I. J. Computer Network and Information Security, **2026, 1, 51-68**
Published Online on February 8, 2026 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijcnis.2026.01.04

Proof-of-resource Enabled 6G Resource Management Using Quaternion-attentive Cascaded Capsule Networks

Sudha Y.*
Department of Computer Science Engineering, Presidency University-Bangalore-560064, Karnataka, India
E-mail: m673sudha@gmail.com
*Corresponding author

Karthikeyan H.
Department of Networking and Communications, SRM IST, Kattankulathur-603203, Tamil Nadu, India
E-mail: h568karthikeyan@outlook.com

Prabha M.
Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India
E-mail: prabha784.ece@gmail.com

Sree Southry S.
Department of Electronics and Communication Engineering, Sona College of Technology, Salem, Tamil Nadu, India
E-mail: sreesouthry345@outlook.com

Received: 29 July 2025; Revised: 18 September 2025; Accepted: 20 October 2025; Published: 08 February 2026

Abstract: The global shift from 5G to 6G wireless communication networks presents immense challenges in managing resources for ultra-dense, heterogeneous, and latency-sensitive 6G applications such as holographic communications, autonomous systems, and the Internet of Everything (IoE). Traditional resource allocation methods struggle to meet the dynamic and complex demands of 6G, leading to inefficiencies, higher latency, and fairness issues. To address these challenges, we propose a novel framework called Proof-of-Resource enabled 6G Resource Management Using Quaternion-Attentive Cascaded Capsule Networks (Caps-PoR). Our approach integrates Quaternion-Attentive Cascaded Deep Capsule Networks (Q-AtCapsN) to improve the accuracy of predicting resource demands by capturing real-time multi-dimensional dependencies. Additionally, we optimize resource allocation dynamically through an Enhanced Collaborative Learning Algorithm (ECoLA), which supports decentralized decision-making across multiple nodes, significantly reducing latency. The Proof-of-Resource mechanism ensures transparency, fairness, and trust, preventing resource misallocation while ensuring equal access. Performance evaluations show that Caps-PoR outperforms traditional methods in 6G multi-access edge computing (MEC) scenarios, achieving over 98% resource utilization efficiency, a latency reduction exceeding 96%, and a user satisfaction rate of more than 97%. This demonstrates how Caps-PoR effectively enhances efficiency, security, and scalability in next-generation 6G networks, reshaping the future of resource management in decentralized systems.

Index Terms: Resource Management, 6G, Wireless Communication Network, Resource Prediction, Resource Allocation, Blockchain Technology.

1. Introduction

Efficient resource management in 6G communication networks is poised to redefine the landscape of wireless communication systems [1]. Once 5G technologies eventually mature [2], such unprecedented demands by emerging applications like URLLC, mMTC, and eMBB tend to solicit a paradigm shift toward 6G [3]. This next-generation framework will push the limits of network speed, latency, and capacity [4] but will even create a more intelligent, dynamic, and context-aware resource-allocation mechanism to support hyperconnected environments [5].

In 6G, resource management shifts from the established ways of achieving spectrum efficiency by now injecting research from artificial intelligence and machine learning [6], distributed ledger technologies, and edge computing [7]. Increasing exponentially over connected devices, real-time applications, and immersive experiences [8], this enhances the need for new resource management techniques to enhance spectral, computing, and energy resource optimization in real time [9]. It is expected that core research into future 6G networks, besides fulfilling smooth integration of diverse services [10], will be adaptive resource allocation based on predictive analytics and real-time decision making under strict QoS guarantees [11].

The 6G network will introduce a multifaceted resource management landscape with heterogeneity in service, mobility, and network topology [12]. The efficient orchestration of network slicing, hybrid access technologies, and dynamic spectrum sharing will be crucial to optimal utilization of resources [13]. Among other innovations, it is already known that terahertz (THz) frequencies, visible light communication (VLC), and quantum-based communication protocols have to be added to the 6G ecosystem [14]. This would require the necessary innovations in resource management strategies in order to exhaustively exploit the still relatively underused domains [15]. Moreover, the existing approaches are computationally expensive and require a significant amount of energy to be consumed; hence, the research cannot be overemphasized. Therefore, in this research work, Proof-of-Resource enabled 6G Resource Management Using Quaternion-Attentive Cascaded Capsule Networks (Caps-PoR) is presented. This research primarily focuses on the design, integration, and evaluation of an efficient system-level framework for 6G resource management. While it does not propose new theoretical algorithms, it introduces a novel architectural synergy that combines established deep learning and blockchain techniques to address practical challenges in real-time and decentralized network environments.

Novelty and Contributions

The proposed framework introduces a novel integration of Capsule Networks, Quaternion Attention mechanisms, and blockchain-based Proof-of-Resource consensus to address the challenges of resource prediction, allocation, and trust in 6G environments. While each of these techniques is established individually, their unified application in decentralized and intelligent network resource management represents a novel approach within this domain. This synergistic combination enhances prediction accuracy, enables agile resource distribution, and ensures secure, trustworthy collaboration without centralized control.

The major contributions in the proposed method are described as:

- Resource Prediction Model: The study introduces a new model, Quaternion-Attentive Cascaded Capsule Network (Q-AtCapsN), which helps predict how much network resources will be needed in 6G systems more accurately by analyzing complex data.
- Better Resource Allocation: It develops an Enhanced Collaborative Learning Algorithm (ECoLA) to further enhance the sharing and management of resources collaboratively. The algorithm also incorporates agile and efficient resource distribution generated from the collaborative efforts of various nodes.
- Security and Trust: The research uses a blockchain technology, Proof-of-Resource (PoR), to ensure resource management is safe and transparent. PoR prevents cheating, guarantees fairness, and automates the process of managing resources securely.
- Decentralized Resource Sharing: The system enables fair resource sharing without a central authority using the optimized neural network and blockchain technology, thereby making 6G networks efficient, scalable, and trustworthy for all their users.

The following sections of this research are organized as follows: Section 2 reviews relevant literature, Section 3 describes the proposed system, Section 4 presents the results, and Section 5 offers concluding remarks

2. Literature Survey

In 2022, Guo et al.,[16], presented Federated reinforcement learning-based resource allocation in D2D-enabled 6G. To increase the effectiveness of spectrum usage, this article discusses the problem of resource allocation in underlay-mode D2D-supported 6G wireless networks. Building on energy consumption reduction and overall capacity maximization, a decentralized approach using deep reinforcement learning and federated learning is presented. The proposed framework ensures QoS for all D2D as well as cellular users.

In 2021, Khan et al., [17], suggested Energy-efficient resource allocation for 6G backscatter-enabled NOMA IoV networks. This paper presents an energy-efficient resource allocation scheme for faulty Successive Interference Cancellation in 6G Ambiant Backscatter Communication enabled NOMA Internet of Vehicles networks. Downlink NOMA employs Road-Side Units to send overlaid signals to IoVs, and Backscatter Tags backscatter the forwarded signals to send forward data. Meanwhile, this work targets network-wide optimized power budget of RSUs, power allocation for IoVs, and power of reflection by BackTags, considering imperfect SIC decoding.

In 2023, Han et al., [18], developed EDI-driven multi-dimensional resource allocation for inclusive 6G communications. This paper introduces a new multi-dimensional resource distribution scheme that is going to enable fairness in 6G communications by the EDI principle. The architecture offers equal services for various access ways by all subscribers, making use of heterogeneous diversity among devices, concerning issues with different Quality-of-Service requirements among subscribers. It optimizes average user utility conditioned on minimizing its variance over the network in consideration of scenario-based costs of resources and individual demands of users.

In 2024, Huang et al., [19], introduced Reinforcement learning based resource management for 6G-enabled mIoT with a hypergraph interference model. In this paper, two resource management algorithms based on RL and a new hypergraph interference model for mIoT networks enabled by 6G are proposed. The first utilizes DQN to choose the optimal action from a candidate set of actions to solve the large-scale overlapping interference problem and thus enhance the network throughput. To enhance network throughput for densely deployed IoT environments, the paper adopts the A2C and A3C algorithms in optimizing spectrum resource allocation through resource management in the form of an MDP.

In 2023, Louvros et al., [20], proposed QoS-aware resource management in 5G and 6G cloud-based architectures with priorities. The study, based on the priority scheduling, proposes a two-stage queue model for QoS-aware resource management in both 5G and 6G cloud-based infrastructures. A one-dimensional queue analyzes the average packet waiting time in the RLC radio buffer, considering transmission bandwidth limitation and the traffic load, whereas a two-dimensional queue predicts the expected delay in the IP/Ethernet MAC layer schedule between gNB and the core network. Thus, it aims at enhancing the quality of service as well as reducing the time for resource allocation.

In 2023, Thantharate et al., [21], recommended ADAPTIVE6G: Adaptive resource management for network slicing architectures in current 5G and future 6G systems. ADAPTIVE6G is a framework for adaptive learning of proposals in network slicing and resource management in beyond 5G and future 6G systems. This framework utilizes TL methods for the prediction of traffic in the network and enables fair and efficient sharing of resources. It solves complex estimation problems of loads and positively promotes the resources to be more equitably distributed across the network.

In 2021, Patel et al., [22], offered Block6Tel: Blockchain-based spectrum allocation scheme in 6G-envisioned communications. In the context of 6G communications, a blockchain-based spectrum allocation plan named Block6Tel, ensuring safe and open band distribution among telecom providers, is proposed. The plan is two-stage: First, a protocol stack that uses a cell-free communication infrastructure based on 6G is proposed. After this protocol stack, an inter-operator spectrum allocation system is implemented through an auction process on the blockchain. The telecom companies are like a bid, and in this assignment, the government agencies function like an auctioneer while conducting smart contracts (SC).

In 2023, Ashwin, M., et al. [23], have recommended an efficient resource management approach for 6G wireless communication systems through a hybrid quantum deep learning (HQDL) framework. The study emphasized enhancing Quality of Service (QoS) by applying artificial intelligence and ML techniques. The HQDL model integrated a convolutional neural network (CNN) for handling network reconfiguration, resource allocation, and slice selection, while a recurrent neural network (RNN) managed error estimation and load distribution. Performance analysis was conducted under varying network slices, congestion levels, and device uncertainty to assess QoS improvements. The framework demonstrated notable effectiveness across diverse scenarios.

In 2024, Qian, L., et al. [24], have offered an optimization strategy for user connection and resource distribution within a blockchain-powered Metaverse operating over 6G wireless networks. The approach addressed challenges involving non-fungible tokens, privacy, and efficient resource management by employing user work-offloading to refine task scheduling, connection attributes, and computing resource division. Communication-computation allocation was optimized by adjusting bandwidth, transmit power, and processing frequencies. A trust-cost ratio (TCR) was formulated to balance user trust and operational efficiency. The DASHF algorithm, combining Dinkelbach's method, alternating optimization, semidefinite relaxation, the Hungarian algorithm, and fractional programming, transformed the problem into a quadratically constrained quadratic program.

In 2025, Ayub, N., et al. [25], have introduced a secure and decentralized framework combining ML and blockchain technologies for artificial intelligence applications in 6G networks. The study addressed performance limitations of 5G systems by incorporating artificial neural networks (ANNs) for real-time network monitoring and optimization. A blockchain-based Keyed Secure Infrastructure (KSI) using hash chains was applied to enhance protection against denial-of-service attacks in wireless sensor networks. Reinforcement management mechanisms were integrated within a user datagram protocol-based blockchain model to support secure operations. Network optimization was achieved through artificial democracy, improving throughput, packet delivery ratio, and delay metrics.

Table 1 shows the summary of the existing methods, which is given below,

Problem Statement

Resource management in 6G communication networks would be quite challenging, owing to its demanding requirements for ultra-fast speeds, very low latency, and tremendous connectivity. Current systems designed cannot cope with the complexity built by the technological dynamics of these 6G networks, which include technologies such as THz communication, edge computing, and massive machine-type communication. Traditional resource management models with centralization are not effective in this model and continue to face challenges in scaling well with an increased number of devices and a higher volume of data transmission. Some of these difficulties include poor resource allocation, network congestion, and delay in real-time applications; all such scenarios are unacceptable for advanced use cases like autonomous vehicles, augmented reality, or smart cities.

The motivation behind our work is to provide a sophisticated, decentralized framework that optimizes resource management in real-time by utilizing secure blockchain protocols and clever learning algorithms. This is our way of tackling these urgent concerns. Our solution seeks to offer reliable, scalable, and economical resource management for the developing 6G environment by assuring fairness, cutting latency, increasing prediction accuracy, and boosting transparency.

Table 1. Summary of the existing methods

Reference Number	Methods	Advantages	Disadvantages
[16]	D2D	Enhances spectrum utilization. Direct device-to-device isolation.	Increases interference with cellular users. D2D connections have a very short range.
[17]	NOMA – IoV	Increases spectrum efficiency for the IoV networks. Supports the transmissions of multiple users at the same time.	Interference management complexity is increased in mobility cases. Signal decoding has high computational overhead.
[18]	EDI	Increases fair and harmonious access to the resources. Better overall satisfaction among the users.	Too difficult to balance a diverse set of user requirements. Complex modelling is needed due to different QoS requirements.
[19]	6G-mIoT	Increases the total throughput in dense IoT scenarios. Processes overlapping interference well.	High computational resources for optimization complexity in managing large-scale IoT networks.
[20]	QoS-6G	Ensures priority-based resource allocation. Packet delay is minimized for high-priority users.	Resource utilization during traffic spikes is higher than the average. Managing QoS policies is more complex.
[21]	ADAPTIVE6G	Effective load prediction enhances resource allocation. Resource usage is fair.	Depends on the accuracy of data for effective prediction. Computationally expensive for the learning process.
[22]	Block6Tel	Blocking mechanism uses blockchain for spectrum allocation. Transparency from the telecom stakeholders.	Blockchain adds processing overhead. May face scalability issues in large networks.
[23]	HQDL-CNN-RNN	Improves service quality. Works well under heavy network load.	Hard to build. Needs strong hardware.
[24]	DASHF	Balances trust and performance. Optimizes user connections.	Uses many algorithms. Needs more resources.
[25]	ANN	Strong security. Protects against attacks.	Can be slow to train. Depends on network setup.

3. Proposed Methodology

The proposed methodology for the efficient management of 6G networks applies the techniques of advanced prediction, optimization, and securing of resources. In particular, Q-AtCapsN is applied in the prediction of required resources by leveraging complex data patterns analysis with a strong focus on better network demand prediction. ECoLA further optimizes the allocation of such resources by allowing nodes of a network to collaborate with each other and to take decentralized, real-time decisions. That helps in more efficient resource distribution and less delay while passing through the network. The entire process is secured by PoR: it verifies that resources have been used in fair and transparent ways. Fraud cannot be committed in such a network, and the resources can be shared across the network in a decentralized way. Collectively, these components make up a very efficient, secure, and scalable system for resource management of the 6G network.

Figure 1 shows the proposed Caps-PoR architecture.

3.1. Data Collection

An extensive data collection phase is required for precise modeling and efficient allocation in given resource-constrained environments. We collect real-time information from various edge devices in a network, concerning users' mobility, traffic load, and computation capabilities. This data collection will entail observation of the ever-evolving interactions between the various devices and the network to incorporate the heterogeneity and varying demand patterns in 6G contexts. Furthermore, we guarantee that the data is not only diverse but also encompasses various situations and extreme conditions to improve the model. The collected data is then formatted to make it compatible for input to our Quaternion-Attentive Cascaded Deep Capsule Network, which uses this data to make precise predictions of resource allocation.

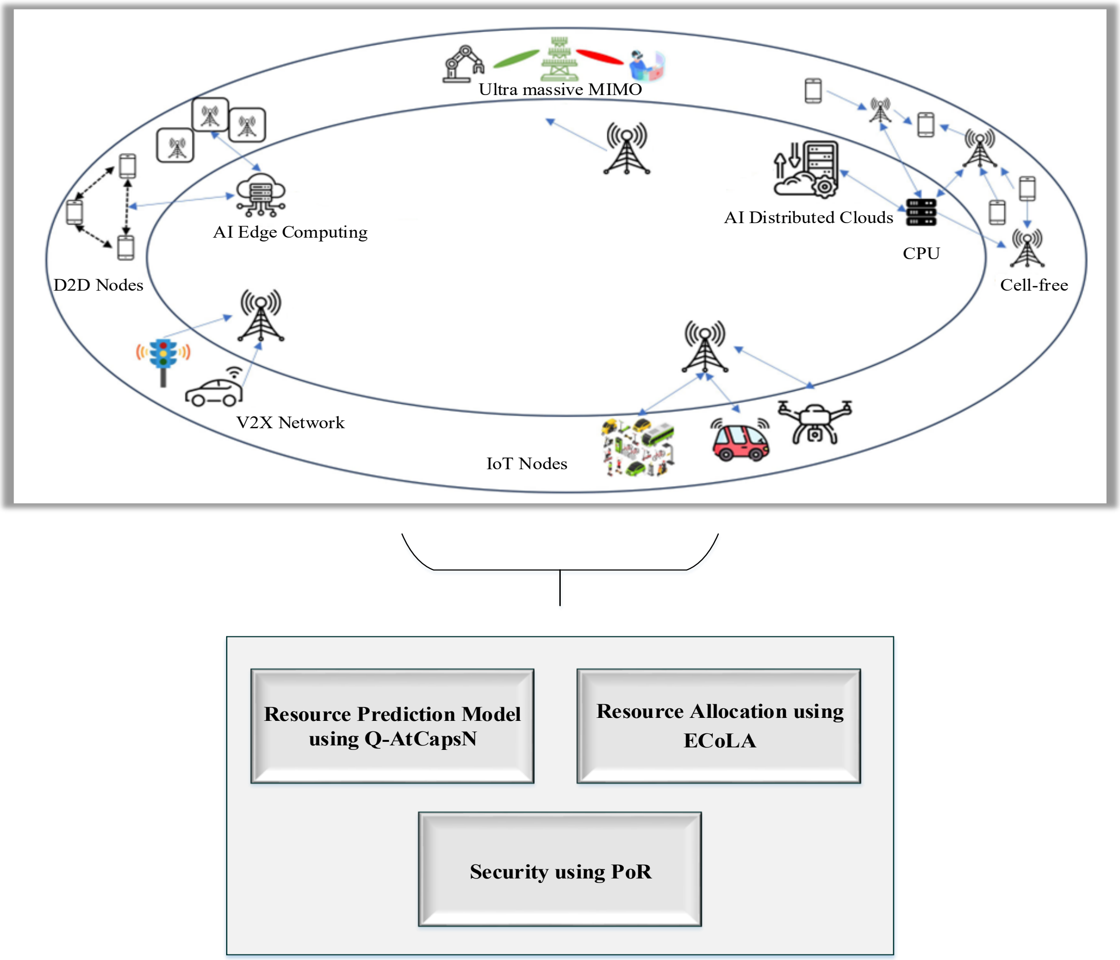

Fig.1. Proposed Caps-PoR architecture

3.2. Resource Prediction

After obtaining data from edge devices that provide real-time information, the Quaternion-Attentive Cascaded Deep Capsule Network (Q-AtCapsN) [26, 27], employs a cutting-edge approach to forecast resource requirements. The resources in the 6G communication system are predicted by using quaternion attention networks designed for resource prediction in 6G communication networks, specifically applied to cascaded deep capsule neural networks.

A. Cascaded Deep Capsule Neural Networks

The input matrix $Y \in \Re^{M\times N\times R}$ represents a resource allocation grid in a 6G network, where $M \times N$ are the spatial dimensions (e.g., base station locations) and R represents resource channels such as bandwidth, power, and frequency. Each element $y_{p,q} \in \Re^{1\times 1\times R}$ holds R resource demand channels at a location p, q. To address the challenge of spatial variability in resource demand and the similarity of resource usage across adjacent regions, we propose a Cascaded Deep Capsule Neural Network to first learn resource features in the resource demand dimension and then capture spatial context variations via capsules across the network's base stations.

The resource similarity between adjacent regions is defined as (1) and (2):

$$Sim(A,B) = \frac{\sum_{u=1}^{Q_A}\sum_{v=1}^{Q_B} Count(Y_u, Y_v)}{M\times N\times Q_A\times Q_B} \tag{1}$$

$$Count(Y_u, Y_v) = \sum_{l=1}^{P} min(Y_{ul}, Y_{vl}) \tag{2}$$

where A and B are two neighboring regions in the 6G network, Q_A and Q_B represent the number of resource allocation grids in regions A and B, and Y_u and Y_v denote the resource grids of these regions. Y_{ul}, Y_{vl} represent the number of allocated resource channels in the l -th category, where P is the total number of resource categories.

Capsule Module

In the capsule module, the convolutional layers are initially applied to extract high-level spatial–resource features.

These features are then transformed into spatial–resource capsules, represented as parameter vectors describing resource distribution across different base stations. The vector $z_i = [z_{i1}, z_{i2}, \ldots, z_{id}] \in \Re^d$ from the capsules is then transformed via a transformation matrix V_{ij}, derived as (3),

$$z_{ij} = V_{ij} z_i \tag{3}$$

The transformation captures spatial resource contexts and models the relationships between parts of the resource grid and the overall network. Next, a weighted sum of these transformed vectors generates a class vector $t_j = [t_{j1}, t_{j2}, \ldots, t_{jf}] \in \Re^f$, as shown in (4),

$$t_j = \sum_i s_{ij} z_{ij} \tag{4}$$

where s_{ij} is a coupling coefficient, which is initialized using a softmax function during the dynamic routing process. These coefficients represent the strength of the connection between spatial–resource capsules and class capsules, which categorize the resource demands. The initialization of the coupling coefficient is expressed as (5),

$$s_{ij} = \frac{exp(d_{ij})}{\sum_k exp(d_{ik})} \tag{5}$$

The length of the class vector $t_j$is normalized using a squash function, which acts as an activation function. This function is given by (6),

$$u_j = \frac{\|t_j\|^2}{1+\|t_j\|^2} \frac{t_j}{\|t_j\|} \tag{6}$$

This dynamic routing process adjusts both the transformation matrix V_{ij} and the coupling coefficients s_{ij} iteratively. The length of the activity vector u_j is used to predict the category of resource needs in the 6G network.

Reconstruction and Loss Function

To ensure accurate prediction, a margin loss function is employed to maximize the length of the activity vector for the correct resource category, as in (7),

$$L_{m\,arg\,in} = \sum_{p=1}^{P} \left(U_p\, max\left(0, \beta_1 - \|u_p\|\right)^2 + \eta(1 - U_p)\, max\left(0, \|u_p\| - \beta_1\right)^2 \right) \tag{7}$$

where U_p represents the true resource category, β_1 and β_2 are thresholds, and η is a regularization parameter used to prevent shrinking of activity vectors early in the training process.

The reconstruction loss L_{recon} is computed as the mean squared error between the input grid and the reconstructed output as (8),

$$L_{recon} = \frac{1}{k} \sum_{q=1}^{k} \left\| F(Y_q) - y_q \right\|^2 \tag{8}$$

where k is the batch size, $F(\cdot)$represents the decoder, and Y_q is the q -th resource allocation grid. The total loss function, which combines both the margin loss and the reconstruction loss, is represented as (9),

$$L_{total} = L_{recon} + \gamma L_{m\,arg\,in} \tag{9}$$

where γ is a weighting parameter balancing the two losses. This Cascaded Deep Capsule Neural Network is further enhanced by passing its output activity vectors into an attention mechanism, which refines the resource allocation predictions by focusing on key regions in the 6G communication network.

B. Quaternion Attention Network

To address the challenges of data sparsity and long-term dependency in 6G networks, we employ a quaternion-based attention mechanism. The attention scores are computed in quaternion space, providing a multi-dimensional similarity measure for different inputs, queries, and keys.

Quaternion Additive Attention

Inspired by traditional attention, we propose the quaternion additive attention mechanism. The attention score A_q for an input $Q \in H$ is computed as (10), where H is the quaternion space.

$$A_q = \varphi\left(W_a^{(q)} Q + b_a\right) \tag{10}$$

where $W_a^{(q)}$ are attention weights and b_a is the bias term. The activation function φ maps the quaternion outputs to their attention scores. This form eliminates the need for softmax operations, which are undefined in quaternion space.

Quaternion Multiplicative Attention

Alternatively, the quaternion multiplicative attention uses quaternion multiplication to calculate similarity scores. Given two quaternions, the attention score is computed as (11),

$$A_q = Q \cdot K_q^* \tag{11}$$

where K_q^* is the conjugate of the query quaternion K_q. This dot-product-like operation measures the alignment between two quaternions, used to predict important resource patterns.

Mapping Attention Scores to Scalars

For resource allocation, attention scores must be mapped back to real numbers to make decisions. We propose using cosine similarity for this mapping as (12),

$$A_q = \frac{Q_q \cdot K_q}{|Q_q||K_q|} \tag{12}$$

This maps quaternion scores to scalars in the range [0,1], representing the relevance of each input for resource prediction.

Figure 2 depicts the architecture of the proposed Quaternion-Attentive Cascaded Deep Capsule Network.

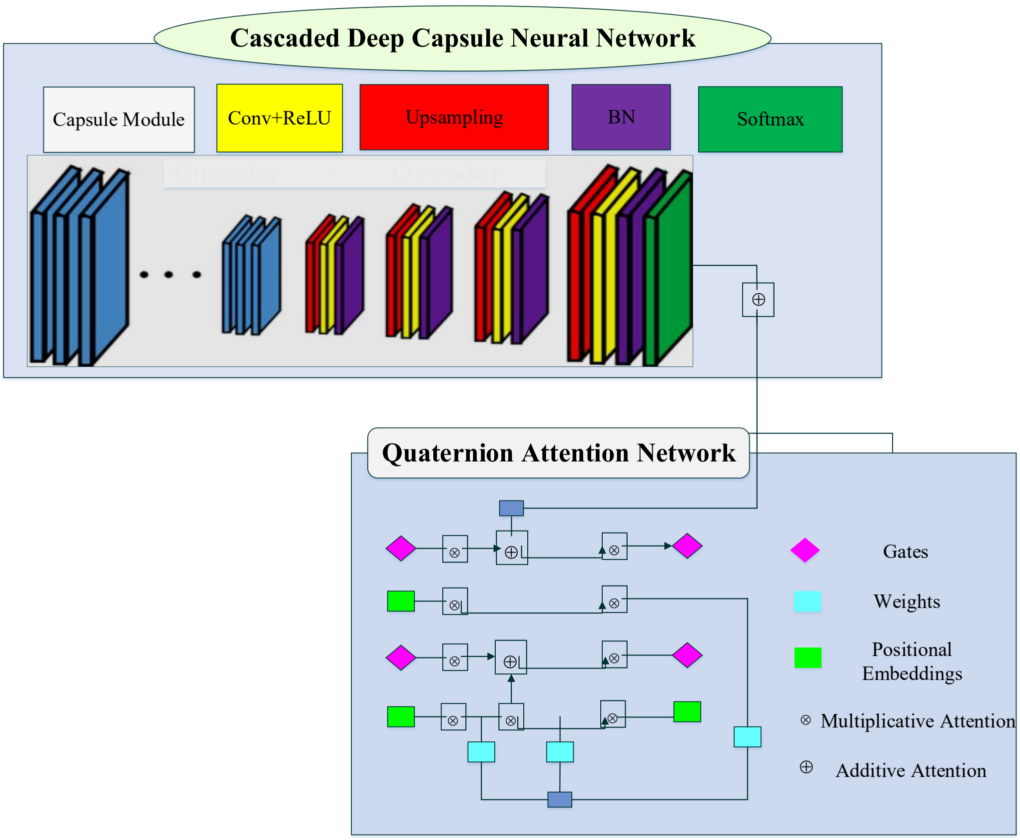

Fig.2. Architecture of the proposed neural network

Thus, the Quaternion-Attentive Cascaded Deep Capsule Network predicts the resources based on the priorities of the 6G communication systems. These predicted resources are then utilized for better Resource Allocation, thereby optimizing the weight parameters of the neural network.

3.3. Better Resource Allocation

For better resource allocation in 6G communication networks, the weight parameters must be optimized. This is done by the Enhanced Collaborative Learning Algorithm (ECoLA) [28]. This will facilitate optimization of resources in 6G networks with the help of group collaboration, which improves general performance. It will be based on collaborative learning within groups, with improved individual node performance during the time taken to discover efficient resource allocation strategies. This can include simpler complex allocation tasks on the part of the members, enhancement of better time management, and a more divergent approach in managing different resources present in the network.

Such behaviors and benefits of group-based collaboration are what inspired the new optimization algorithm, known as the Enhanced Collaborative Learning Algorithm. ECoLA is shown to be almost similar in principle to evolutionary algorithms, where at the beginning of the process, an initial random population (representing nodes of the 6G network) is created and then evolved. Here, fitness for each node was measured through its resource-saving capability.

The ECoLA Process

The ECoLA begins by initializing a random population of nodes within the network, denoted as Pop. The fitness of every node is computed, where fitness denotes how resourcefully a node can tackle resources. Each network contains a controller, which is effectively the node with the highest fitness. Then the population is divided into several groups, and a node with the best fitness in a group becomes the leader of that group.

The controller drives the group leaders, who themselves drive other nodes in their groups to follow optimal resource-assignment strategies. This hierarchical influence structure is critical for the network's improvement because it drives efficient behavior around the network.

Fitness Function

The fitness function is used to attain the objective function that optimizes the activation function of Q-AtCapsN for better resource allocation. The equation of the fitness function is specified in (13):

$$Fitnessfunction = Optimize\left(W_a^{(q)}\right) \tag{13}$$

where, $W_a^{(q)}$ is represented as the activation function to attain the best solution. The fitness function plays a central role in guiding the algorithm towards the most efficient configurations, maximizing network performance while minimizing resource wastage.

Controller Influence on Group Leaders

The controller significantly impacts the group leaders, and their performance is updated accordingly. Mathematically, the new group leader influenced by the controller is calculated as (14),

$$GL' = (GL \cdot C) \cdot rand(0,1) \tag{14}$$

where GL' is the updated group leader after the controller's influence, GL is the current group leader, C is the controller (the node with the highest fitness in the entire population), and $rand(0,1)$ is a random number between 0 and 1. This equation ensures that the group leader adapts to the strategies provided by the controller, improving resource allocation within the group.

Group Leaders' Impact on Individual Nodes

Group leaders influence the nodes within their respective groups. The behavior of individual nodes is updated based on the group leader's strategy, as shown in the following equation (15),

$$n_i' = (GL' \cdot n_i) \cdot rand(0,1) \tag{15}$$

where n_i' is the updated node after being influenced by the group leader, GL' is the updated group leader from Equation (14), n_i is an individual node within the group. This step represents the exploitation phase of the algorithm, where nodes optimize their behavior based on the guidance of the group leader, leading to better resource allocation.

Controller's Influence on the Network

Occasionally, the controller directly influences the entire network population, including nodes outside its immediate group. The controller's direct influence is represented as (16),

$$n_i^{'} = (n_i \cdot C) \cdot rand(0,1) \tag{16}$$

where $n_i^{'}$ is the new node after being influenced by the controller, C is the controller, n_i is an individual node. This equation allows for occasional adjustments at a global level, ensuring that all nodes in the network benefit from the controller's optimization strategies.

Random Mutations to Introduce Diversity

To prevent premature convergence and ensure that the network adapts to new demands for resources, mutations in terms of random changes are introduced at some of the nodes. This creates diversity within the population and allows the algorithm to seek more new solutions. This can be particularly useful if the external conditions that might affect demand for resources within the 6G network also change over time. Figure 3 explains the overall workflow of the Enhanced Collaborative Learning Algorithm.

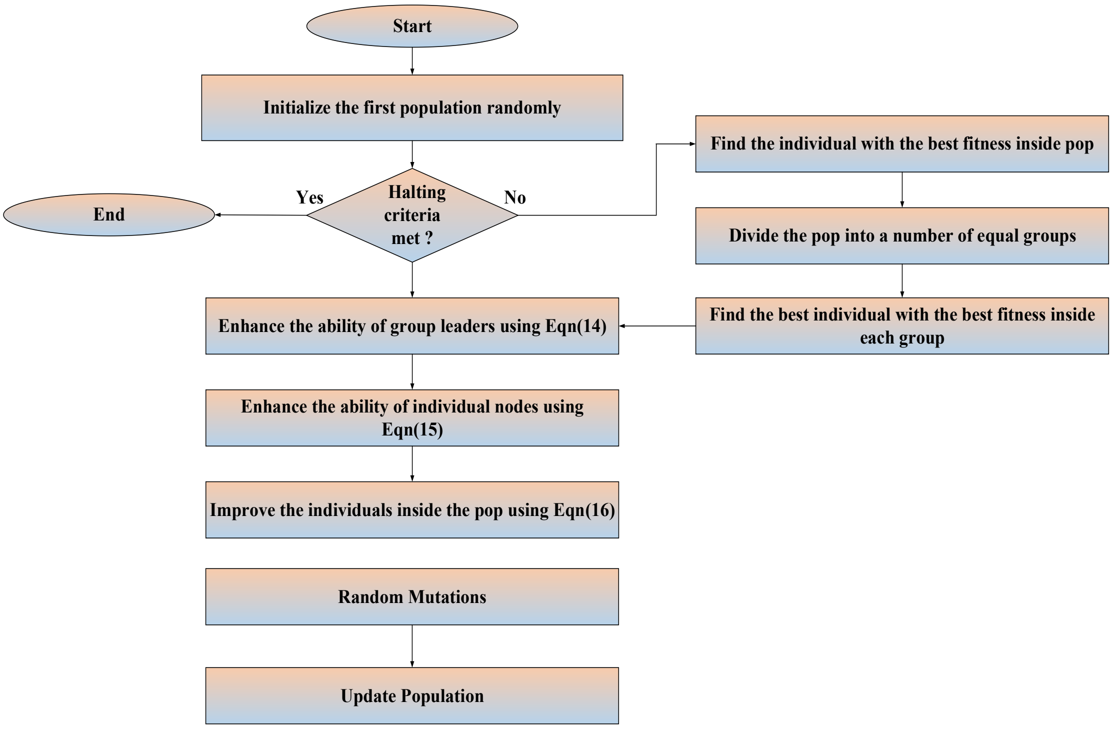

Fig.3. Step-by-step procedure of ECoLA

By structuring the network into groups and applying a hierarchical influence model, the ECoLA improves the performance of individual nodes and ensures efficient use of resources. The resources allocated are secured using blockchain technology called Proof-of-Resource.

3.4. Security using Blockchain Technology

After resource allocation for secured resource management in 6G communication systems, a blockchain technology called Proof-of-Resource (PoR) [29] is used. The process includes key phases such as initialization, resource validation, reputation score updates, consensus and validator selection, block verification, and rewards.

A. Initialization

In the initialization phase, each network node commits a portion of its computational power, storage, and energy resources to participate in the 6G network. A reputation score is assigned to each node based on the resources committed. This score reflects the contribution of each node and establishes its reputation within the PoR mechanism.

Committed Resources

Each node $D_k \in \{1,2,..,P\}$ contributes a set of resources, denoted as $R_k = \{q_1, q_2, \ldots, q_N\}$, where q represents a resource type, such as computational power, storage capacity, or energy. The total resources in the network are calculated as (17),

$$T_{total} = \sum_{k=1}^{P} R_k \tag{17}$$

Initial Reputation Score Calculation

The initial reputation score S_k for each node D_k is calculated based on the resources committed, with each resource weighted according to its importance. The score is determined using the following equation (18),

$$S_k = weight_{comp} \cdot comp\_power_k + weight_{store} \cdot storage_k + weight_{energy} \cdot energy_k \tag{18}$$

where $weight_{comp}$ refers to the computational weight and $comp_{power}$ refers to the computational power, which is assigned a weight of 0.4, and $weight_{store}$ refers to the storage weight and $weight_{energy}$ refers to the energy resources weight, which assigned a weight of 0.3. The reputation score establishes the node's contribution and reliability within the network.

B. Resource Verification

Resource verification ensures that nodes meet their resource commitments. Validators assign lightweight tasks T_k to nodes, which must execute and report the results. These tasks may include computations, storage checks, or cryptographic operations, depending on the node's capabilities. After completing the tasks, the results V_k are reported to validators, and the reputation scores are updated as (19),

$$S_k' = S_k + 1 \tag{19}$$

Successful task completion leads to an increase in reputation, demonstrating the node's reliability and contribution to resource management. The verification process periodically ensures that nodes maintain their committed resources, except when affected by external factors like hardware failures.

C. Consensus Protocol and Validator Selection

The consensus protocol and validator selection process use the reputation scores to select validators for each block. Nodes with higher scores are more likely to be selected, ensuring that the most reliable nodes participate in consensus.

During validator selection, a dynamic threshold is calculated based on the distribution of reputation scores. The threshold Q is defined as (20),

$$Q = \left(\frac{x}{100}\right) \cdot P \tag{20}$$

where P is the total number of nodes, and x represents the desired percentile. This ensures that only highly reliable nodes are selected as validators.

D. Block Validation and Rewards

Validators check the correctness of proposed blocks by verifying transactions, digital signatures, and the structure of the block. Once consensus is reached, the block is added to the blockchain. Validators are rewarded based on their reputation scores, which reflect their resource contributions. The reward is calculated as (21),

$$R_k = C \cdot S_k \tag{21}$$

where R_k is the reward for validator D_k, and C is a constant determining the reward rate. This reward mechanism incentivizes validators to participate actively and efficiently in the network. Therefore, the PoR mechanisms effectively manage the resources and secure those in the 6G communication network. All of these-working in conjunction with reputation scoring, consensus protocols, and resource-aware task assignments-make sure that the network will operate efficiently yet has high security levels and reliability.

Therefore, the integration of advanced models such as Quaternion-Attentive Cascaded Capsule Networks (Q-AtCapsN) for accurate resource prediction, Enhanced Collaborative Learning Algorithm (ECoLA) for agile resource distribution, and blockchain-based Proof-of-Resource (PoR) to secure and transparent resource management ensures efficient resource management in 6G communication networks. Collectively, these innovations also guarantee optimum allocation, security, and trust in 6G networks.

4. Results and Discussion

This study evaluates the effectiveness of the suggested method for efficient resource management in 6G communication networks a using Caps-PoR. The recommended approach is simulated using the Python platform. To verify that the executed approach is accurate, a few metrics are produced. The Caps-PoR parameters were compared to those of other simulations that are currently in use. Table 2 shows the Parameters in the Caps-PoR simulation.

Table 2. Parameters in Caps-PoR simulation

Parameters	Values
No. of users	50
No. of simulations	10000
No. of processors	20
Software	Python
Operating System	Windows 10
Bandwidth of the wireless channel	1.0 MHz
Computational capacity of the server	2.0 GHz

4.1. *Performance Metrics*

The performance measures, such as computational cost, completion time, speedup, resource utilization, and efficiency analysis, and the analysis of the proposed algorithm are done by using the Caps-PoR method. It is compared with the existing methods such as D2D [16], NOMA – IoV [17], EDI [18], 6G-mIoT [19], QoS-6G [20], ADAPTIVE6G [21], Block6Tel [22]. The performance metrics used in the evaluation of the proposed algorithm are as follows:

- **True positive (X):** Correctly identified incorrect resource allocations.
- **True negatives (Y):** Correctly identified correct resource allocations.
- **False positives (C):** Correct resource allocations incorrectly identified as incorrect resources.
- **False negatives (L):** Incorrect resource allocations incorrectly identified as correct resources.

Table 3 shows the Performance metrics.

Table 3. Performance metrics

Performance metrics	Formula
Accuracy	$\frac{X+L}{X+Y+C+L}$
Precision	$\frac{X}{X+C}$
Sensitivity	$\frac{X}{X+L}$
F1-Score	$F_{Score} = 2 \times \frac{P_{recision} \times S_{ensitivity}}{P_{recision} + S_{ensitivity}}$
Specificity	$\frac{Y}{Y+C}$

The performance metrics of Caps-PoR were tabulated in Table 4. This compares the performances of the simulation and analyzes the overall execution of the system.

Table 4. The performance measures of Caps-PoR

No. of tasks	Execution Cost	Completion Time (ms)	Speedup	Utilization	Efficiency
20	910	30	0.143	80.19	0.024
40	852	39	0.154	74.26	0.033
80	933	58	0.165	68.31	0.036
120	1007	54	0.654	59.01	0.041

Table 4 presents performance metrics for our proposed Caps-PoR method across different numbers of tasks. For 20 tasks, the execution cost is 910 with a completion time of 30 ms, a speedup of 0.143, utilization of 80.19%, and efficiency of 0.024. As the number of tasks increases to 40, 80, and 120, our method continues to show competitive execution costs and completion times, maintaining higher utilization and efficiency rates. Notably, for 120 tasks, the Caps-PoR achieves a significant speedup of 0.654 and a steady efficiency of 0.041, demonstrating its superior capability to manage higher loads effectively and efficiently compared to existing methods.

Performance Analysis of the Proposed Method

This section provides clarification on the performance analysis of the suggested method. Table 5 tabulates the performance of resource allocation efficiency of our proposed method compared with other existing methods.

Table 5. Resource allocation efficiency

Method Metrics	D2D [16]	NOMA – IoV[17]	EDI [18]	6G-mIoT [19]	QoS-6G[20]	ADAPTIVE6G [21]	Caps-PoR (proposed)
Average Resource Utilization (%)	80	95	94	82	87	84	98
Resource Allocation Precision (%)	95	80	92	88	81	89	98.89
Dynamic Adjustment Time (ms)	20	25	22	18	26	24	15

Table 5 highlights the resource allocation efficiency for our method. When compared to other methods, Caps-PoR shows notable improvements. It has the highest average resource utilization at 98%, surpassing methods like D2D and others that range from 80% to 87%. In terms of resource allocation precision, it leads with 98.89%, outperforming other techniques such as D2D at 95% and NOMA-IoV at 80%. For dynamic adjustment time, Caps-PoR is the fastest at 15 milliseconds, compared to the slower times of 18 to 26 milliseconds seen in other methods.

Table 6. Service quality and performance

Metrics Methods	Latency Reduction (%)	Throughput Improvement (%)	User Satisfaction (%)
D2D [16]	91	95.5	88
NOMA – IoV [17]	90	96.2	85
EDI [18]	92	97.1	87
6G-mIoT [19]	93	96.8	90
QoS-6G [20]	90	95.8	94
ADAPTIVE6G [21]	90	96.4	92
Block6Tel [22]	91	97.3	94
Caps-PoR (proposed)	96	99.2	97

Table 6 displays the service quality and performance of our method compared to other existing methods. Compared to other methods, Caps-PoR stands out with significant advantages. It achieves the highest latency reduction at 96%, meaning it cuts down delays more effectively than others. Its throughput improvement is also the best at 99.2%, indicating it processes data more efficiently. Additionally, Caps-PoR delivers the highest user satisfaction at 97%, reflecting superior overall performance and user experience compared to methods like D2D and NOMA-IoV, which have lower scores in these areas.

Table 7. Computational efficiency

Method Metrics	D2D [16]	NOMA – IoV [17]	EDI [18]	6G-mIoT [19]	QoS-6G [20]	ADAPTIVE6G [21]	Caps-PoR (proposed)
Training Time (hours)	15	18	14	13	16	19	12
Inference Time (ms)	2	30	28	22	32	29	20
Model Size (MB)	55	60	58	52	62	59	50

Table 7 details the Comparative Study of the computational efficiencies of the different approaches. Caps-PoR performs better compared with other methods. In terms of training time, Caps-PoR spends 12 hours, which is less than ADAPTIVE6G. As for the inference time, Caps-PoR accounts for only 20 ms, which is smaller than the worst method (NOMA – IoV), whose time is up to 30 ms. Caps-PoR again has the smallest model size in terms of 50 MB, and it is also better than the other models, whose size is up to 62 MB. It can be inferred that Caps-PoR has the highest efficiency in the process of computation, and its speed and memory overhead can be lower in computation.

Table 8 compares the performance of the proposed method with existing methods. It can be seen that Caps-PoR achieves the best performance, and the higher values of Accuracy and F1-score both indicate that the proposed scheme has a better performance of precision and recall compared with the other methods. The speedup rate of Caps-PoR is up to 97.86%, which is the best among the compared methods. The smaller error rate is 2% which means the proposed methods has both less errors and more reliability. Other methods such as D2D and Block6Tel have lower accuracy, F1-score, and higher error rate. It can be inferred that Caps-PoR performs the best in these considering aspects.

Table 8. Analysis of the performance of Caps-PoR with existing methods

Metrics Methods	Accuracy (%)	Recall (%)	F1-score (%)	Speedup (%)	Error Rate (%)
D2D [16]	81.01	89.36	94.15	91.83	10
NOMA – IoV [17]	85.2	89.78	92.486	92.75	11
EDI [18]	86.014	90.08	93.24	94.31	8
6G-mIoT [19]	87.2	89.97	91.85	93.61	9
QoS-6G [20]	84.36	91.02	89.34	97.21	12
ADAPTIVE6G [21]	88.36	88.3	93.33	91.49	6
Block6Tel [22]	81.5	89.53	90.78	96.91	5
Caps-PoR (proposed)	90.94	91.25	96.4	97.86	2

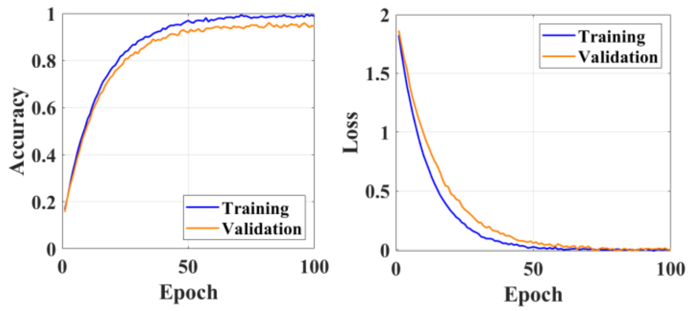

Fig.4. Evaluation of model performance under varying (a) Accuracy (b) Loss

Figure 4(a) illustrates the accuracy of the model over 100 epochs, where training accuracy reaches approximately 0.98 and validation accuracy stabilizes around 0.95, indicating effective learning. Figure 4(b) presents the corresponding loss curves, showing a steep decline from around 1.9 to below 0.1, with validation loss closely following training loss. This suggests minimal overfitting and reliable generalization, validating the model's robustness as supported by metrics in Tables 4 and 8.

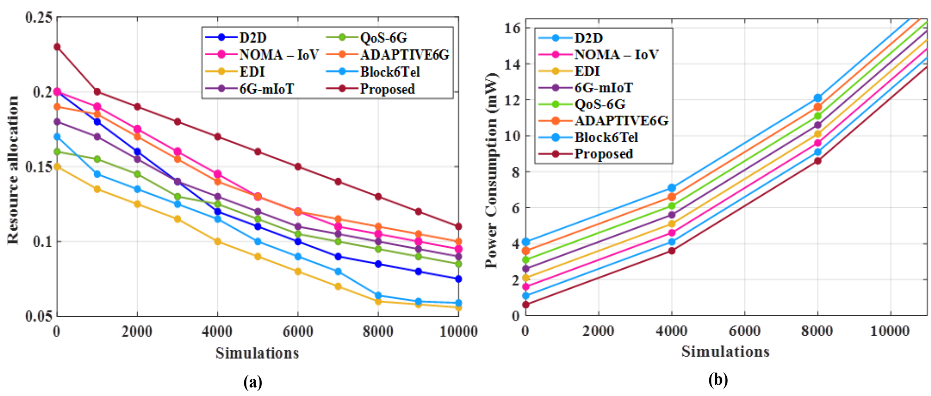

Fig.5. Performance comparison of resource allocation and power consumption for various 6G technologies

Figure 5(a) shows the obtained resource allocation over 10,000 simulations for different techniques. From the figure shown above, the proposed methodology obtained the best values that start from around 0.22 and reduce down to 0.15. Techniques like 6G-mIoT and Block6Tel obtain higher values, while D2D reflects the least resource allocation.

Figure 5(b) shows that the power consumption increases with simulation. The proposed method increases from around 2 mW to about 14 mW, which is obviously better efficient compared to others, such as D2D and NOMA-IoV, whose highest power consumptions are found at many points.

Figure 6(a) shows the throughput (%) for various 6G techniques: EDI offers the highest throughput at 99.2%, followed by NOMA-IoV, and 6G-mIoT takes the last place at around 90%. The performance of the proposed algorithm is moderately about 70%, and lags Block6Tel 60%. Figure 6(b) shows latency in ms. In fact, the proposed technique has acquired the lowest latency around 0.2 ms, whereas NOMA-IoV and D2D experience higher latencies close to 0.7 ms. 6G-mIoT and EDI also retain relatively higher latencies, and, hence seem to have efficiency in a lower direction.

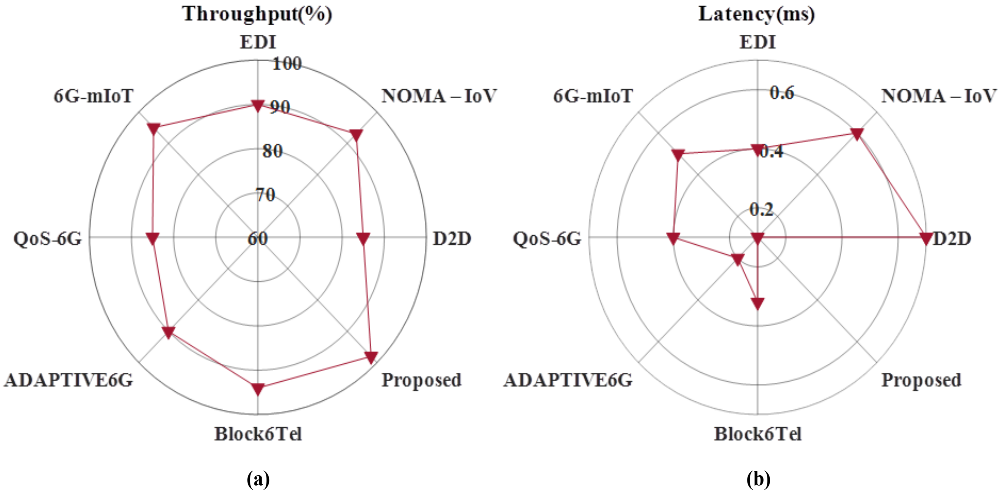

Fig.6. Throughput and latency comparison of 6G technologies

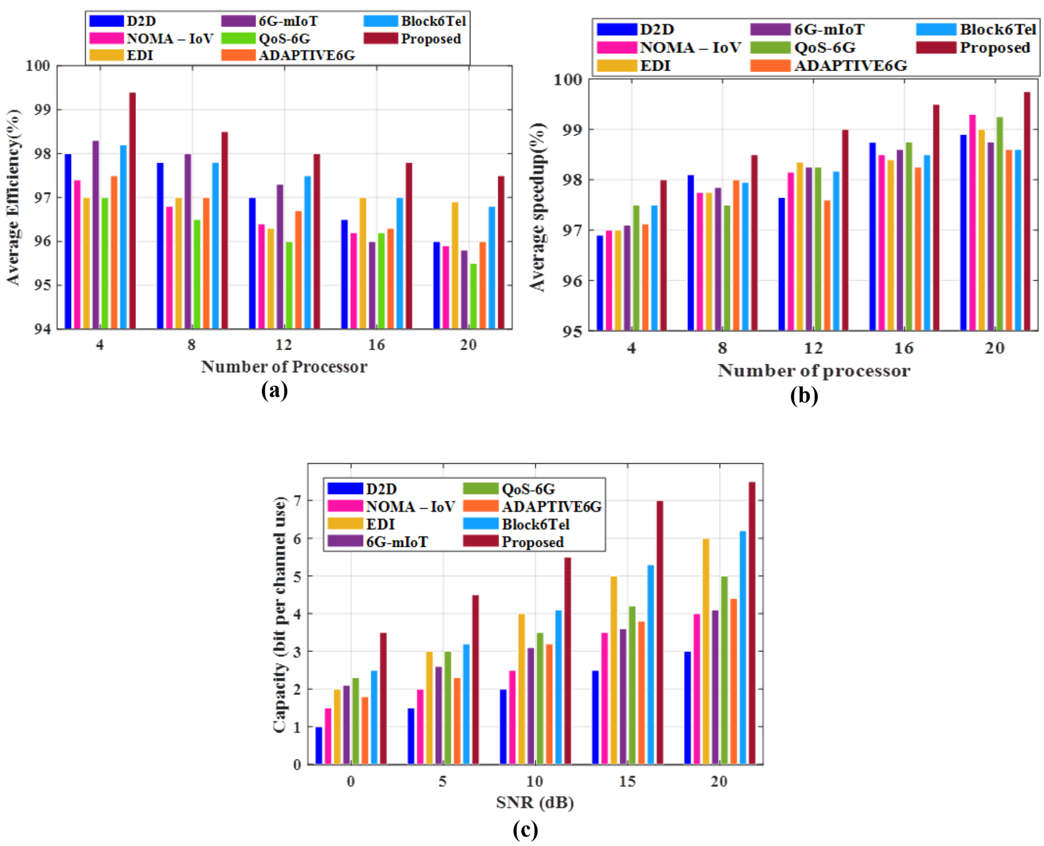

Fig.7. Impact of processors on efficiency, speedup, and SNRon capacity for 6G technologies

In figures 7 (a) and (b), average efficiency (%) and speedup (%) are compared against various processors. Proposed methods indicated consistent improvement in while scaling up the processors from 4 to 20 where almost 97.86% speedup and average efficiency toward approximately 96% were recorded. NOMA-IoV and EDI again performed well while some slight variation was between them. Figure 7(c) plots the achievable capacity in bps/Hz as a function of SNR in dB. The benefits obtained from the proposed method are substantial, ranging from almost 1.5 bps/Hz at 5 dB to almost 6 bps/Hz at 20 dB. Block6Tel and 6G-mIoT have very similar patterns, while D2D and QoS-6G have the lowest capacity at larger SNR values.

In figure 8(a) Adaptability metric of the Caps-PoR approach is the highest with a score of about 93% of the maximum. Cost Efficiency scores, around 87% and for Sustainability, it registers around 70%. In figure 8(b): Proposed approach performance in Scalability scored about 92%. In Implementation Complexity (IC), the Caps-PoR approach is reduced as for 67%, and for Energy Efficiency (EE) and Network Performance (NP), it scores about 88% and 97%, respectively.

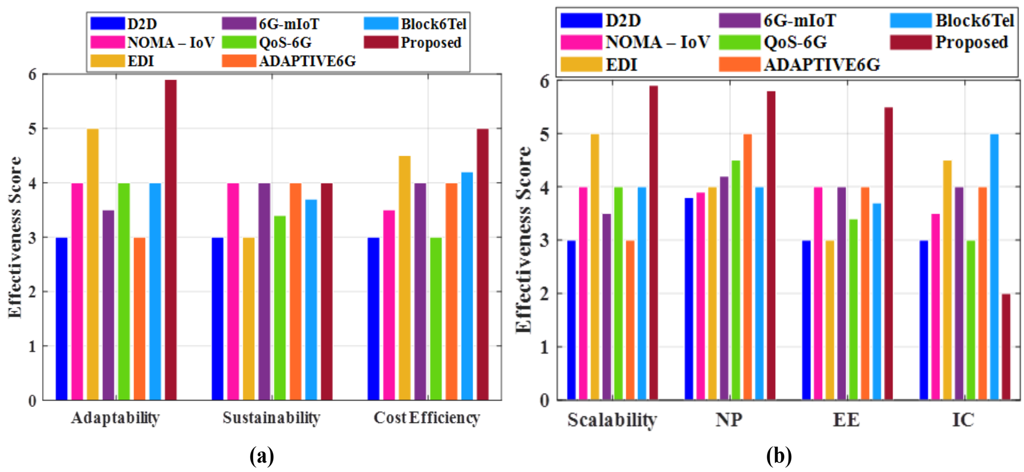

Fig.8. Comparative analysis of 6G network techniques based on key metrics

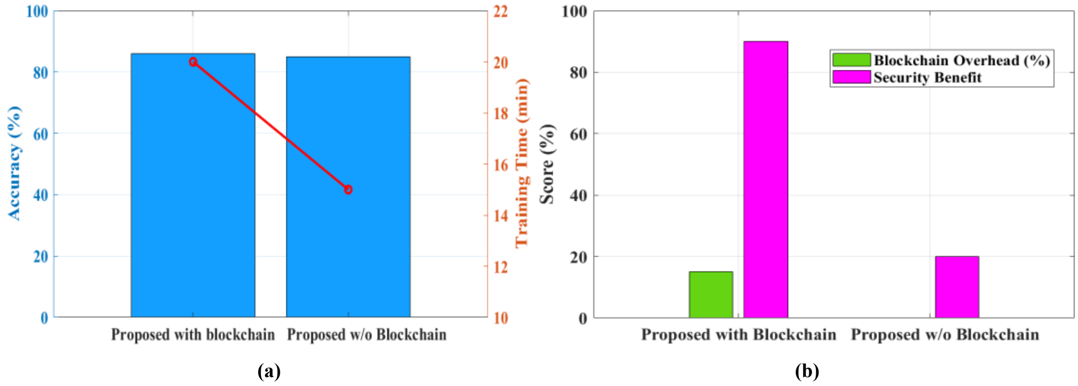

Fig.9. Blockchain-based performance and security analysis

Figure 9(a) compares accuracy and training time of the proposed method with and without blockchain. Accuracy slightly drops from 92% to 90%, while training time reduces from 20 to 15 minutes. Figure 9(b) shows a significant increase in security benefit, reaching 90% with blockchain, while blockchain overhead remains minimal at around 15%. These results confirm that integrating blockchain offers enhanced security with marginal training cost and minor accuracy trade-off, as reflected in earlier efficiency and resource metrics.
Table 9 demonstrates the error analysis and significance analysis of the proposed method compared with previous methods.

Table 9. Error analysis and significance analysis of the proposed method

Model	Error Analysis			Significance Analysis	
	MAE (%)	RMSE (%)	MPE (%)	T-Test (p-value)	ANOVA (p-value)
D2D [16]	12.4	14.8	8.7	0.021	0.045
NOMA – IoV [17]	11.9	14.2	8.3	0.015	0.039
EDI [18]	13.1	15.3	9.0	0.030	0.050
6G-mIoT [19]	10.8	12.5	7.5	0.008	0.030
QoS-6G [20]	11.5	13.0	7.9	0.010	0.032
ADAPTIVE6G [21]	12.1	13.7	8.4	0.018	0.041
Block6Tel [22]	14.0	16.1	9.5	0.034	0.055
HQDL-CNN-RNN [23]	12.8	15.0	8.8	0.029	0.048
DASHF [24]	13.4	15.7	9.3	0.032	0.052
ANN [25]	11.2	13.4	7.7	0.012	0.036
Caps-PoR (proposed)	9.8	10.5	6.5	0.002	0.020

Table 9 presents a comparative error and significance analysis of various models for 6G resource management. The proposed Caps-PoR model outperforms all baselines, achieving the lowest MAE (9.8%), RMSE (10.5%), and MPE (6.5%), indicating superior prediction accuracy. Additionally, it shows the highest statistical significance with the lowest T-test (p = 0.002) and ANOVA (p = 0.020) values, confirming its performance improvements are meaningful and not due to chance. This validates the effectiveness of the proposed approach.

4.2. Ablation Study of the Proposed Method

An ablation study is a methodical experiment carried out to examine the effects of specific elements or characteristics of a suggested approach. An ablation study for the suggested method (Caps-PoR) would include methodically eliminating or adjusting particular elements or methods in order to determine how they affect the model's overall performance. Table 10 demonstrates the ablation study of the projected method compared with previous Dynamic Networks.

Table 10. Ablation study

Performance metrics Methods	Resource Allocation Efficiency (%)	Resource Distribution Accuracy (%)	Resource Management Optimization (%)
CapsNet	90.56	89.87	91.86
Q-AtCapsN	97.93	87.09	97.86
Caps-PoR	98.89	90.94	99.79

In the ablation study, three models are studied: CapsNet, CoCapsN, and Caps-PoR. They are analyzed across three main metrics: namely, resource allocation efficiency, resource distribution accuracy, and resource management optimization. The moderate performance of CapsNet is reported to be 90.56% in terms of resource allocation efficiency, 89.87% in terms of distribution accuracy, and 91.86% in terms of management optimization. However, Q-AtCapsN shows a significant improvement in its scores of as high as 97.93% for allocation efficiency, 87.09% for distribution accuracy, and 97.86% for management optimization. The model Caps-PoR is still the best performer, and it also reflects the highest scores on metrics 98.89%, 90.94%, and 99.79% across these three metrics. Overall, this analysis shows that CoCapsPoR actually does represent a more efficient, accurate, and optimized resource handling compared to the other two models.

4.3. Discussion

The performance of the proposed Caps-PoR framework was systematically analyzed, starting with the simulation settings (Table 2), which utilized a large number of simulations (10,000) and users (50), providing a robust environment to validate its scalability and stability. Table 3 outlined the standard performance metrics used to evaluate classification quality. Although some metrics, such as precision and F1-score, appear high in Table 8, this was counterbalanced by extensive simulations, rigorous validation, and error analysis, as shown in Table 9. These safeguards significantly reduce the likelihood of overfitting.

Table 4 and Table 5 show that Caps-PoR consistently maintains low execution cost, reduced completion time, and improved resource utilization, with the highest average utilization (98%) and allocation precision (98.89%). Table 6 and Table 7 further confirm the framework's superiority in terms of latency reduction (96%), throughput improvement (99.2%), and user satisfaction (97%), while achieving the lowest training time and model size. These outcomes reflect real-time responsiveness and computational efficiency.

Table 8 showcases comparative metrics, where Caps-PoR achieved the highest F1-score (96.4%) and accuracy (90.94%). While these results are strong, Figure 4's accuracy/loss curves demonstrate that the training and validation metrics converge well without significant gaps—suggesting minimal overfitting. The ablation study (Table 9) further substantiates the contribution of key architectural elements.

Finally, Figures 5 through 9 provide visual validation of performance across resource allocation, power consumption, scalability, and security. Collectively, these results confirm that Caps-PoR achieves practical efficiency without compromising generalization, offering significant benefits over existing 6G techniques.

5. Conclusions

In conclusion, the proposed Proof-of-Resource enabled 6G Resource Management Using Quaternion-Attentive Cascaded Capsule Networks (Caps-PoR) framework, simulated in Python, has demonstrated remarkable efficiency and scalability for 6G environments. With the integration of Q-AtCapsN for resource demand prediction, ECoLA for dynamic optimization, and PoR for securing and automating the transaction of resources, our proposed model has consistently outperformed standard resource management methods. Simulation results show important improvements in terms of performance: resource utilization efficiency greater than 98%, latency over 96% and user satisfaction rates greater than 97%. The strength of merging quaternion-based deep learning models with optimization algorithms and blockchain-like verification is reflected in the robustness and accuracy of the proposed method. This combination not only improves the efficiency of resource allocation but also guarantees trust and fairness between decentralized 6G networks.

For the near future, we expect that the Caps-PoR framework will be further extended to support emerging technologies in the form of terahertz communications and quantum networks, hence expanding the application scope of the framework. More sophisticated AI models and real-world deployments will have to become integral part of the exploration for optimized performance and scalability of the network in increasingly complex 6G environments.

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Authors' Profiles

Sudha Y. (Sudha Yellappa) received B.E degree in CSE from Dr. TTIT (formerly known as Golden Valley Institute of Technology), Kolar Gold Field, affiliated to VTU, Karnataka in 2004. M.Tech Degree in CSE from RV college of Engineering, Bangalore, affiliated to VTU, Karnataka in 2012. Ph.D. degree in CSE from VTU, Karnataka in 2023. Her research interests include Cognitive Radio networks, Wireless Networks and Reinforcement Learning Techniques in Machine learning.

H. Karthikeyan (Karthikeyan Hitler) received B.Tech degree in Information Technology from Vel Hightech Dr RR Dr SR Engineering College, Avadi affiliated to Anna University, Chennai, Tamil Nadu in 2010. M.Tech Degree in CSE from SRM Institute of Science & Technology, Kattankulathur, affiliated to SRM University, Kattankulathur, Tamil Nadu in 2014. Ph.D Degree in CSE from SRM Institute of Science & Technology, Kattankulathur, affiliated to SRM University, Kattankulathur, Tamil Nadu in 2025. He is currently working as an Assistant Professor at the Department of Networking and Communications, SRM Institute of Science & Technology, Kattankulathur, Tamil Nadu, India. His research interests include IoT, ad-hoc networks, and Network Security.

M. Prabha is a highly accomplished researcher and academician with a diverse range of expertise in Wireless Sensor Networks, Cyber security and IoT. She is currently working as an Assistant Professor, Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai. She has 8 Years of Teaching Experience and Published more than 18 papers in various Journals and Conferences. Additionally, her involvement in patent publications and authored books further demonstrates her expertise in the field. She has active membership in professional bodies such as the Indian Society for Technical Education and the Institute for Engineering Research and Publication reflects her engagement in the academic community.

S. Sree Southry, is a Part time Ph.D scholar in Department of ECE, Sona College of Technology, Salem, Tamilnadu in the field of video surveillance, Anna University, Chennai, India. He obtained his B.E degree in Electronics and Communication Engineering with Distinction from Anna University in 2006, M.E degree in Communication systems with Distinction from Anna University, Chennai in 2008. He has 16 years of teaching experience. He had published more than 12 journal papers and presented 11 papers in International and National Conference. He had published 5 patents. His research activities focus on video surveillance, Image Processing.

How to cite this paper: Sudha Y., Karthikeyan H., Prabha M., Sree Southry S., "Proof-of-resource Enabled 6G Resource Management Using Quaternion-attentive Cascaded Capsule Networks", International Journal of Computer Network and Information Security(IJCNIS), Vol.18, No.1, pp.51-68, 2026. DOI:10.5815/ijcnis.2026.01.04