

Swarm Knowledge Exchange: An Edge-Assisted Semantic Communication Framework for Resource-Constrained Multi-Robot Systems

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Abstract - Swarm robotics evolved from the study of social insect behaviour, and modern research has shifted its focus toward exchanging structured knowledge instead of raw sensor data. This paper proposes a swarm robotics framework that enables robots to exchange structured knowledge rather than raw sensor data, improving communication efficiency and collective decision-making. Swarm robots must work together to complete complex tasks; however, sharing raw sensor data between robots increases communication overhead. A knowledge-based approach instead allows robots to exchange only meaningful information, communicating more efficiently. A Swarm Knowledge Exchange (SKE) framework that uses AI to generate and share compact Knowledge Objects through a lightweight communication network is developed. The framework uses ESP32-based robots fitted with ESP32-CAM modules, together with an AI server running OpenCV and YOLO for perception. Detected information is converted into Knowledge Objects containing object identity, location, confidence, and timestamp, which are shared between robots using MQTT. Swarm Knowledge Exchange (SKE) provides an efficient framework for collaborative multi-robot systems. It improves communication and swarm intelligence and is suitable for search and rescue, warehouse automation, industrial inspection, agriculture, and autonomous exploration.

Key Words – Swarm Robotics, Semantic Communication, Knowledge Capsule, MQTT, ESP32, YOLO, Edge AI, Multi-Robot Systems.

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I. INTRODUCTION

Swarm robotics technology utilises multiple robots working collaboratively to achieve shared objectives, such as target searching, surveillance, exploration, disaster management, and environmental monitoring. This cooperative approach distributes key functions like sensing, processing, navigation, and decision-making among the robots. Effective cooperation requires information exchange about the environment, traditionally carried out through raw data transmission — a method prone to high bandwidth demands and increased communication load as the number of robots grows. Moreover, repeated observations by different robots on the same object can lead to unnecessary redundancy in sensing and computation.

To mitigate these issues, recent research has explored semantic communication, which focuses on sharing only the information necessary for collaborative tasks, thereby reducing communication overhead while enhancing cooperative perception and navigation. Innovations in behaviour trees, experience sharing, and action advising in multi-robot systems show that knowledge transfer can significantly enhance performance, allowing agents to leverage insights from one another rather than learning independently.

The proposed Swarm Knowledge Exchange (SKE) framework embodies this concept by prioritising the sharing of relevant environmental knowledge over raw data transfer. In this framework, robots observe their surroundings and utilise AI-based perception tools like YOLO and OpenCV to generate meaningful insights, which are then condensed into 'Knowledge Capsules.' These capsules are transmitted via MQTT to other robots, which validate them by checking their confidence, timestamp, TTL, and duplication status before storage. The

SKE framework aims to establish a lightweight communication system that enables robots to collectively accumulate and reuse environmental knowledge efficiently.

II. LITERATURE SURVEY

Recent research has focused on semantic communication and knowledge transfer for multi-robot and multi-agent systems. The first study emphasises task-oriented semantic communication, which shares task-relevant information rather than complete raw sensory data, motivating the use of compact semantic information in the proposed Swarm Knowledge Exchange (SKE) framework. The second study, known as KT-BT, explores structured knowledge transfer using Behaviour Trees, highlighting the significance of representing knowledge in a transferable format. The third work, SEAC, examines experience sharing among agents in multi-agent reinforcement learning, illustrating that information generated by one agent can enhance learning efficiency for others.

A comparison of these studies indicates that task-oriented semantic communication reduces the necessity of transmitting full sensory data, KT-BT provides structured knowledge transfer, and SEAC facilitates experience reuse among agents. In contrast, the proposed SKE method focuses on Knowledge Capsule-based semantic exchange, utilising YOLO/OpenCV and MQTT for sharing validated semantic knowledge, incorporating features like confidence, timestamps, Time-To-Live (TTL), and duplicate checking. Table I summarises this comparison.

TABLE I. COMPARISON WITH EXISTING APPROACHES

Paper No.	System Description	Key Features	Results / Outcome
[1]	Task-oriented semantic communication framework that shares 3-D semantic scene information rather than complete raw sensory data for multi-robot collaboration.	Compresses perception output into task-relevant semantic descriptors before transmission.	Reduces transmission bandwidth and motivates the use of compact semantic representations for swarm communication.
[2]	KT-BT: a structured knowledge-transfer framework using Behaviour Trees to represent and share robot knowledge in multi-robot systems.	Encodes knowledge in a transferable, human-readable behaviour-tree format.	Improves knowledge reuse, but does not define a lightweight wireless messaging protocol for real-time exchange.
[3]	SEAC: a Shared Experience Actor-Critic framework for experience sharing among agents in multi-agent reinforcement learning.	Agents share learning experience with one another to accelerate training.	Improves learning efficiency across agents, though it targets simulated RL agents rather than embedded swarm robots.
Our Work	Knowledge Capsule-based semantic exchange framework built on ESP32 swarm robots, using YOLO and OpenCV for perception and MQTT for communication.	Compact JSON Knowledge Capsules carrying confidence, timestamp and TTL, with duplicate-ID validation before reuse.	Reduces communication payload, minimises redundant processing, and enables validated knowledge reuse for search and rescue, warehouse automation, industrial inspection, agriculture, and exploration.

III. MATERIALS AND METHOD

This section describes the hardware and software components used to build the proposed Swarm Knowledge Exchange (SKE) prototype.

III.1 Components

III.1.1 ESP32 Microcontroller

The ESP32 is a low-cost, low-power system-on-chip microcontroller with integrated Wi-Fi and Bluetooth connectivity, widely used in IoT and robotics applications. In the SKE framework, the ESP32 acts as the on-board controller of each swarm robot, running the motor-control logic, publishing and subscribing to Knowledge Capsules over MQTT, and coordinating the robot's local decision-making.



Fig. 1. ESP32 development board ×2

III.1.2 ESP32-CAM Module

The ESP32-CAM is a compact camera module built around the ESP32 chip that streams image frames over Wi-Fi. It serves as the visual sensor for each robot, providing the raw frames that are pre-processed and analysed for object detection.



Fig. 2. ESP32-CAM module ×2

III.1.3 YOLO Object Detection

YOLO (You Only Look Once) is a real-time object-detection algorithm that predicts object classes, bounding-box locations, and confidence scores in a single forward pass. A lightweight YOLOv8n model deployed on the AI server performs object detection on incoming camera frames, providing the semantic fields — object identity, location, and confidence — used to build each Knowledge Capsule.

III.1.4 OpenCV

OpenCV is an open-source computer-vision library used for image pre-processing tasks such as frame cleanup and resizing before detection, and for auxiliary image-processing operations that support the object-detection pipeline.

III.1.5 Knowledge Capsule

A Knowledge Capsule is a compact representation of detected information, containing the following fields:

- Knowledge ID
- Source Robot
- Object
- Location

- Confidence
- Timestamp
- Time-To-Live (TTL)

Example: Knowledge ID K1024 from Robot_01 identifies a Person at (12.4, 8.7) with 0.94 confidence, timestamped at 10:32:18 and a TTL of 30 seconds.

III.1.6 MQTT Protocol

MQTT (Message Queuing Telemetry Transport) is a lightweight publish-subscribe messaging protocol suited to resource-constrained devices and low-bandwidth networks. In the SKE framework, a Mosquitto broker enables communication between robots, allowing Knowledge Capsules to be published by one robot and subscribed to by others over a shared topic.

III.1.7 Knowledge Repository and Validation Module

The Knowledge Repository stores valid Knowledge Capsules for future use in decision-making. Before storage, each incoming capsule passes through the Validation Module, which checks its confidence score, timestamp, TTL, and Knowledge ID to reject low-confidence, expired, or duplicate capsules.

III.1.8 TP4056 Li-Po Charging Module

The TP4056 module manages safe lithium-polymer battery charging over USB and provides over-charge and over-discharge protection for each robot's battery.



Fig. 3. TP4056 Li-Po charging module ×2

III.1.9 MT3608 Boost Converter

The MT3608 is a DC-DC boost converter that steps up the Li-Po battery voltage to a stable, regulated supply for the ESP32, camera module, and motor driver.



Fig. 4. MT3608 DC-DC boost converter ×2

III.1.10 MG90S Micro Servo

The MG90S micro servo provides pan-tilt actuation for the on-board camera, widening each robot's field of view during perception.



Fig. 5. MG90S micro servo $\times 2$.

III.1.11 Motion and Display Peripherals

Each robot additionally uses a TB6612 dual-channel motor driver to control its micro gear motors for movement, a 3.7 V Li-Po battery as the power source, and a 0.96-inch OLED display used to indicate the robot's current status.



Fig. 6. TB6612 motor driver $\times 2$, 0.96" OLED display $\times 2$ and 3.7 V Li-Po battery $\times 2$

III.2 Wiring Diagram:

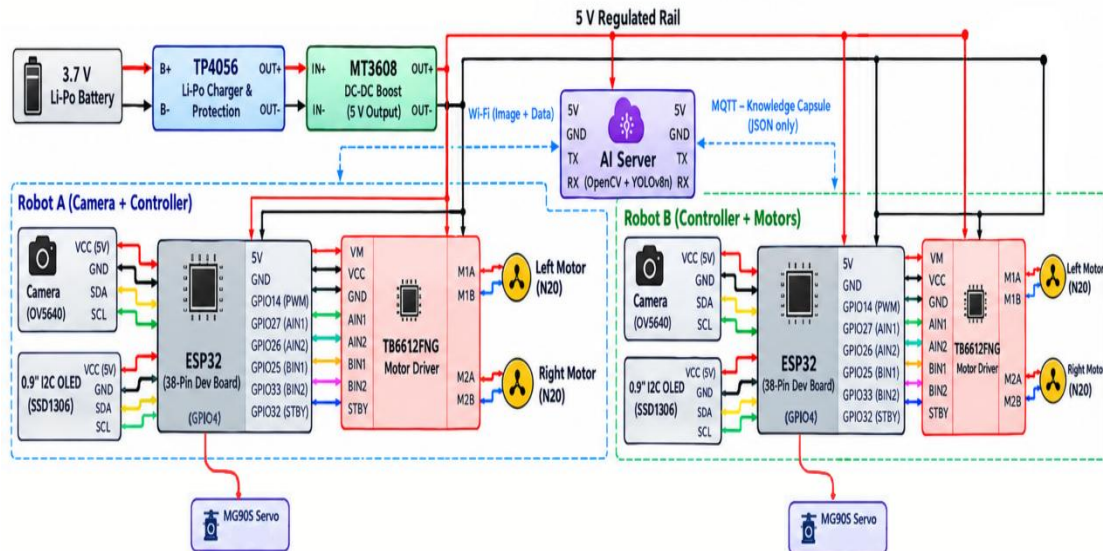


Fig. 7. Wiring diagram.

III.3 Computer and Software Tools Arduino IDE:

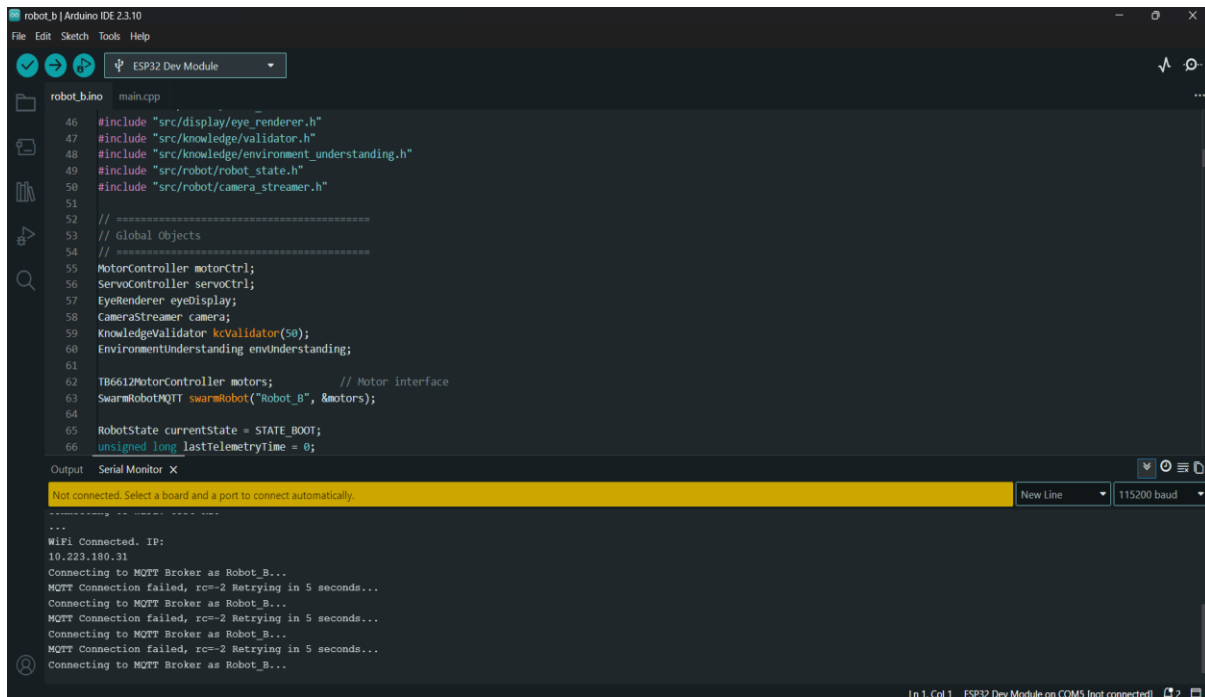


Fig. 8. Arduino Software IDE.

IV. PROPOSED METHODOLOGY

The proposed SKE workflow proceeds through the following stages:

Camera/Sensor → YOLO + OpenCV → Semantic Information → Knowledge Capsule → Validation → MQTT → Receiving Robot → Knowledge Repository → Decision-Making

First, the robot captures real-time observations from its environment. These observations are processed using YOLO and OpenCV to detect relevant objects. The identified information is then transformed into a Knowledge Capsule that includes critical semantic data such as object type, location, confidence level, timestamp, and Time-To-Live (TTL). This capsule is transmitted using MQTT to another robot, which validates the information prior to storage.

The validation process checks confidence levels, timestamps, TTL, and duplicates to ensure that only high-quality knowledge is retained. Low-confidence data or expired capsules are discarded, and each Knowledge Capsule is assigned a unique identifier to avoid redundancy. Only validated information is stored and used for decision-making.

Swarm Knowledge Exchange

YOLO performs perception; Knowledge Capsules represent semantic knowledge; MQTT enables validated swarm exchange.

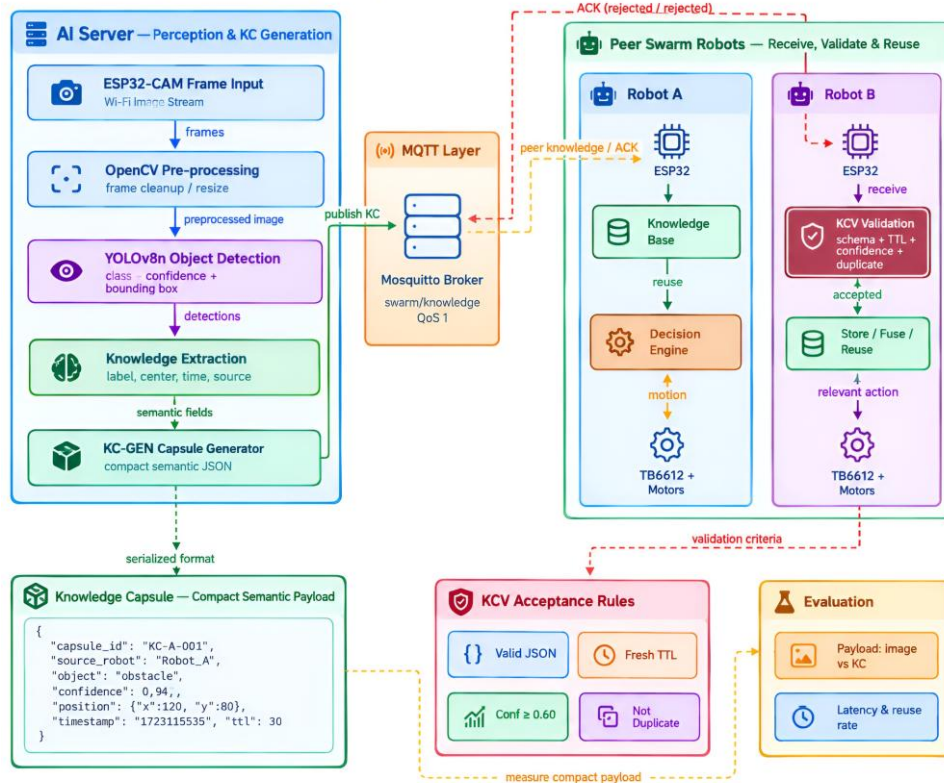


Fig. 9. System architecture of the proposed Swarm Knowledge Exchange (SKE) framework.

V. IMPLEMENTATION

V.1 Implementation Overview

The system comprises the following key modules:

- Image Acquisition Module
- YOLO Object Detection Module
- OpenCV Processing Module
- Knowledge Capsule Generator
- MQTT Communication Module
- Knowledge Validation Module
- Knowledge Repository
- Decision-Making Module

V.2 Object Detection Process

Upon detecting an object, a Knowledge Capsule is created and published via MQTT. Other robots receive and validate the capsule's information.

V.3 Information Handling

Valid and new information is stored in the Knowledge Repository. Duplicate, expired, or low-confidence information is rejected. The system improves efficiency by allowing robots to reuse information gathered by their peers.



Fig. 10. Assembled prototype of two ESP32-based SKE swarm robots used for experimentation.

VI. RESULT AND DISCUSSION

VI.1 Benefits of the Framework

- Reduces communication payload by transmitting semantic information instead of raw data.
- Minimises redundant processing through knowledge reuse.
- Enhances information sharing using MQTT for communication.
- Increases knowledge reliability through confidence and timestamp validation.
- Reduces duplicate information using Knowledge ID checks.
- Manages knowledge lifetime through Time-To-Live (TTL).
- Promotes improved collaboration among robots by sharing acquired information.

VI.2 Comparison with Conventional Communication

- SKE transmits compact semantic knowledge instead of raw images or sensor data.
- Message sizes are limited in SKE, contributing to efficient communication.
- SKE features enhanced duplicate handling and information validation.
- Knowledge reuse is a key feature of SKE, unlike traditional raw-data approaches.

VI.3 Performance Evaluation Criteria

- Communication data size
- Communication latency
- Knowledge reuse rate
- Duplicate rejection rate
- Valid knowledge rate
- Task completion time

Numerical results for the above criteria are to be obtained through further experimentation on the physical prototype.

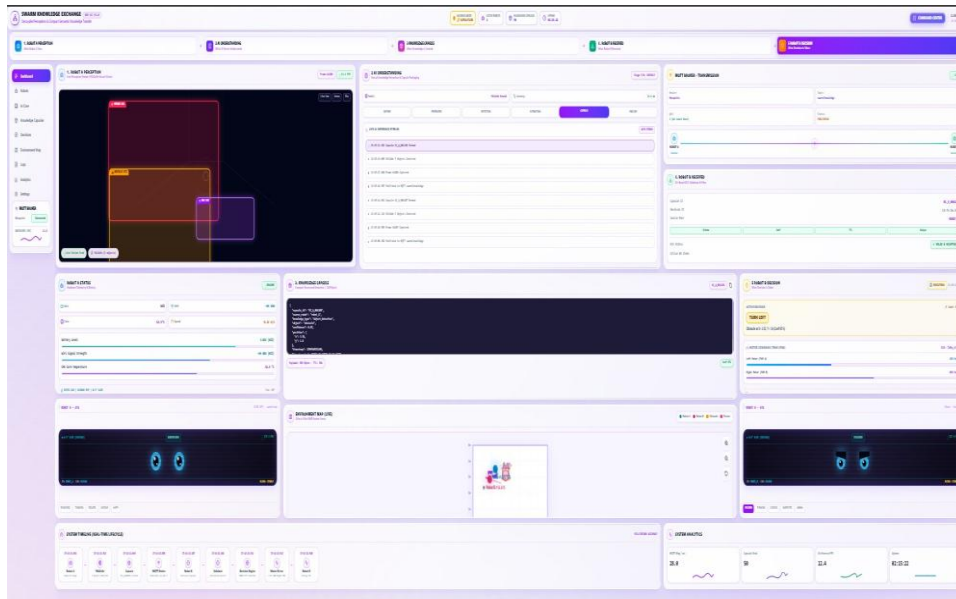


Fig. 11. Real-time SKE simulation dashboard showing robot perception, knowledge-capsule generation, MQTT transmission, and robot decision-making.

VII. CONCLUSION

This paper introduced Swarm Knowledge Exchange (SKE), a semantic knowledge-sharing framework designed for multi-robot systems. The core concept revolves around exchanging compact, meaningful knowledge instead of complete raw observations. The system employs YOLO and OpenCV for perception, transforming detected data into Knowledge Capsules that are exchanged via MQTT.

It utilises mechanisms such as confidence ratings, timestamps, Time-To-Live (TTL), and duplicate checking to validate incoming information before storage and reuse. This framework aims to minimise communication overhead, prevent redundant processing, and enhance information reutilisation among swarm robots.

Future work will involve implementing SKE on the physical prototype at scale and empirically assessing communication efficiency, latency, knowledge reuse, and collaborative task performance. Ultimately, SKE offers a lightweight solution for creating swarm robots that effectively share and reuse crucial environmental insights.

REFERENCES

- [1] R. Xue, J. Tan, F. Liu, J. Tong, T. Wang, and S. Wang, "From Raw Data to Shared 3D Semantics: Task-Oriented Communication for Multi-Robot Collaboration," arXiv preprint arXiv:2602.08624, 2026.
- [2] S. Oruganti Venkata, R. Parasuraman, and R. M. Pidaparti, "KT-BT: A Framework for Knowledge Transfer Through Behavior Trees in Multi-Robot Systems," arXiv preprint arXiv:2209.02886, 2022.
- [3] F. Christianos, L. Schäfer, and S. V. Albrecht, "Shared Experience Actor-Critic for Multi-Agent Reinforcement Learning," arXiv preprint arXiv:2006.07169, 2020.
- [4] S. Oruganti Venkata, R. Parasuraman, and R. M. Pidaparti, "IKT-BT: Indirect Knowledge Transfer Behavior Tree Framework for Multi-Robot Systems Through Communication Eavesdropping," arXiv preprint arXiv:2312.11802, 2023.
- [5] K. Tsukahara, K. Tanaka, D. Iwata, and J. T. Y. Liang, "Multi-Robot Data-Free Continual Communicative Learning from Black-Box Visual Place Recognition Models," arXiv preprint arXiv:2503.02256, 2025.
- [6] F. Liu et al., "Hybrid Knowledge Transfer for MARL Based on Action Advising and Experience Sharing," *Frontiers in Neurorobotics*, 2024.
- [7] D. Shi et al., "Knowledge Reuse of Multi-Agent Reinforcement Learning in Cooperative Tasks," *Entropy*, vol. 24, no. 4, 2022.
- [8] T. Wang, X. Peng, and D. Xu, "S²ES: A Stationary and Scalable Knowledge Transfer Approach for Multiagent Reinforcement Learning," *Complex & Intelligent Systems*, 2021.
- [9] B. Chen, Y. Zhang, X. Xia, M. Martinez-Garcia, and G. Jombo, "Knowledge Sharing Enabled Multi-Robot Collaboration for Preventive Maintenance in Mixed Model Assembly," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 11, pp. 8098–8107, 2022.
- [10] Y. Liang and B. Li, "Parallel Knowledge Transfer in Multi-Agent Reinforcement Learning," arXiv preprint arXiv:2003.13085, 2020.