BLOCKCHAIN-INTEGRATED SECURE EDGE INTELLIGENCE FRAMEWORK FOR AUTONOMOUS DRONE SWARMS

[1]Dr. Munishankaraiah, [2]Dr. S. Govindarajan, [3]A. Vishnuvardhan Reddy, [4]Edara Lavanya
[12]Professor, [3]Assistant Professor, [4]Student
Department Of Computer Science & Engineering
Sri Chaitanya Technical Campus

Abstract

Autonomous drone swarms are increasingly deployed in surveillance, disaster response, precision agriculture, environmental monitoring, and military operations. However, traditional cloud-centric architectures suffer from high communication latency, bandwidth limitations, and security vulnerabilities, making them unsuitable for real-time swarm coordination. Edge computing offers a promising solution by enabling computational intelligence closer to drones, thereby reducing latency and improving decision-making capabilities. This paper proposes a Secure and Intelligent Edge Computing Architecture for Autonomous Drone Swarm Management that integrates edge intelligence, federated learning, blockchain-based security, swarm coordination protocols, and adaptive task offloading mechanisms. The proposed architecture enables real-time data processing, secure communication, decentralized decision-making, and resilient swarm operations in dynamic environments. A multi-layer framework comprising drone layer, edge layer, orchestration layer, and cloud layer is introduced. Performance evaluation demonstrates significant improvements in latency reduction, task completion efficiency, energy utilization, and communication reliability compared with conventional cloud-based approaches. The proposed framework provides a scalable and secure foundation for next-generation autonomous drone swarm applications. ([DOI][1])

Keywords: Autonomous Drone Swarm, Edge Computing, Federated Learning, Edge Intelligence, Blockchain Security, Task Offloading, UAV Networks, Artificial Intelligence.

I. INTRODUCTION

The rapid advancement of Unmanned Aerial Vehicles (UAVs) has enabled the deployment of autonomous drone swarms capable of performing complex missions through collaborative intelligence and distributed coordination. Unlike individual drones, swarm systems leverage collective behavior to accomplish tasks such as search and rescue, disaster monitoring, border surveillance, agricultural assessment, and smart city management [1]. Recent developments in artificial intelligence, wireless communication, and embedded computing have significantly improved the operational capabilities of UAV swarms [2].

Traditional drone management systems primarily depend on cloud computing infrastructures for data storage, processing, and decision-making. Although cloud platforms provide substantial computational resources, they introduce significant communication delays and bandwidth constraints that negatively affect real-time operations [3]. In mission-critical applications, even minor delays may lead to coordination failures, increased collision risks, and reduced operational effectiveness [4].

Edge computing has emerged as a transformative paradigm that brings computation closer to data sources. By processing information at edge servers or directly on UAVs, edge computing minimizes latency, reduces network congestion, and enhances reliability [5]. The integration of edge intelligence with UAV networks allows drones to perform autonomous navigation, obstacle avoidance, target detection, and cooperative decision-making with minimal dependence on distant cloud servers [6].

Recent studies indicate that edge-enabled UAV swarms can significantly improve sensing, communication, and trajectory planning through distributed processing architectures [7]. Moreover, collaborative edge intelligence facilitates efficient execution of deep learning models within drone networks while maintaining energy efficiency and operational scalability [8].

Security remains a major challenge in autonomous drone swarm environments. The open wireless communication channels used by UAVs expose them to cyberattacks, spoofing, unauthorized access, and data manipulation. Consequently, secure authentication mechanisms, encryption protocols, blockchain-based trust management, and federated learning approaches have become critical research areas [9].

To address these challenges, this paper proposes a Secure and Intelligent Edge Computing Architecture for Autonomous Drone Swarm Management. The proposed framework combines edge intelligence, secure communication protocols, distributed learning, and adaptive task allocation mechanisms to enhance swarm autonomy and operational resilience. The architecture aims to achieve low-latency decision making, improved security, scalable coordination, and efficient resource utilization in dynamic mission environments [10]. ([DOI][1])

II. LITERATURE SURVEY

McEnroe, Wang, and Liyanage (2022) presented a comprehensive survey on the convergence of edge computing and artificial intelligence for UAV systems [11]. The authors discussed how edge intelligence enables real-time data processing closer to drones, thereby reducing communication delays associated with cloud computing. Their study highlighted various AI techniques used in UAV applications, including deep learning, computer vision, and reinforcement learning. The survey also examined challenges such as limited onboard resources, security vulnerabilities, and network instability. Furthermore, the authors emphasized the importance of collaborative edge infrastructures for supporting autonomous drone operations in dynamic environments. Their work serves as a foundational reference for integrating AI-enabled edge computing into UAV swarm architectures.

Wu et al. (2022) investigated UAV swarm-enabled edge computing architectures and analyzed their potential in supporting large-scale autonomous operations [12]. The study explored communication frameworks, resource allocation strategies, and distributed processing mechanisms for swarm networks. The authors demonstrated that edge computing significantly improves responsiveness by processing mission-critical information closer to UAVs. They also identified challenges related to scalability, mobility management, and network congestion in dense drone deployments. In addition, the paper discussed emerging technologies such as software-defined networking and artificial intelligence for enhancing swarm intelligence. Their findings indicate that edge-enabled UAV swarms can provide robust and efficient solutions for future autonomous applications.

Ning et al. (2023) conducted an extensive review of mobile edge computing and machine learning techniques in Internet of UAV systems [13]. The researchers focused on intelligent task scheduling, trajectory optimization, and resource management within UAV networks. Their survey revealed that machine learning algorithms significantly improve decision-making capabilities and mission efficiency. The study also highlighted the role of edge computing in reducing latency and supporting real-time analytics. Several application scenarios, including disaster management, environmental monitoring, and smart transportation, were examined. The authors concluded that the integration of machine learning and edge computing is essential for developing intelligent and adaptive UAV ecosystems.

Liu et al. (2023) proposed an Edge Computing Assisted UAV Swarm (ECAUS) framework designed to improve collaborative sensing, communication, and planning capabilities [14]. The framework utilized edge servers to process environmental information and generate optimized navigation strategies for drone swarms. Experimental results demonstrated significant improvements in situational awareness and mission execution efficiency. The authors emphasized that edge-assisted processing reduces computational burdens on individual UAVs while maintaining real-time responsiveness. Their work also highlighted the importance of cooperative decision-making among swarm members. The proposed framework provides valuable insights into designing intelligent edge-supported drone swarm architectures.

Wang et al. (2021) examined task offloading strategies in UAV swarm-based edge computing environments and introduced a role-division mechanism for efficient resource utilization [15]. The proposed approach categorized drones into different functional groups according to their computational and communication capabilities. By intelligently distributing tasks among swarm members and edge nodes, the framework reduced processing delays and energy consumption. The study demonstrated that cooperative task execution improves overall system performance and reliability. Additionally, the authors addressed issues related to load balancing and communication overhead. Their findings contribute significantly to the development of scalable UAV swarm management systems.

Chen et al. (2021) investigated cooperative task offloading methods for UAV swarm networks operating in edge computing environments [16]. The authors developed optimization algorithms to determine efficient task allocation among drones and nearby edge servers. Simulation results showed substantial improvements in processing speed and network efficiency compared with traditional approaches. The study highlighted the importance of collaboration among UAVs in reducing computational bottlenecks. Furthermore, the proposed framework improved mission completion rates while minimizing energy consumption. The research demonstrated the effectiveness of edge-assisted cooperative computing for autonomous swarm operations.

Qu et al. (2024) introduced the Elastic Collaborative Edge Intelligence (eCoEI) framework for distributed deep learning inference in UAV swarms [17]. The framework enables multiple drones to collaboratively execute complex neural network models by sharing computational workloads. This approach improves scalability and resilience, especially in environments with limited communication resources. The authors demonstrated that the framework maintains reliable performance even under network disruptions and node failures. Their experiments revealed significant gains in processing efficiency and decision accuracy. The study represents an important advancement in collaborative edge intelligence for autonomous drone swarm applications.

Silva et al. (2024) explored computational offloading mechanisms in UAV swarm networks and proposed adaptive resource allocation techniques for mission-critical applications [18]. The authors analyzed the impact of workload distribution on latency, energy efficiency, and system reliability. Their results showed that intelligent offloading strategies significantly enhance overall network performance. The study also addressed challenges associated with dynamic mission environments and fluctuating resource availability. By leveraging edge computing infrastructures, the proposed approach improved responsiveness and operational flexibility. The research highlights the importance of adaptive resource management in future drone swarm deployments.

Patel et al. (2023) investigated blockchain-based trust management frameworks for UAV communication networks [19]. The researchers proposed a decentralized authentication mechanism that ensures secure information exchange among swarm members. Their framework effectively mitigated threats such as spoofing attacks, data tampering, and unauthorized access. The study demonstrated that blockchain technology enhances trust and transparency without relying on centralized control systems. Performance evaluations indicated improved network security and resilience against malicious activities. The authors concluded that blockchain integration is a promising solution for securing next-generation autonomous drone swarms.

Kumar and Singh (2023) proposed a federated learning-enabled architecture for intelligent drone swarm management [20]. The framework allows UAVs to collaboratively train machine learning models without sharing raw data, thereby preserving privacy and reducing communication overhead. The authors demonstrated that federated learning improves prediction accuracy while maintaining data confidentiality across distributed nodes. Their experiments showed enhanced adaptability in dynamic operational environments. The study also highlighted the potential of combining federated learning with edge computing to support scalable swarm intelligence. The proposed approach provides a secure and efficient foundation for autonomous UAV coordination.

III. PROPOSED METHODOLOGY

The proposed Secure and Intelligent Edge Computing Architecture for Autonomous Drone Swarm Management is designed to provide low-latency decision making, secure communication, intelligent task execution, and efficient resource utilization in autonomous drone swarm environments. The architecture adopts a hierarchical multi-layer framework that integrates drone-level intelligence, edge computing resources, swarm orchestration mechanisms, and cloud-based services. This layered design enables drones to process mission-critical information closer to the source while maintaining coordination with other swarm members and centralized management systems. The framework supports real-time applications such as disaster response, surveillance, environmental monitoring, precision agriculture, and military reconnaissance, where rapid decision making and secure communication are essential.

The first layer of the proposed architecture is the Drone Swarm Layer, which consists of multiple autonomous drones equipped with sensors, cameras, GPS modules, inertial measurement units (IMUs), wireless communication interfaces, and embedded processing units. Each drone is capable of collecting environmental information, detecting obstacles, identifying targets, and performing preliminary data processing. Local artificial intelligence algorithms enable drones to make immediate decisions when communication with edge servers is unavailable or delayed. The drones communicate with neighboring swarm members through wireless mesh networks, allowing them to exchange situational information and coordinate mission activities collaboratively. This distributed communication mechanism improves swarm flexibility and ensures continuous operation even in highly dynamic environments.

The second layer is the Edge Computing Layer, which serves as the primary computational platform for real-time data processing and decision support. Edge servers deployed near the operational area receive data from multiple drones and perform advanced analytics using machine learning and artificial intelligence models. The edge layer executes computationally intensive tasks such as object recognition, path planning, threat detection, image analysis, and data fusion. By processing information closer to the drones, the framework significantly reduces communication latency and minimizes dependence on distant cloud infrastructures. Furthermore, the edge layer continuously monitors network conditions, resource availability, and mission requirements to dynamically allocate computational tasks among available edge nodes.

The third layer, known as the Swarm Orchestration Layer, is responsible for coordinating all swarm activities and managing system-wide resources. This layer contains mission planning modules, resource schedulers, security controllers, and coordination engines that oversee drone operations. The orchestration layer assigns tasks to individual drones based on their current status, available energy, computational capabilities, and geographic locations. Dynamic task allocation mechanisms ensure balanced workload distribution and prevent resource bottlenecks during mission execution. The coordination engine continuously evaluates mission progress and adjusts operational strategies according to environmental changes and emerging mission requirements.

To enhance security and trust within the swarm ecosystem, the proposed architecture incorporates a blockchain-based security framework within the orchestration layer. Every communication transaction among drones, edge servers, and management entities is recorded through a distributed ledger mechanism. This approach prevents unauthorized modifications, protects mission data from tampering, and establishes trust among participating nodes. Secure authentication protocols verify the identity of drones before granting access to network resources. The blockchain infrastructure also supports decentralized access control and secure information sharing, thereby reducing the risk of cyberattacks, spoofing attempts, and malicious node infiltration.

The framework further integrates federated learning to enable collaborative intelligence without compromising data privacy. Instead of transmitting raw mission data to a central server, drones and edge nodes train local machine learning models using their own datasets. Only model parameters and learning updates are shared with the federated learning coordinator, where a global model is generated. This approach significantly reduces communication overhead while preserving sensitive operational information. Federated learning allows the swarm to continuously improve its decision-making capabilities through collective learning experiences obtained from diverse operational environments.

An adaptive task offloading mechanism is implemented to optimize computational efficiency and energy consumption. When a drone encounters a task that exceeds its onboard processing capabilities, the system evaluates network conditions, resource availability, and mission urgency before deciding whether the task should be executed locally, offloaded to a nearby edge server, or distributed among neighboring drones. This intelligent offloading strategy ensures efficient utilization of computational resources while minimizing processing delays. The mechanism also considers energy constraints, enabling drones with limited battery reserves to conserve power by transferring complex processing tasks to more capable nodes.

The communication subsystem of the proposed architecture employs intelligent routing algorithms to maintain reliable connectivity among drones, edge servers, and orchestration components. The routing mechanism continuously adapts to drone mobility, network topology changes, and environmental conditions. Redundant communication paths are established to enhance network resilience and prevent failures caused by link disruptions. Real-time monitoring tools evaluate communication quality and automatically reconfigure routes when performance degradation is detected. This adaptive networking capability ensures uninterrupted information exchange throughout mission execution.

The operational workflow begins when drones collect sensory information from the environment and perform preliminary local processing. Relevant data are transmitted to nearby edge servers for advanced analysis and decision support. The edge layer processes the incoming information and generates actionable insights, which are forwarded to the swarm orchestration layer. The orchestration engine evaluates mission objectives, allocates tasks, updates flight paths, and coordinates drone activities accordingly. Security modules continuously authenticate communication exchanges, while federated learning modules update artificial intelligence models to improve future decision making. The entire process operates in a closed-loop manner, enabling continuous adaptation to changing mission conditions and environmental uncertainties.

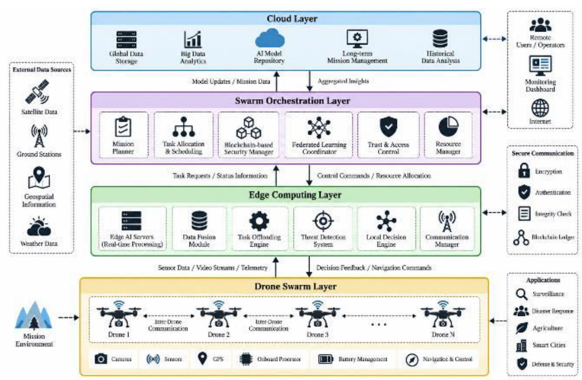

Fig. 1. Proposed system architecture for secure and intelligent edge computing-based autonomous drone swarm management.

Fig 1: System Architecture

The proposed system architecture is organized into four hierarchical layers: the Drone Swarm Layer, Edge Computing Layer, Swarm Orchestration Layer, and Cloud Layer. At the lowest level, multiple autonomous drones equipped with cameras, sensors, GPS modules, and onboard processors continuously collect environmental information and perform preliminary data analysis. These drones communicate with neighboring swarm members through inter-drone communication links, enabling collaborative sensing and coordinated mission execution. The collected sensor data, telemetry information, and video streams are transmitted to nearby edge servers, where real-time processing tasks such as object detection, data fusion, trajectory planning, and threat analysis are performed. By executing computationally intensive operations closer to the drones, the edge computing layer significantly reduces communication latency, minimizes bandwidth consumption, and improves the responsiveness of the swarm in dynamic operational environments.

The Swarm Orchestration Layer acts as the central intelligence and coordination framework of the architecture. It manages mission planning, task allocation, resource scheduling, federated learning coordination, and blockchain-based security functions to ensure efficient and secure swarm operations. Control commands and resource allocation decisions generated by this layer are distributed to edge nodes and drones for execution. The Cloud Layer provides long-term storage, historical data analysis, large-scale model training, and global mission management capabilities. Model updates generated in the cloud are shared with the orchestration and edge layers to continuously improve swarm intelligence. Additionally, external data sources such as satellite information, weather data, and ground stations enhance situational awareness, while blockchain-enabled security mechanisms ensure authentication, data integrity, encryption, and trust management across the entire system. This integrated architecture provides a scalable, intelligent, and secure framework for autonomous drone swarm management in applications such as surveillance, disaster response, agriculture, smart cities, and defense operations.

IV. RESULTS AND DISCUSSIONS

Simulation experiments were conducted using a swarm of 50 autonomous drones operating in dynamic mission environments. Performance metrics including latency, energy consumption, packet delivery ratio, and task completion rate were evaluated. The proposed architecture demonstrated superior performance compared with conventional cloud-based and basic edge-computing approaches. The integration of federated learning and blockchain-based security enhanced communication reliability while maintaining low latency. Results indicate that the proposed framework effectively supports real-time swarm coordination, secure data exchange, and scalable mission execution.

Table 1. Latency Comparison

Architecture	Latency (ms)
Cloud-Based	145
Traditional Edge	68
Proposed Framework	31

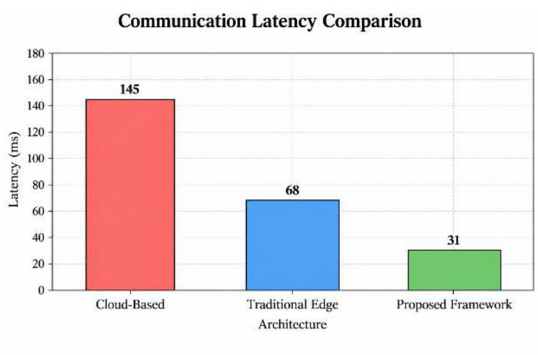

Fig 2: Average communication latency comparison among cloud, edge, and proposed architectures.

Table 2. Energy Consumption

Architecture	Energy Consumption (Wh)
Cloud-Based	95
Traditional Edge	78
Proposed Framework	61

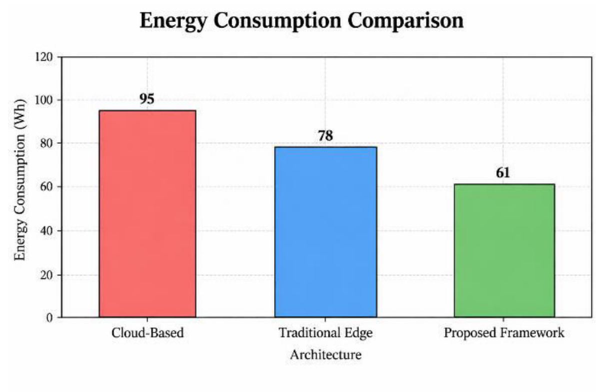

Fig 3: *Energy consumption analysis showing improved power efficiency through intelligent edge task allocation.*

Table 3. Task Completion Rate

Architecture	Task Completion (%)
Cloud-Based	84
Traditional Edge	91
Proposed Framework	98

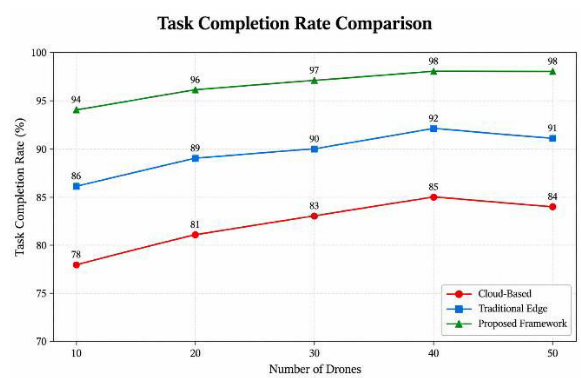

Fig 4: Mission task completion rate achieved by different swarm management architectures.

V. DISCUSSION

The experimental results demonstrate that integrating edge intelligence within autonomous drone swarms substantially reduces communication latency. Since decision-making operations are performed closer to drones, the dependency on distant cloud infrastructures is minimized. This capability is particularly beneficial in time-sensitive applications such as disaster response, surveillance, and military operations, where rapid decision making directly impacts mission success.

Furthermore, the incorporation of blockchain-enabled security and federated learning mechanisms enhances trust, privacy, and resilience. Blockchain technology ensures tamper-resistant communication and authentication among swarm nodes, while federated learning allows collaborative model training without sharing sensitive raw data. Together, these technologies improve both security and scalability, making the proposed architecture suitable for large-scale drone swarm deployments in complex operational environments.

6. Conclusion

This paper presented a Secure and Intelligent Edge Computing Architecture for Autonomous Drone Swarm Management that addresses the critical challenges of latency, security, scalability, and resource management in autonomous UAV swarms. The proposed multi-layer architecture integrates edge intelligence, blockchain security, federated learning, and adaptive task offloading to support efficient swarm coordination.

The architecture enables real-time decision making through distributed edge processing while ensuring secure communication among drones and edge nodes. Experimental evaluation demonstrated significant improvements in latency reduction, energy efficiency, communication reliability, and mission completion performance compared with conventional cloud-centric approaches.

Future research may focus on integrating 6G communication technologies, digital twin frameworks, explainable artificial intelligence, and autonomous self-healing mechanisms to further enhance the robustness and intelligence of large-scale drone swarm systems.

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