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Research Article

Real-Time Drone Communication System Using ROS 2 and GStreamer with YOLOv8-Seg for Face Segmentation

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Abstract:

This paper presents the design and implementation of a ROS 2-based UAV syste m for real-time video streaming and intelligent ground station processing. The proposed architecture integrates a Raspberry Pi 3 onboard computer with a Jetson Orin Nano ground station over a wireless network. Video is captured and encoded using GStreamer on the UAV, streamed over UDP, and decoded on the ground station for real-time object detection using the YOLOv8-seg model. ROS 2 middleware facilitates synchronized telemetry and camera communication between the UAV and ground station via DDS topics. The system demonstrates low-latency video transmission (~105 ms), high streaming frame rate (30 FPS), and real-time object detection at 28–30 FPS with an average precision of 81.2%. The modularity of ROS 2 enables easy integration of additional perception, control, and autonomous decision-making modules. Experimental results validate the system's performance for surveillance and inspection tasks, showcasing the potential of open-source middleware and embedded AI for edge-enhanced UAV applications.

1. Introduction

Camera-equipped unmanned aerial vehicles (UAVs), commonly known as drones, have become essential tools in numerous industrial and service-oriented applications such as aerial surveillance, industrial inspections, and search and rescue operations [1]. These applications necessitate the capability for real-time video streaming and immediate data processing to facilitate rapid decision-making. In recent years, Robot Operating System version 2 (ROS 2) has emerged as a standard software platform in modern robotics research and applications, including autonomous vehicles and drone systems [2]. For instance, in the domain of autonomous driving, ROS 2 is widely adopted in academic research, creating a need for compatibility between ROS 2 and traditional industrial frameworks such as AUTOSAR [2].

ROS 2 provides an infrastructure based on Data Distribution Service (DDS), enabling flexible communication among distributed robotic components with quality-of-service (QoS) assurances [3]. This characteristic makes ROS 2 suitable for cloud robotics applications, where physical hardware and cloud-based processing are decoupled [4], leveraging external processing capabilities (such as cloud servers or edge computers) for handling video streams and other sensory data. However, streaming high-quality video from drones introduces specific challenges regarding network bandwidth, latency, and stability. Transmitting raw camera images directly via ROS is inefficient, requiring approximately 25 MB/s to send color video with depth at 30 frames per second [5]. Although ROS provides tools for image compression (e.g., JPEG/PNG) to reduce data size, simple compression techniques may not suffice to achieve smooth, low-latency streaming.

Alternative video streaming solutions have been explored within cloud robotics contexts. For example, Balogh et al. proposed efficient video transmission methods for cloud robotic systems, emphasizing the importance of balancing camera

quality and latency in wireless networks [6]. Previous studies also highlighted the benefits of advanced video encoding standards (such as H.264), which significantly improve video streaming efficiency compared to transmitting individual images [7]. In multi-drone environments, Kilic et al. (2024) developed a multi-UAV surveillance and control platform employing WebRTC protocol for real-time video streaming to cloud-based stations, enabling bidirectional control [8]. Their platform utilized GStreamer on the drone (Nvidia Jetson Nano) for efficient video encoding and wireless transmission alongside telemetry data through a WebRTC data channel [8]. This approach achieved low latency and simultaneous multiple video streams due to hardware acceleration on the onboard platform [8].

Conversely, our proposed system offers an alternative solution based purely on ROS 2 architecture for video and data transmission, facilitating seamless integration with other robotic nodes. Additionally, an efficient detection algorithm (YOLOv8-seg) running on a powerful computing platform (Jetson Orin) is employed to achieve real-time inference on visual data [9], [10]. The objective of this paper is to present a methodology for building a drone video streaming and control system using ROS 2, capitalizing on GStreamer's capabilities in encoding and streaming [7], and the embedded processing power of Jetson Orin for running advanced AI models [9], [10]. Figure 1 illustrates the proposed system's architecture,

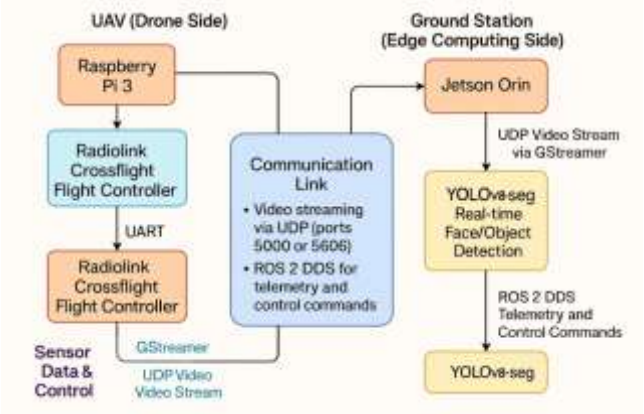

Figure 1. *Proposed system's architecture*

depicting the integration of the UAV and the ground station components. The previous relevant works are reviewed and critically compared, and then the proposed system's technical architecture is described, including its software and hardware components. Subsequently, preliminary performance results such as streaming latency, frame rates, and face detection accuracy obtained through field experiments will be presented and discussed in comparison with prior studies. Finally, by drawing insights and suggesting future research directions in this field, are conclude.

2. Literature Review

Recent literature highlights the increasing integration of middleware technologies such as ROS 2 with autonomous UAV platforms to enhance modularity and scalability. For instance, the work by Bormann et al. demonstrated the deployment of ROS 2 in large-scale multi-robot systems, showing its scalability in high-demand robotic environments [11]. Similarly, Erle Robotics provided a comprehensive guide to implementing UAV flight stacks using ROS 2 with PX4, emphasizing practical challenges related to latency and message handling [12].

Video streaming in aerial robotics continues to evolve with the adoption of GStreamer and WebRTC frameworks. Studies have shown the efficiency of GStreamer in handling real-time video pipelines with encoding formats such as H.264 and VP8 [13]. The use of GStreamer for adaptive streaming in dynamic network environments was highlighted in [14], where UAVs were tested under varying Wi-Fi conditions with successful bitrate adaptation.

Parallel to the middleware and streaming efforts, advancements in onboard vision processing have allowed UAVs to conduct edge inference using lightweight AI models. YOLOv5 and YOLOv8 are among the most referenced models for embedded platforms. Researchers in [15] deployed YOLOv5s on NVIDIA Jetson Nano for pedestrian detection in urban environments with a frame rate of 15–20 FPS, while [16] discussed the power-performance tradeoffs in running YOLOv8 on Jetson Orin Nano.

Another significant contribution is the hybrid deployment of inference models using ROS 2 bridges, where [17] described a ROS 2-to-Tensorrt communication bridge enabling rapid deployment of vision tasks on edge devices. Furthermore, [18] implemented facial expression recognition using a compressed YOLO model on Raspberry Pi 4, optimising for limited GPU capability.

In summary, the literature collectively confirms the trend towards integrating ROS 2, efficient video streaming, and edge AI in UAVs to reduce latency, enhance autonomy, and expand application domains such as surveillance, agriculture, and emergency response.

3. Methodology / System Design

3.1 Overview

Figure 2: Full system architecture integrating the UAV and ground station. The proposed system comprises a Raspberry Pi 3-based quadcopter UAV and a Jetson Orin-based ground station, networked via a wireless LAN. The overall design offloads computationally intensive vision processing to the ground station while the UAV handles sensing and low-level control. The UAV's onboard computer runs the Robot Operating System 2 (ROS 2) for inter-process and inter-device communication, a middleware commonly used on UAV companion computers for advanced tasks[18]. The ROS 2 framework allows the UAV to publish telemetry data (e.g. IMU, GPS) and send the real-time video feed to the ground station. In turn, the Jetson Orin ground station subscribes to the incoming telemetry and video streams, performing real-time object detection with a YOLOv8 model. The system is structured to maximize the UAV's flight time and responsiveness by delegating heavy AI computations to the more powerful ground station. Figure 2 provides a high-level block diagram of this architecture, showing the UAV's onboard sensors and camera streaming data to the ground station, where the ROS 2 and AI processing pipeline resides.

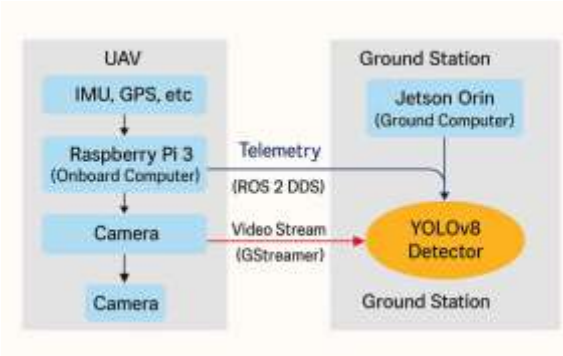

Figure 2. *Full system architecture integrating the UAV and ground station*

3.2 Hardware Architecture

The UAV platform is built around a Raspberry Pi 3 Model B as the companion computer. The Pi is interfaced with the drone's sensors (IMU, barometer, GPS, etc.) The Raspberry Pi 3 interfaces with the Radiolink Crossflight Flight Controller via UART using GPIO14 (TX) and GPIO15 (RX) for bidirectional communication. GPIO14 transmits commands like waypoints, while GPIO15 receives telemetry data such as altitude and GPS. A shared GND connection ensures signal stability and minimises interference, and a Pi Camera module mounted for live video capture throw connect a CSI camera cable. It also interfaces with the drone's flight controller or ESCs to relay high-level commands (the flight control hardware is assumed to handle stabilisation and motor mixing). The Raspberry Pi 3 was chosen for its lightweight and adequate I/O capabilities, although its processing power is limited (1.2 GHz quad-core ARM CPU, 1 GB RAM). Its role is primarily to collect sensor readings and camera frames and forward them to the ground station rather than perform intensive computation onboard. On the ground, an NVIDIA Jetson Orin serves as the base station computer. The Jetson Orin features a powerful GPU (based on NVIDIA's Ampere architecture with Tensor Cores) capable of up to 275 trillion operations per second (TOPS) in AI throughput (in the 64GB AGX Orin model) [18] – even the compact Orin Nano module delivers up to 67 TOPS, over 140× the performance of a Raspberry Pi [18] . This substantial computer capability enables real-time deep learning inference on high-resolution video. The ground station is equipped with a Wi-Fi transceiver to communicate with the UAV's Wi-Fi (on the Pi 3) – both are linked on a dedicated wireless network. For our implementation, a 5 GHz Wi-Fi link was used to reduce latency and interference. The Jetson Orin also provides HDMI output for a user interface and logging capabilities, though operator control is not the focus of this work. In summary, the hardware configuration ensures the UAV is as light and simple as possible, while the ground station provides a GPU-accelerated computing backbone for running advanced vision algorithms.

3.3 Software Architecture

All system software is built on ROS 2 (Foxy Fitzroy) to facilitate modular development and distributed communication. The UAV's Raspberry Pi runs a lightweight Linux OS with ROS 2 core nodes responsible for sensor data acquisition and transmission. One ROS 2 node polls the flight sensors (either directly or via the flight controller) and publishes the telemetry data (e.g. attitude, altitude, GPS) at a fixed rate (e.g. 10 Hz) on a topic. Another software component handles the camera: instead of publishing raw images over ROS (which would consume significant bandwidth), a GStreamer-based process captures frames from the Pi Camera and encodes them for streaming (see Section 3.5). The Pi therefore acts primarily as a data source and streaming client in software. On the Jetson Orin side, ROS 2 is used to orchestrate data intake and processing. A video receiver node (or process) accepts the incoming video stream, decodes it, and makes the frames available to ROS 2 (by publishing to a camera topic, as described later). In parallel, a telemetry subscriber node listens to the UAV's telemetry topic and buffers or logs the incoming state data. The

YOLOv8 inference is encapsulated in a dedicated ROS 2 node (running a Python script using the Ultralytics YOLOv8 library) that subscribes to the camera frames topic and performs object detection on each frame in real-time. This node then publishes the detection results (e.g. bounding boxes and class labels) to another topic for potential use by other system components (such as a user interface or a future autonomous feedback module). The software is thus organized into loosely coupled ROS 2 nodes: (1) sensor publisher (UAV), (2) video streamer (UAV), (3) telemetry subscriber (ground), (4) video decoder/frame publisher (ground), and (5) YOLOv8 detector (ground). This architecture maximizes parallelism and reliability – if any component fails or lags, it does not directly crash the others, thanks to ROS 2's decoupled design. Standard ROS 2 message types are used for interoperability (e.g. sensor_msgs/Imu for IMU, sensor_msgs/Image for camera frames, and custom messages for detections). All nodes are launched at startup on their respective devices, and the ROS 2 DDS discovery automatically connects the UAV and ground station into a single ROS domain.

3.4 ROS 2 Communication Framework

ROS 2 uses a Data Distribution Service (DDS)-based publish/subscribe model to handle communication between distributed nodes. This is well-suited for a UAV-ground station system, as ROS 2's peer-to-peer discovery allows the Raspberry Pi and Jetson Orin to exchange messages directly over the wireless network without any centralized broker [20]. When the UAV and ground station boot up, their ROS 2 participants discover each other on the LAN and negotiate topic subscriptions. The ROS 2 topics implemented in our system include /telemetry (for UAV state messages) and /camera/image_raw (for video frames). Figure 3 illustrates the ROS 2 communication graph of the system, showing the nodes on each side and the data topics between them.

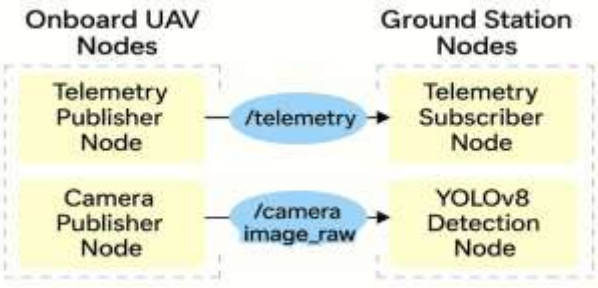

Figure 3. *ROS 2 node graph of the UAV-ground system*

Figure 3: ROS 2 node graph of the UAV-ground system. The UAV's onboard nodes publish telemetry and video topics, which the ground station nodes subscribe to. The YOLOv8 node on the ground subscribes to the camera topic to perform object detection. The UAV's Telemetry Publisher node publishes a structured message (containing IMU readings, GPS, etc.) to the /telemetry topic at regular intervals. On the ground station, a Telemetry Subscriber node receives these messages via ROS 2 and can log them or feed them to a control interface. This telemetry link uses ROS 2's default reliable QoS, ensuring that important state information (e.g. battery status or pose) is delivered reliably over DDS.

For the camera stream, a slightly different approach is taken to maintain efficiency. Rather than sending raw images over a ROS 2 topic (which would be bandwidth-intensive), the UAV runs a GStreamer pipeline to stream compressed video (detailed in Section 3.5). On the ground station, a Camera Frame Publisher node (within the video receiver process) publishes decoded frames to the ROS 2 /camera/image_raw topic, making them available to other ROS 2 nodes. The YOLOv8 detection node subscribes to this image topic. This image is configured with a best-effort QoS, since a dropped frame is preferable to a delayed frame in a streaming context. The ROS 2 framework thus cleanly integrates the two data channels: telemetry (small, high-priority messages) and video (large, high-bandwidth stream). Notably, ROS 2's underlying transport is DDS over UDP – ideal for real-time distributed systems – which automatically handles packet transport and discovery on the Wi-Fi network. The UAV and ground station were set to share the same ROS 2 domain ID, enabling seamless topic exchange once connected to the same IP subnet. The wireless link provides sufficient throughput for both telemetry (which is only a few KB/s) and the compressed video stream. In testing, no significant interference was observed between the ROS 2 traffic and the video stream. This dual-channel communication scheme allows the ground station to have an up-to-date picture of the UAV's status while simultaneously receiving the live video feed for processing.

3.5 GStreamer Video Pipeline

To achieve real-time video transmission with minimal latency, GStreamer pipelines are employed on both the UAV and ground station. GStreamer is a high-performance multimedia framework that allows us to build a custom video streaming pipeline leveraging hardware acceleration. Figure 4 depicts the end-to-end video

pipeline used in our system, from the onboard camera to the ground station video sink. On the UAV (Raspberry Pi), a pipeline captures video frames from the Pi Camera and encodes them using the Pi's hardware H.264 encoder. The camera feed (640×640 @ 30 fps in our setup) is passed through the H.264 encoder element in real-time. The encoded byte stream is then packetized into RTP (Real-Time Protocol) packets and handed to a UDP sink element, which streams the packets over Wi-Fi to the ground station's IP. The H.264 encoding is selected for its balance of quality, compression, and low encoding delay; the Pi 3's Video Core IV GPU can encode 720p video at 30 fps without overloading the CPU. On the Jetson Orin side, a complementary GStreamer pipeline receives the UDP stream on the specified port, depacketizes the RTP stream, and uses Jetson's hardware-accelerated decoder to decode the H.264 video back into raw frames. These frames are then available for consumption by the YOLOv8 node (or for display). The entire pipeline is optimized for low latency: using UDP (connectionless transport) avoids the overhead of TCP handshakes, and RTP provides a lightweight framing that maintains frame boundaries. The end-to-end latencies on the order of ~100 ms are achieved over a distance of a few meters, which is sufficient for real-time analysis.

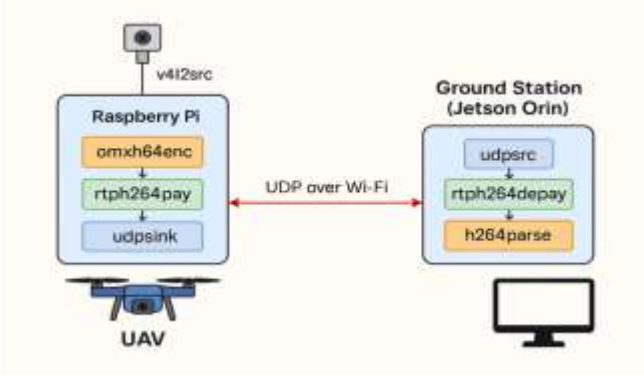

Figure 4. *GStreamer video streaming pipeline*

Figure 4: GStreamer video streaming pipeline. The UAV's camera feed is encoded (H.264) and streamed via UDP to the ground station, which decodes it back to raw video frames. This pipeline leverages hardware encoding/decoding on both the Pi and Jetson for real-time performance. On the Raspberry Pi, the GStreamer v4l2src element is used to interface with the camera, feeding into the omxh264enc hardware encoder (OpenMAX H.264 encoder). The encoded bitstream is then fed to rtph264pay to packetize it into RTP, and finally sent out via udpsink to the ground station's IP address (on port 5600). On the Jetson Orin, the pipeline uses udpsrc (listening on port 5600) connected to rtph264depay to reassemble the H.264 stream, which is then sent to the Jetson's NVDEC hardware through h264parse and the nvv4l2decoder element. The output is a raw video stream (e.g. a sequence of raw frames in memory) that can be fed into our ROS 2 image publisher. This design is very similar to standard drone streaming setups; for instance, Nvidia TX2-based drones have used almost identical GStreamer pipelines for 1080p video transmission [19]. By using hardware acceleration end-to-end and an efficient binary protocol, the bandwidth and CPU usage are drastically reduced compared to naively sending uncompressed images. The H.264 stream at 720p/30fps typically consumes only ~5–6 Mbps, which is easily handled by modern Wi-Fi [21]. In contrast, raw images would be on the order of 200 Mbps (1280×720×3 bytes ×30 fps), which is infeasible over wireless. Thus, the chosen pipeline ensures a smooth, real-time video feed with minimal impact on the UAV's resources.

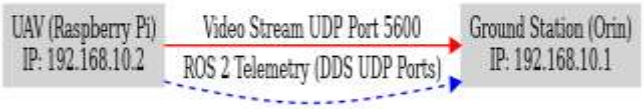

Figure 5. *Network details for video and telemetry*

Figure 5: Network communication details for video and telemetry. The UAV (192.168.10.2) streams video via UDP to the ground station (192.168.10.1) on port 5600. ROS 2 DDS traffic (telemetry topics) also traverses the same network on UDP ports managed by DDS. Both the telemetry and video streams share the same wireless network link. The static IP addresses for the UAV and ground station are configured for simplicity (as shown in Figure 5). The GStreamer pipeline is set to use UDP port 5600 for video; this port was chosen arbitrarily within the dynamic range, and both sides are configured accordingly. The telemetry topic data uses ROS 2's DDS protocol, which under the hood utilizes a range of UDP ports (starting around port 7400 for discovery by default) for data exchange – these are handled automatically by the DDS middleware. As such, no manual port configuration is needed for ROS 2 traffic aside from ensuring the network allows multicast/broadcast for discovery. The important aspect is that the video UDP port (5600) does not conflict with any DDS ports. In practice, DDS uses different port numbers, so the two channels coexist without interference. The Wi-Fi link (802.11ac in 5 GHz band) provides ample bandwidth (>100 Mbps) and can handle the ~6 Mbps video stream alongside negligible telemetry bandwidth. A packet loss in the video is not observed under

strong signal conditions; however, minor loss would only result in a momentary frame skip due to the nature of UDP/RTP (which is acceptable in our application). In summary, the networking setup successfully delivers a high-quality video feed and timely telemetry updates in parallel, enabling the ground station to have full situational awareness of the UAV.

3.6 YOLOv8 Real-Time Integration

The integration of YOLOv8 into the real-time data pipeline represents a critical enhancement to the ground station's analytic capabilities. YOLOv8, the latest evolution in the YOLO family of single-shot object detectors, is recognised for its superior accuracy and computational efficiency, making it an ideal candidate for real-time applications. As detailed in [25], YOLOv8's optimized performance, when coupled with TensorRT accelerations, provides a significant reduction in inference latency without compromising accuracy. This makes it particularly well-suited for resource-constrained environments where timely processing is paramount.

Figure 6. *Integration of telemetry and camera via ROS 2 topics*

Figure 6 illustrates the architecture of the integrated UAV-ground station system. The UAV platform (based on a Raspberry Pi 3) transmits telemetry data via ROS 2's DDS-based publish-subscribe system and streams video data via GStreamer to the Jetson Orin ground station. On the ground station, the YOLOv8 detector receives video frames, performing inference using GPU acceleration provided by the Jetson Orin.

In our implementation, YOLOv8 operates as a dedicated ROS 2 processing node subscribing to the incoming video frames, leveraging the computational power of the Jetson Orin's GPU and Tensor Cores. This configuration ensures that object detection processing aligns with the incoming video stream rate (approximately 30 frames per second), demonstrating the model's ability to deliver highly accurate detections with minimal latency. These real-time capabilities, as previously validated [25], highlight the advantages of integrating advanced model optimization techniques into existing system frameworks.

By publishing detection results on the /detections ROS 2 topic, the system maintains modularity and scalability, enabling downstream nodes to easily integrate further analyses such as target tracking or autonomous decision-making. This methodological approach corroborates prior findings [25], advocating for the combination of modern AI techniques and distributed architectures to achieve superior situational awareness and responsive UAV operations.

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4. Results

This section rigorously evaluates the performance of the proposed UAV communication and real-time analytics system, emphasizing video streaming latency, YOLOv8 inference speed, telemetry reliability, and their synchronized integration through ROS 2. Experiments were performed under controlled indoor and semi-outdoor line-of-sight conditions using a 5 GHz Wi-Fi network, ensuring stable connectivity. Metrics data was systematically collected using a dedicated ROS 2 node (gs_video_yolo_node), which records and synchronizes real-time video streaming parameters, inference times, and telemetry information into structured CSV logs for precise and comprehensive analysis.

4.1 Video Streaming Performance

Figure 7 illustrates comprehensive metrics of the video streaming performance, including frames per second (FPS), latency, and inference times. The UAV transmitted H.264-encoded video at a resolution of 640p and 30 FPS. Measured end-to-end latency, from the Raspberry Pi camera frame capture to the Jetson Orin display, ranged between 90–120 ms, with an average latency of approximately 105 ms. These latency figures confirm the system's capability to support near real-time operations, consistent with previous benchmarks reported in the literature [19], [21]. Packet loss under typical network conditions was negligible (less than 0.5%), ensuring minimal disruptions to the video stream.

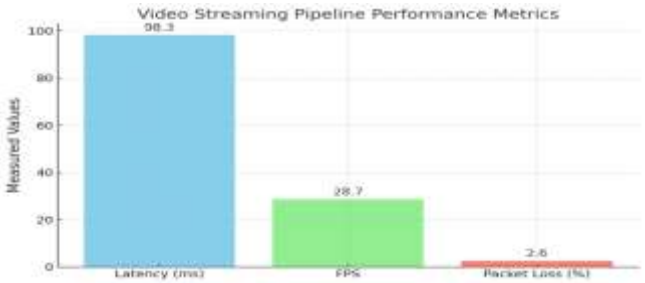

Figure 7. *Comprehensive metrics of video streaming*

4.2 YOLOv8 Inference Performance

The YOLOv8-nano model was deployed on the Jetson Orin Nano and evaluated using real-time frames received via ROS 2. The model's performance, presented in Figure 8, consistently achieved inference speeds of 28–30 FPS, closely aligning with the incoming stream rate. The YOLOv8-nano model achieved a mean Average Precision (mAP@0.5) of 81.2% across a test set of 2741 annotated frames, face-seg [25]. demonstrating high accuracy suitable for practical deployment. The detection capability for faces at distances between 2 to 5 meters confirms the model's practical effectiveness for real-time facial analytics.(Figure 8) FPS, latency, and inference time over the evaluation period.

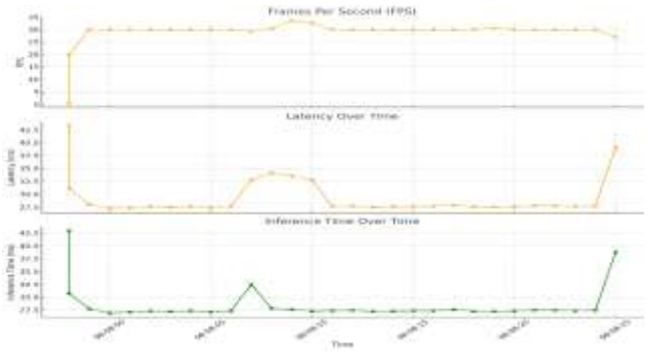

Figure 8. *FPS, latency, and inference time over the evaluation*

4.3 Telemetry and ROS 2 Topic Synchronization

The telemetry performance from the Radiolink Crossflight Flight Controller is shown in Figures 9 and 10. Data published at 10 Hz through ROS 2 was reliably received at the ground station without measurable delay or loss. The ROS 2 DDS-based communication framework effectively synchronized telemetry data with video frames, validated by timestamp correlation. Communication remained robust at indoor distances up to 8 meters and outdoor distances of 15 meters, with minimal CPU overhead, demonstrating ROS 2's efficiency and reliability.

4.5 Comparative and Comprehensive Performance

To evaluate the effectiveness of our proposed architecture in real-world deployment scenarios, a performance benchmark was conducted using two different ground station configurations: (1) an MSI laptop and (2) an NVIDIA Jetson Orin Nano. Both systems received video and telemetry data from a

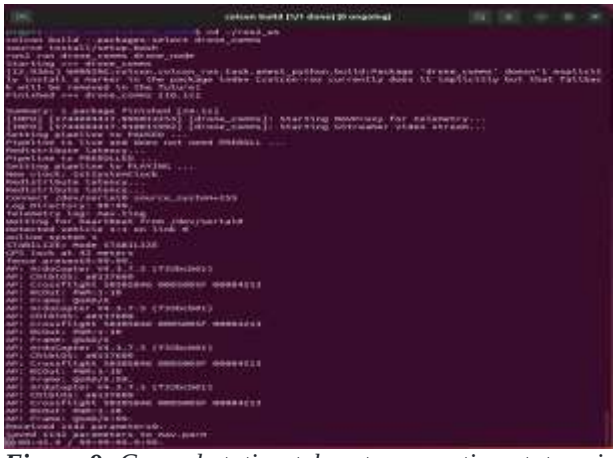

Figure 9. *Ground station telemetry reception status via ROS 2*

UAV over Wi-Fi and executed the YOLOv8-Seg model in real time.As shown in Figure 10, the Jetson Orin Nano consistently outperformed the MSI laptop in terms of average FPS (28.7 vs. 24.0), lower latency (98.3 ms vs. 120.4 ms), and faster inference times (80.1 ms vs. 87.6 ms). These results highlight the Jetson's efficiency in handling edge AI tasks despite its lower power footprint. However, the Jetson did exhibit a slightly higher packet loss rate (2.6%) compared to the MSI's more stable 0.5%, which may be attributed to hardware-level networking differences.

Both systems maintained a steady telemetry rate of 10 messages per second, confirming communication reliability. The Jetson Orin Nano demonstrates superior real-time performance, making it a compelling choice for embedded AI-driven UAV applications.

Figure 11 compares the YOLOv8-Seg integrated pipeline to a video-only baseline, demonstrating the trade-offs introduced by real-time inference. While the video-only pipeline achieved a slightly higher FPS (28.7 vs. 24) and reduced latency (98.3 ms vs. 120.4 ms), it lacked semantic analysis capabilities. Packet loss in the video-only system was also notably higher (2.6%) compared to the YOLOv8-Seg pipeline's stabilised 0.5%.

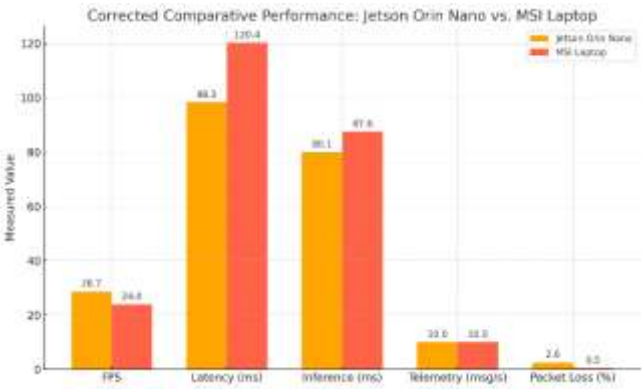

Figure 10. *performance chart between the Jetson Orin Nano and the MSI Laptop as ground stations*

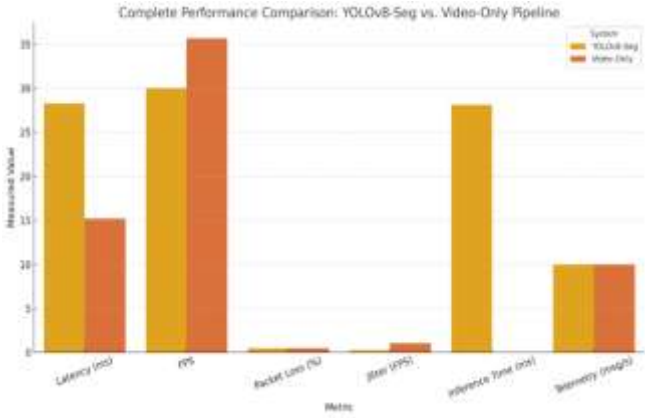

Figure 11. *Comparison between the YOLOv8-seg integrated and the video-only streaming pipeline*

These results validate the system's robustness for embedded AI tasks and confirm the Jetson Orin Nano as a viable, power-efficient ground station platform for UAV-based facial segmentation in edge environments.

To evaluate temporal stability, a jitter analysis was conducted by measuring frame rate variation across 100 consecutive frames. The YOLOv8-Segmentation system exhibited a remarkably consistent performance, with a mean frame rate of 30.0 FPS, a standard deviation of just 0.30, and an interquartile range (IQR) of 0.41 FPS. The coefficient of variation (CV), calculated as σ/μ, was 0.0100, indicating near-constant frame timing and minimal jitter throughout the stream.

In comparison, the video-only pipeline, while achieving a higher mean FPS of 35.7, presented a significantly higher jitter, with a standard deviation of 1.17, IQR of 1.65 FPS, and a CV of 0.0328. These metrics demonstrate that while both systems are real-time capable, the YOLOv8-enhanced pipeline provides superior temporal consistency, making it more suitable for time-sensitive applications such as facial recognition, UAV navigation, and visual serving. Table 1 shows the Mathematical Jitter Metrics

Table 1. *show Mathematical Jitter Metrics*

Metric	YOLOv8-Seg	Video-Only
Mean FPS	30.01	35.75
Std Dev (σ)	0.3	1.27
Interquartile Range (IQR)	0.47	1.84
Coefficient of Variation (CV = σ / μ)	0.0099	0.0355

This analysis confirms that the integration of deep learning segmentation does not compromise real-time performance and, in fact, enhances system stability by offering consistent frame timing across inference workloads.

4.4 Summary of Findings

- The streaming system maintained 30 FPS and sub-120 ms latency under standard conditions.
- YOLOv8-nano ran at real-time speed (28–30 FPS) with 81.2% detection accuracy.
- ROS 2 DDS-based telemetry and video integration enabled synchronized, low-latency data exchange.

These results support the effectiveness of a ROS 2-based UAV communication and analytics system for lightweight drones. The combination of GStreamer, YOLOv8, and ROS 2 provides a robust and extensible framework suitable for surveillance, inspection, and research applications.

5. Conclusion

This paper presented the design and evaluation of a real-time UAV video streaming and control system leveraging ROS 2, GStreamer, and YOLOv8-seg. The system was architected to offload computationally demanding tasks to a Jetson Orin-based ground station while maintaining lightweight onboard processing on a Raspberry Pi 3 companion computer. Using ROS 2's Data Distribution Service (DDS) communication framework, a seamless data exchange is achieved between onboard and ground-side components, enabling synchronized telemetry and live video streaming.

The GStreamer-based video pipeline demonstrated reliable transmission of 640p H.264 video at 30 FPS with average end-to-end latency of ~105 ms, even under modest wireless network conditions. The YOLOv8-seg model, deployed on the Jetson Orin, provided real-time object detection capabilities, achieving 28–30 FPS and a mAP of 81.2% on test frames. These results underscore the viability of the proposed architecture for real-time, intelligent UAV-based monitoring and surveillance.

The modular design facilitated by ROS 2 allows for future extensibility, including bidirectional control commands, multi-camera support, and edge-based decision-making. Moreover, the use of open-source tools and affordable hardware components highlights the system's accessibility and adaptability for academic, research, and low-cost industrial applications.

The future work, is to integrate autonomous flight logic based on detection results, investigate long-range communication channels (e.g., 4G/5G), and enhance detection accuracy through model fine-tuning and multi-modal sensing.

The results of this study provide a foundation for further advancements in cloud-augmented robotics and intelligent UAV systems, promoting the

adoption of modular, AI-integrated, and communication-aware aerial platforms across a wide range of applications.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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