1) composite convolution, (2×2) max pooling, and a residual connection unit. The output feature maps of each DCGC module can be presented as follows:

$$F^{DCGC1}_{out} = F^{GC}_{(1\times3)}\left(F^{C}_{(1\times1)}\left(F^{DCGC1}_{concat}\right)\right), \qquad (8)$$

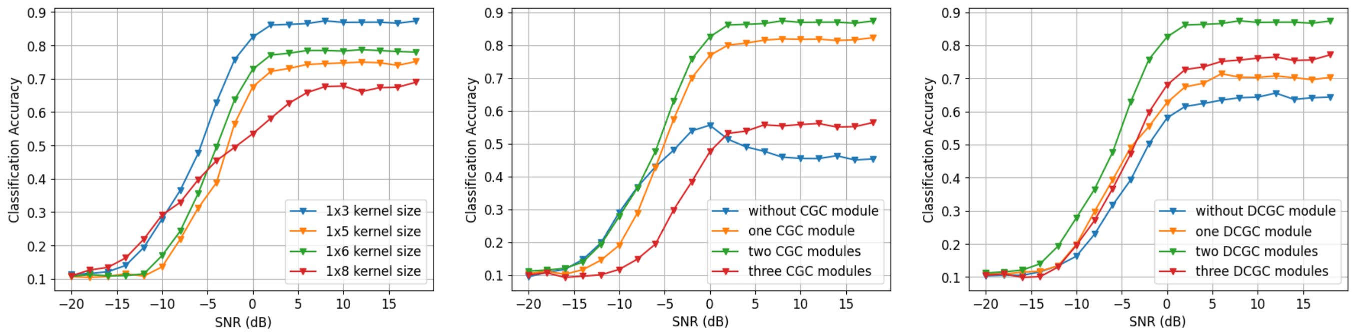
$$F^{DCGC2}_{out} = F_{DCGC2}\left(F^{DCGC1}_{out}\right) + F^{GC}_{(3\times1)}\left(F^{C}_{(1\times1)}\right). \qquad (9)$$

where F^{DCGC1}_{out} and F^{DCGC2}_{out} denote the output of the first and second DCGC modules, respectively.

III. Trusted BFL-based AMC Framework with Incentive Mechanism

A. Blockchain-based Decentralized Aggregation

The group of miners in the blockchain network layer is represented as $M = \{M_1, M_2, M_3, ...M_{N_m}\}$, where $M_j\,(i = 1, 2, 3, ...N)$ is the j-th of the miner and N_m is the number of miners. Miner M_j is randomly assigned to node D_i. Moreover, i and j related to the node address $add_{i,j}$ in the blockchain. In every communication round, the updated local model is stored in the IPFS and a $\mathrm{URI}_{\mathrm{local}}$ is generated and uploaded in the blockchain by accessing the smart contract (StoreLocalModel function). The miners received a URI from the client and verified the transaction. Subsequently, the blockchain performed the PoA consensus to generate a block. The smart contract provides four functions, including StoreLocalModel, StoreGlobalModel, AccessLocalModel, and AccessGlobalModel. The A_c collects the updated local model $\mathbb{W} = \left\{\omega^l_1, \omega^l_2, \omega^l_3, ...\omega^l_{add}\right\}$ from the selected clients by accessing the IPFS based on the node address add using the output of AcessLocalModel function. The aggregated result is stored in IPFS, and URI_{global} is saved in the blockchain by accessing StoreGlobalModel function. For further local training, the A_c shares an updated global model with the clients as the output of the AccessGlobalModel function.



(a) (b) (c)

Fig. 3. Classification performance of the proposed model with (a) different kernel size, (b) different number of CGC module, and (c) different number of DCGC module

B. ERC-20 Token-based Incentive Mechanism

This study integrates the iACM technique with an incentive mechanism to motivate high-quality clients to contribute to the decentralized collaborative learning system. In each round, the selected clients of the iACM technique results receive an incentive token to compensate the client's resources for local training usage. The A_c deploys smart contracts containing $\mathrm{TokenGeneration}$ and $\mathrm{TokenTransfer}$ functions to implement this incentive mechanism. The $\mathrm{TokenGeneration}$ function is used to deposit a specific number of tokens. Moreover, For incentivizing, the A_c transfers the token using the $\mathrm{TokenTransfer}$ function to the selected clients' Ethereum wallet address.

TABLE II
COMPARISON OF THE PROPOSED MODEL WITH DIFFERENT AMC MODELS

Model	Average Accuracy	Time-cost	Trainable Parameter
CNN [7]	83.00%	0.065 s	287,434
IC-AMCNet [3]	83.40%	0.048 s	625,073
Proposed	86.80%	0.022 s	17,090

IV. EXPERIMENTAL AND RESULTS

This system uses the modulation classification DeepSig RadioML 2016.10b dataset [10] to analyze the performance of the proposed BCFedAMC system. This dataset was collected using GNURadio, which has ten classes (8PSK, AM-DSB, BPSK, CPFSK, GFSK, PAM4, QAM16, QAM64, QPSK, and WBFM) with $1,200,000$ samples. A range of signal-to-noise ratios (SNRs), varying from -20 dB to 18 dB with a 2 dB interval, is employed. This study utilized the Flower framework to develop an FL-based AMC model using TensorFlow. This simulation applied the Adam optimizer with a learning rate of 0.0001 and 50 as the number of training epochs for training configuration. The public blockchain built on Ethereum employs the PoA consensus mechanism to establish a trustworthy and decentralized aggregation technique.

A. Classification Performances

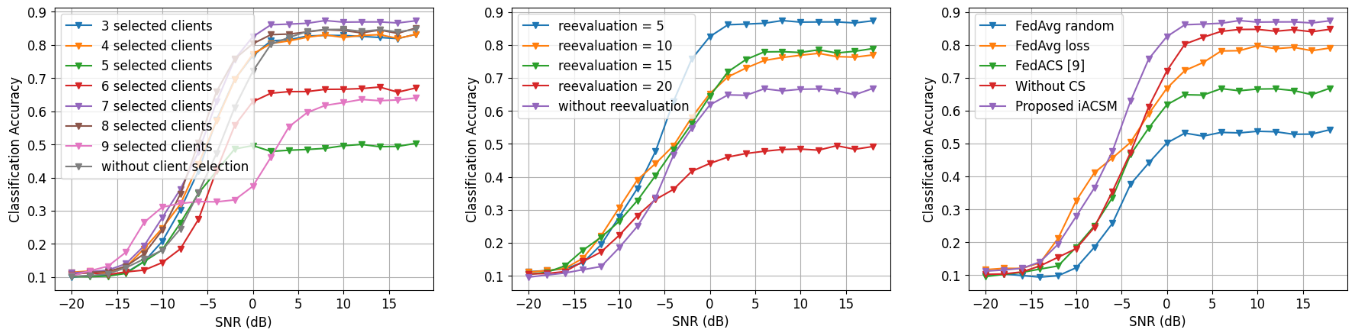
As shown in Fig. 3, the classification performance of the proposed model is analyzed with different scenarios. Fig. 3(a) presents the comparison performance regarding kernel size used for the composite convolution layer in the model. Based on this result, (3×1) kernel size achieves the highest classification accuracy. To investigate the effectiveness of two main modules (CGC and DCG) of the model, Fig. 3(b) and Fig. 3(c) present the CGC and DCGC modules architecture investigation results. In this investigation, we analyze various number CGC and DCGC module architectures. Two CGC and two DCGC modules architecture that performs high accuracy for all SNRs. Fig. 4 presents the robustness of the proposed iACSM technique and comparison with state-of-the-art client selection techniques. Based on the results in Fig. 4(a) and Fig. 4(b), the highest accuracy is achieved using 7 selected clients with perform reevaluation every 5 round. Fig. 4(c) shows the comparison of proposed iACSM performance with various client selection techniques (random, loss-based, and ACS [9]). Based on this comparison, the proposed iACSM outperforms other client selection techniques with achieved high accuracy. The comparison performance of the proposed model with different models for 18 dB SNR is shown in Table II. The proposed model outperforms state-of-the-art AMC models with an average accuracy of 86.80% and computing time of 0.022 s. Moreover, the proposed model provides a low-complexity structure with $17,090$ trainable parameters.

TABLE III
BLOCKCHAIN-BASED DECENTRALIZED AGGREGATION PERFORMANCE WITH DIFFERENT CONSENSUS

Consensus	Transaction Time (s)			
	Store Global Model	Store Local Model	Access Global Model	Access Local Model
PoA	11.7741	11.2256	0.0687	0.0538
PoW	14.9844	14.5875	0.1018	0.1205

TABLE IV
ERC-20 TOKEN-BASED INCENTIVE MECHANISM PERFORMANCE

Blockchain	Transaction Time (s)	
Testnet	Generate Token	Transfer Token
Georli	13.9508	12.4970
Sepolia	12.7123	11.8779



(a) (b) (c)

Fig. 4. Classification performance of BCFedAMC with (a) different number of selected clients, (b) different number of reevaluation number, and (c) different client selection technique

B. Blockchain Performance for Decentralized AMC

The efficiency of the proposed decentralized aggregation technique with various consensus algorithms was evaluated by assessing the transaction time. The performance of blockchain-based decentralized aggregation with different consensus mechanisms is shown in Table III. The evaluation compares the transaction time between PoA and proof-of-work (PoW) consensus. The measurement outcomes reveal that the PoA consensus outperforms the PoW consensus regarding transaction time across all function operations involved in the decentralized aggregation process. The PoA consensus exhibits a transaction time of 11.7741 seconds for storing the global model while storing the local model takes 11.2256 seconds. Accessing the global model requires only 0.0687 seconds, and accessing the local model takes 0.0538 seconds using the PoA consensus. Due to its exceptionally low latency and energy efficiency performance, the PoA consensus is selected for decentralized aggregation in the FL environment. Table IV presents the ERC-20 token-based incentive mechanism performance. The incentive mechanism has a lower transaction time when tested in Sepolia Tesnet, with 12.7123 seconds for token generation and 11.8779 seconds for token transfer.

V. Conclusion

In this letter, we propose the BCFedAMC framework, a blockchain-based federated AMC technique that provides trusted decentralized aggregation using the PoA consensus algorithm. An iACSM technique was implemented to address the communication overhead in the vanilla FL technique. An ERC-20 token-based incentive mechanism was deployed to incentivize the selected FL clients for motivating client contributions. The blockchain-based decentralized aggregation performs well with a low transaction time of 11.7741 seconds for storing the global model, 11.2256 seconds for storing the local model, 0.0687 seconds for accessing the global model, and 0.0538 seconds for accessing the local model when using PoA consensus. For future work, consider delay-tolerant blockchain networks with homomorphic encryption for secure aggregation mechanisms in a trusted federated AMC framework.

Acknowledgment

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