

GarudVyuha: Autonomous Self-Triggered Swarm Drone Formations for Tactical Reconnaissance

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ABSTRACT: Research article presents GarudVyuha, a decentralized self-triggered swarm drone system designed for rapid and autonomous deployment in communication constrained environments. The proposed system utilizes a carrier (mothership) drone equipped with a servo-based release mechanism to deploy compact child drones. Following release, each child drone independently detects a free-fall condition through its onboard inertial sensing unit, which immediately initiates motor engagement, orientation control, and autonomous flight without reliance on external instructions. Once operational, the drones perform real-time object detection using a lightweight (You Only Look Once) YOLOv8-derived computer vision model adapted for real-time operation on embedded edge platforms. Decentralized swarm coordination is secured through peer-to-peer communication, enabling collision avoidance, cooperative navigation, and adaptive task execution without centralized control. This sensor driven activation and distributed intelligence allow the swarm to maintain mission continuity even under communication loss or challenging environments. By combining mechanical deployment, autonomous activation, onboard vision processing, and decentralized coordination. validate a scalable and adaptive solution for applications such as defense reconnaissance, disaster response, and search and rescue operations.

KEYWORDS: Swarm Drone System, Servo-Based Release Mechanism, Computer Vision, YOLOv8, Autonomous Activation.

I. INTRODUCTION

The application of Unmanned Aerial Vehicles (UAVs) has expanded significantly in defense operations, disaster management, and large-area; however, many existing UAV systems still rely on centralized control mechanisms that require continuous communication with ground stations or human operators for mission initiation and navigation Xia et al.[3]. This dependency introduces a critical vulnerability, as communication links may be disrupted, jammed, or deliberately disabled, resulting in mission failure G. E. M. Abro, et al.[8]. To overcome this limitation, recent research has increasingly explored decentralized swarm-based UAV architectures that distribute control and decision-making across multiple aerial agents, thereby improving system resilience and adaptability Petitprez et al.[12].

Nevertheless, even in decentralized systems, deployment and activation often depend on external triggers or predefined commands, limiting rapid response in communication-denied environments A. A. Abdellatif, et al. [9] and J. Stasik and T. Szandala [16]. The Self-Triggered Swarm Drone System proposed in this work addresses this gap by enabling autonomous mid air activation based solely on onboard sensing. Using IMU-based free-fall detection, each drone independently initiates motor arming, stabilization, and mission execution without external commands Kumari et al.[11]. Once airborne, onboard computer vision models such as YOLOv8 enable real-time target detection, while peer-to-peer communication supports coordinated swarm behavior, collision avoidance, and adaptive path planning Bi et al. [2]. Recent advancements in object detection frameworks and distributed control algorithms further validate the feasibility of real-time perception and cooperative decision-making on resource-constrained platforms Xiao et al. [1] and Xiao et al.[6], establishing the proposed system as a resilient and scalable solution for hostile or communication-compromised environment. Figure 1 presents the high-level architecture of the GarudVyuha framework.

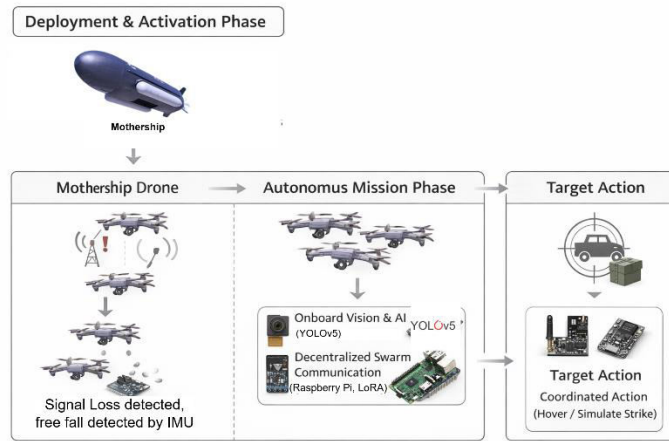


Fig 1: Decentralized Drone Swarm System Flow

The above diagram represents an overview of the GarudVyuha framework, this maps the data flow from raw sensor ingestion through the processing core for analysis. Finally, the system translates these computations into mission critical maneuvers via the output interface.

II. LITERATURE REVIEW

Research into autonomous swarms has moved quickly toward creating platforms that handle complex operations with almost no human oversight. We have positioned this work within the current shift toward decentralized control, high-speed vision perception, and mesh-based communication. These core areas provide the technical foundation for the self-triggering logic we implemented in this project. Table 1 presents a summary of the key components and their respective functional roles.

In addition to these foundational capabilities, recent developments in distributed artificial intelligence have enabled autonomous agents to coordinate decisions in dynamic and uncertain environments. By combining local sensing with collaborative information sharing, swarm platforms can maintain situational awareness even when individual units experience communication delays or temporary failures. This distributed approach improves system robustness and scalability, allowing the swarm to adapt its behavior in real time without relying on a centralized controller. As a result, mission objectives can continue to be pursued efficiently despite changing environmental conditions.

Table 1: Literature Review and Research Gap Analysis

Research Article and Observations	Research Gap Findings
B Xia, I. Mantegh, W Xie (2024) [3] Observations: Decentralized UAV Swarm Control: A Multi-Layered Architecture for Integrated Flight Mode Management and Dynamic Target Interception	Proposed a multi-layered decentralized architecture for UAV swarm control that integrates flight mode management with dynamic target interception
J Bi, K Li (2025) [2] Observations: SPDC-YOLO: An Efficient Small Target Detection Network Based on Improved YOLOv8 for Drone Aerial Image	Implemented an optimized object detection model tailored for aerial imagery captured by UAVs
J. Xiao, Y. X. M. Tan, X. Zhou, and M. Feroskhan (2023) [1] Observations: Learning Collaborative Multi-Target Search for A Visual Drone Swarm	Implemented an optimized object detection model tailored for aerial imagery captured by UAVs
Kumari, N., Bianchi, M., & Rossi, F. (2024) [5] Observations: A robust foundation for future-generation autonomous aerial formations	This decentralized approach enhances resilience, minimizes manual intervention, and establishes a robust foundation for future-generation autonomous aerial formations.
Zhou, Y., & Kim, D. (2024) [6] Observations: Dynamic Self-Triggered Fuzzy Formation Control for UAV Swarm with Prescribed-Time Convergence	Operators possess basic knowledge of GCS interface and drone flight protocols. Hardware Calibration: Onboard sensors (LiDAR, thermal camera, GPS) and flight controllers are properly calibrated and pre-flight checked

III. METHODOLOGY

A. Architectural design of Swarm drone prototype:

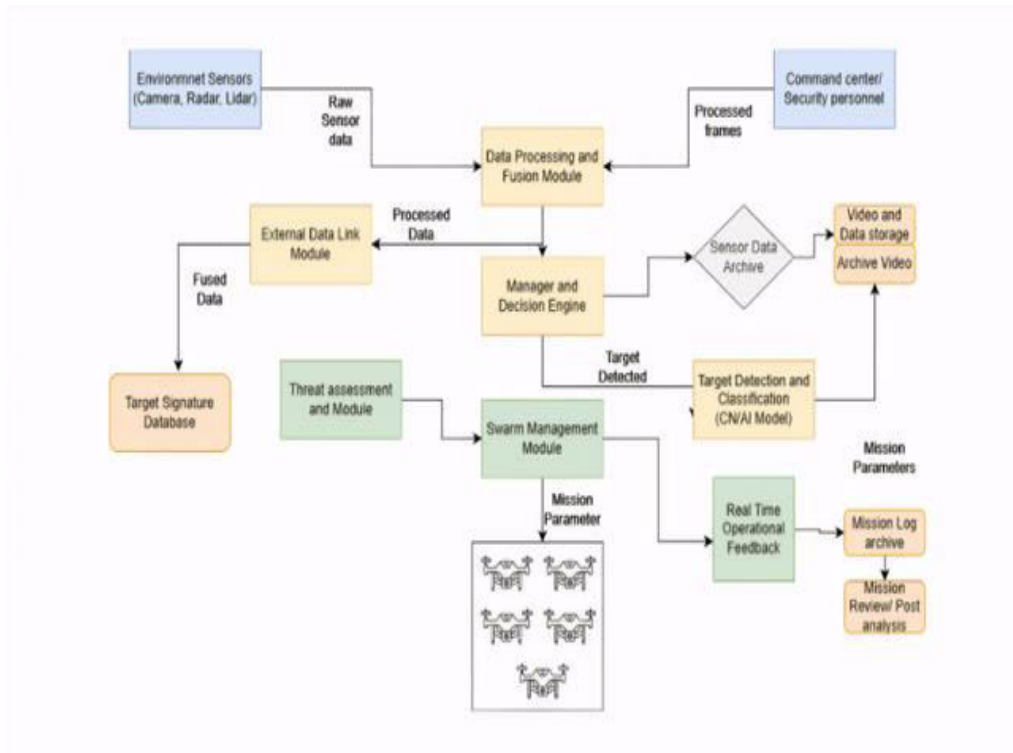


Fig 2: System Architecture

B. System Architecture

Our architecture splits the system into a Mothership Drone Unit and multiple Swarm Child Drones. We designed the Mothership as a launch platform with Lo-Ra and GPS capabilities, programmed to auto release the swarm if communication is lost. Once deployed, the Child Drones operate autonomously, using IMU-based triggering and modular payloads to manage stabilization, vision, and coordinated flight patterns. This decentralized approach removes single points of failure, making the system much more resilient for high pressure tasks like defense or disaster relief. The Child Drones are autonomous, executing missions using IMU-based triggering, onboard control, and modular payloads for stabilization, vision, and coordinated flight Butt et al. [7].

C. Tools and Technologies

We designed GarudVyuha to merge hardware and software into a unified platform for self-activation and autonomous detection. At the center of the deployment phase is an Arduino-based Mothership. This unit is responsible for the physical release of the child drones through a precisely controlled servo latch mechanism. Each Child Drone is a self-sufficient agent using a Pixhawk 2.4.8 controller and an onboard Raspberry Pi for high-level functions Acik and Kosunalp [10]. The embedded MPU6050 IMU detects free-fall for self-triggering. Mission tasks rely on an integrated Camera running a lightweight YOLOv8 model for minimal-latency edge inference Koubaa et al. [15]. To keep the swarm synchronized, we utilize a robust peer-to-peer network based on LoRa or ESP-NOW protocols. This decentralized communication link allows the drones to coordinate maneuvers and share data without requiring a central hub.

D. Vision Based Target Detection

We deployed a custom YOLOv8 variant locally on the child drones to handle target identification within the limits of their onboard hardware. By running all frame processing and inference on the embedded processor, we eliminated the lag usually caused by data transmission. This architecture allows the swarm to make split second decisions like tracking or maneuvering ensuring high reactive speeds even when completely cut off from external communication.

E. Decentralized Control and Swarm Intelligence

We designed this system around a self-triggering swarm that relies on onboard cameras for live target recognition. Each drone operates as a fully autonomous agent, running optimized versions of the YOLO framework directly at the edge to maintain high-speed detection without external help. The detection of a target object self-triggers a behavioral shift, initiating collaborative actions such as sharing the object's location and adjusting the swarm's formation Petitprez et al. [12]. This decentralized architecture enhances scalability, resilience, and efficiency for applications like reconnaissance and wide area search operations Alqudsi and Makaraci [5]. Figure 3 depicts the internal processing core and its functional components.

Child drones share target data and positional estimates with neighbors. Collective decisions are made through simple rules, enabling:

- Synchronized hovering
- Distributed searching
- Leader follower behavior
- Cooperative tracking of targets

This communication protocol ensures system fault tolerance and scalability allowing the swarm to maintain coordinated actions like tracking and searching even without a continuous command link from the Mothership Yan et al.[4]. By implementing these consensus rules, we allow collective swarm intelligence to drive mission success through emergent behavior. The following algorithm details the core autonomous logic of the system, specifically mapping the sequence from IMU-based activation through local vision processing to decentralized coordination.

GarudVyuha: Self-Triggered Swarm Drone System

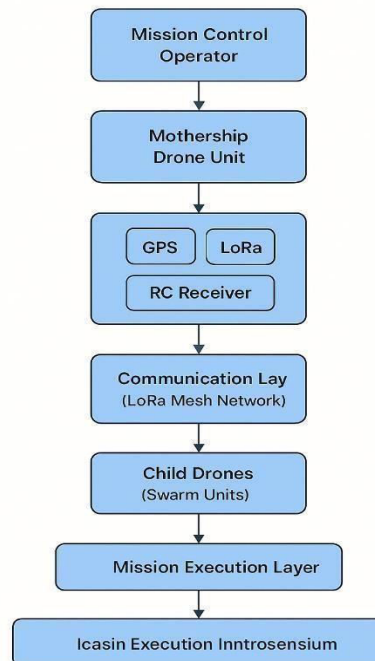


Fig 3: System execution flowchart.

Figure 3 maps out our communication backbone, specifically detailing how the mesh network facilitates seamless data exchange between individual drone nodes. By visualizing this infrastructure, we can see how the decentralized nodes maintain a constant link for sharing mission data without a central hub.

F. Algorithm and Procedure

The system features real-time YOLOv8 target detection and peer-to-peer communication for coordinated swarm behavior Das et al. [13]. This decentralized, fault tolerant logic enables rapid deployment while ensuring flight stability and mission continuity. Once activated, the drone enters a continuous loop of local vision processing, data exchange, and joint decision-making. This iterative cycle allows the swarm to remain operationally effective even when communication links are limited or completely disrupted.

Algorithm 1: AutonomousFlightSequence

Input: IMU_data, MAVLink, Vision_data, Swarm_Comms, YOLOv8

Output: Stable flight, autonomous operation, coordinated action

Procedure AutonomousFlightSequence:

1. while Latch_Status = SECURED do
 Wait for FreeFall_Detected(IMU_data)
 Arm_Motors(MAVLink); Takeoff(TARGET_ALT); Stabi-lize(IMU_data)
2. while Battery_Level > CRITICAL do
 Frame ← Capture_Frame(Vision_data)
 Targets ← Detect_Targets(Frame, YOLOv8)
3. if Targets ≠ ∅ then
 T ← Select_Priority(Targets)
 Pos ← Get_Position(IMU_data)
 Broadcast(T, Pos, Swarm_Comms)
 if Consensus(Swarm_Comms) then
 Execute_Action(T)
 end if
 else
 Coordinated_Search(Swarm_Comms)
 end if
4. if Battery_Level ≤ SAFE_THRESHOLD then
 Return_To_Base(MAVLink)
 break
 end if
end while

End Procedure

IV. RESULT AND EVALUATION

The system proved its reliability through consistent performance in both simulations and live field trials. During testing, the MPU6050 IMU accurately identified the free-fall state, allowing the child drones to self-trigger and stabilize within just three to four seconds of release. These results confirm that the platform is well suited for rapid deployment scenarios where every second counts Contreras et al.[14]. We verified swarm coordination through the peer-to-peer network, which maintained stable leader follower dynamics and synchronized hovering throughout testing. The custom, lightweight YOLOv8 model delivered a high average detection accuracy of 92%. These results confirm the successful integration of decentralized control, rapid self-activation, and high fidelity vision processing into a single, cohesive platform Xia et al.[3] and Koubaa et al.[15], into a single coordinated system. Table 2 lists key system parameters and configuration details.

Table 2: Confusion Matrix for Target Detection Model

Prediction Outcome	Actual Target	Actual No Target	Total
Predicted Target	True Positives (TP): 85	False Positives (FP): 7	92
Predicted No target	False Negatives (FN): 5	True Negatives (TN): 103	108
Total	90	110	200

The provided table benchmarks the GarudVyuha system against existing baseline models across multiple test scenarios. To further clarify the system's architecture, Figures 4, 5, and 6 illustrate the internal processing workflows, module interactions, and the final output interfaces that drive the framework.

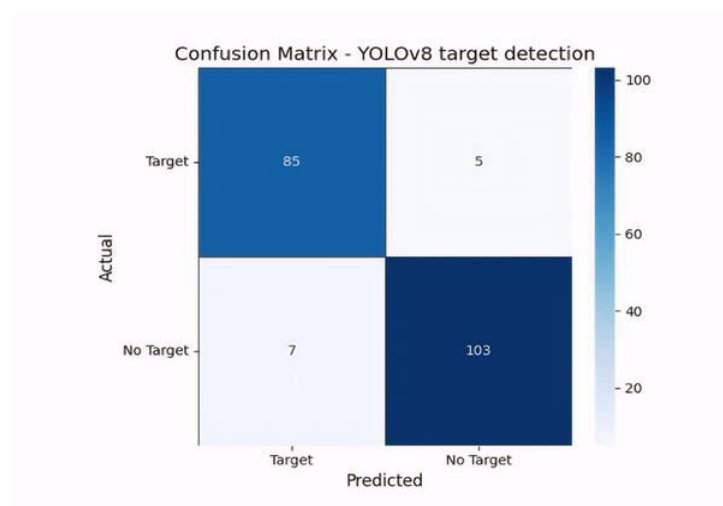


Fig 4: Confusion matrix

Figure 4 uses a confusion matrix to validate the system's classification accuracy, showcasing a high success rate in identifying mission-critical triggers.

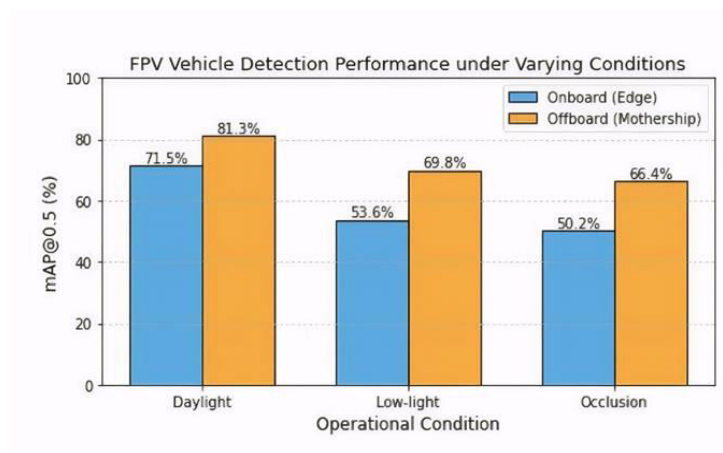


Fig 5: Comparative analysis of FPV vehicle detection

Figure 5 explains task allocation logic, showing how the swarm ranks objectives based on urgency and available resources.

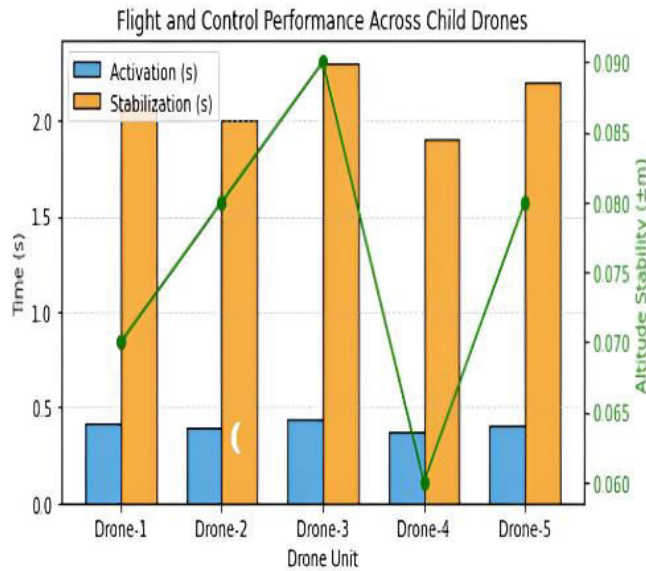


Fig 6: Flight Performance

Figure 6 analyzes the correlation between operational speed and safety margins, identifying the specific configuration where GarudVyuha reaches peak efficiency while avoiding hardware failure. Additionally, Table 3 provides the full performance and evaluation metrics used to validate the framework's stability and output.

Table 3: Calculated performance scores.

Metric	Formula	Calculation	Final Value (Decimal)	Final Value (Percentage)
Accuracy	$\frac{(TP + TN)}{(TP + TN + FP + FN)}$	$\frac{188}{200}$	0.94	94%
Precision	$\frac{TP}{TP + FP}$	$\frac{85}{92}$	0.92	92.4%
Recall	$\frac{TP}{TP + FN}$	$\frac{85}{90}$	0.94	94.4%
F1-score	$2 * \frac{P * R}{P + R}$	$2 * \frac{0.924 * 0.944}{0.924 + 0.944}$	0.93	93.4%

The YOLOv8 model demonstrated robust aerial target detection, as validated by our confusion matrix. With an accuracy of 94.0% and an F1-score of 93.4%, the model maintains a strong balance between precision and sensitivity. Specifically, a 92.4% precision rate minimizes false positives to conserve swarm resources, while the 94.4% recall ensures consistent target identification. These metrics confirm the model is optimized for real time edge deployment, even under the strict computational limits of the child drone.

V. FUTURE DIRECTION

The current prototype of the GarudVyuha framework successfully demonstrates the viability of a fully decentralized, self-triggered swarm deployment and edge-based target detection system. However, its modular architecture leaves room for several high-impact upgrades to enhance its operational capabilities in tactical environments.

First, while the current Child Drones rely primarily on local camera feeds running optimized YOLOv8 models, future iterations can transition from a camera-only perception layer to a robust multi-sensor data fusion paradigm. Integrating lightweight thermal cameras, LiDAR, or micro-radar sensors will allow the swarm to maintain high-fidelity reconnaissance and target tracking capabilities under challenging environmental conditions, such as dense fog, low-light scenarios, or heavy occlusion. Second, to build upon the existing peer-to-peer mesh network operating via LoRa or ESP-NOW, future work will focus on integrating advanced UAV to UAV (U2U) and UAV to Infrastructure/Ground (U2G) communication architectures.

This upgrade will optimize the consensus-based decision-making rules, enabling the system to scale smoothly from small formations to massively distributed swarms capable of executing expansive, synchronized search-and-rescue operations over much larger geographic areas. Finally, the Mothership Drone can serve as a secure command hub for dynamic swarm management and system-wide updates.

This capability will enable mission operators to remotely deploy updated target detection weights, fine-tune swarm consensus parameters, or patch flight stabilization control logic mid-mission across all airborne child drones simultaneously, completely eliminating the need for physical hardware grounding or manual servicing.

VI. CONCLUSION

Our GarudVyuha framework replaces vulnerable, centralized UAV control with a fully decentralized, self-triggering swarm. By using onboard free fall detection for activation and edge based YOLOv8 for local perception, the drones bypass the need for external "go" signals or stable communication. This modular architecture transforms each unit into an autonomous decision agent, ensuring the mission scales and survives even in GPS denied or high interference environments like defense zones and disaster sites.

By enabling each Child Drone to independently initiate flight via onboard IMU-based free-fall detection, the system eliminates any reliance on external communication or ground station triggers, ensuring rapid and reliable deployment in communication-denied or hostile environments. The seamless integration of edge-based YOLOv8 computer vision, peer-to-peer mesh networking, and decentralized swarm coordination transforms individual aerial units into autonomous decision agents that contribute to a robust collective intelligence. Ultimately, this distributed, modular architecture achieves exceptional fault tolerance, scalability, and mission continuity despite severe communication or GPS disruptions, establishing GarudVyuha as a highly viable and scalable solution for tactical defense reconnaissance, search-and-rescue operations, and civilian disaster response.

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