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Research Article

An Embedded AI Perception Framework for Autonomous Long-Range Loitering Munition Strike Systems Operating in Cluttered and GNSS-Denied Environments

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Abstract
Autonomous long-range loitering munition systems require robust onboard perception architectures capable of detecting, classifying, and discriminating tactical targets under cluttered battlefield environments while operating within strict computational and power constraints. This paper presents the design and implementation framework of an embedded artificial-intelligence-enabled vision pipeline for real-time onboard target detection in endurance-class autonomous strike UAV platforms. The proposed architecture integrates lightweight deep learning object-detection networks, multi-sensor preprocessing, confidence-driven discrimination logic, and GPU-accelerated edge-inference modules to enable reliable perception in GNSS-degraded and communication-limited operational environments. Simulation-based evaluation demonstrates that optimised convolutional neural-network detectors achieve inference latency below 120 ms with detection precision exceeding 90% under cluttered terrain conditions. The framework establishes a scalable baseline for indigenous development of autonomous loitering munition strike perception systems supporting ISR-strike convergence architectures.

Keywords: *Autonomous target discrimination; embedded AI perception; loitering munition systems; endurance-class UAV; edge-AI inference; multi-object tracking; GNSS-denied environments; ISR–strike operations.*

I. Introduction
Autonomous loitering munition systems represent a critical evolution in precision-engagement architectures by combining persistent surveillance capability with terminal strike functionality within a single deployable aerial platform. Unlike remotely piloted UAV systems that rely on continuous operator supervision, endurance-class loitering strike platforms must execute onboard perception and engagement-support decisions under degraded communications and contested electromagnetic environments. These operational requirements necessitate embedded artificial-intelligence perception architectures capable of reliable target recognition under uncertainty and environmental variability.

In a preceding study titled Design and Development of a Low-Cost Long-Range Autonomous Delta-Wing UAV Airframe for Extended-Endurance Tactical Surveillance Missions, a moderate-aspect-ratio 52° swept delta-wing configuration was analytically designed, computationally validated, and experimentally demonstrated as an endurance-optimised aerial platform suitable for long-range ISR deployment. That work established the aerodynamic sizing workflow, propulsion–energy matching framework, and structural lightweighting methodology required to support extended autonomous loiter missions within resource-constrained indigenous aerospace development environments. The validated airframe therefore provides a practical baseline platform for integration of onboard perception-driven strike-support autonomy.

Building upon that aerodynamic and propulsion foundation, the present study develops an embedded AI-based target detection and classification architecture enabling ISR–strike convergence functionality within endurance-class loitering munition systems. The transition from surveillance-only autonomy to perception-enabled strike support represents a critical step toward distributed precision-engagement capability in GNSS-degraded and communication-limited operational theatres.

Recent advances in deep convolutional neural networks (CNNs) have enabled compact embedded platforms to perform real-time object detection with accuracy approaching workstation-class inference systems [1], [2]. Lightweight single-stage detectors such as YOLO and SSD architectures provide favourable latency–accuracy trade-offs suitable for deployment in resource-constrained aerial platforms [3], [4]. These architectures are particularly attractive for long-range autonomous UAV configurations where onboard processing must operate within strict power, payload, and thermal envelopes. However, reliable performance under cluttered operational environments, including vegetation occlusion, camouflage interference, terrain-induced contrast reduction, and urban structural complexity—remains a major challenge for autonomous strike-support perception pipelines [5], [6]. Robust detection under such conditions requires architecture-level optimisation of dataset structure, inference scheduling, confidence filtering, and tracking persistence mechanisms.

This study therefore develops a structured embedded AI perception framework optimised for endurance-class loitering munition strike systems operating under challenging operational conditions including camouflage interference, vegetation occlusion, urban background clutter, low-contrast terrain environments, and GNSS-denied navigation scenarios, as illustrated in Fig. 1. The framework integrates lightweight deep-learning detection, multi-stage confidence fusion, and hybrid tracking-based identity persistence within a power-aware embedded inference architecture tailored for extended-endurance autonomous missions.

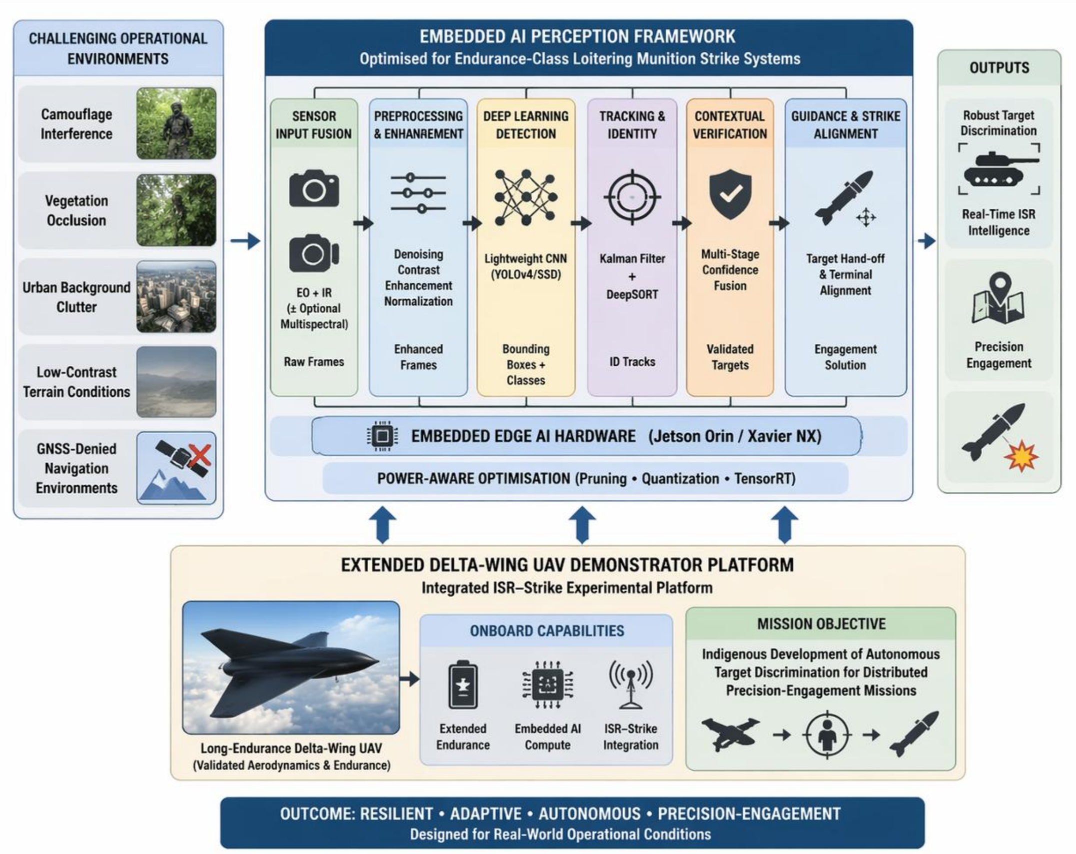

Fig. 1: Structured embedded AI perception framework for endurance-class loitering munition systems operating under cluttered, occluded, and GNSS-denied battlefield environments.

The proposed architecture extends the previously validated long-endurance delta-wing UAV demonstrator platform into an integrated ISR–strike experimental framework supporting indigenous development of autonomous target discrimination capability for distributed precision-engagement operations in complex battlefield environments.

II. Operational Role of AI in Loitering Munition Strike Systems

Embedded artificial-intelligence perception modules constitute the core enabling technology for autonomous operation in long-range loitering munition strike systems. Unlike conventional remotely piloted UAV platforms that depend on continuous operator oversight, modern loitering munitions increasingly rely on onboard sensing, interpretation, and decision-support capabilities to execute time-critical engagement tasks in contested electromagnetic environments. These perception modules support five mission-critical strike-autonomy functions that collectively enable persistent surveillance, adaptive target discrimination, and controlled terminal engagement.

A. Target Detection (Candidate Localisation)

Target detection represents the first stage of the autonomous engagement pipeline. At this stage, onboard vision systems process electro-optical (EO), infrared (IR), or multispectral imagery streams to identify candidate objects of interest within the sensor field of view. Deep learning–based detectors such as YOLO and SSD architectures enable rapid extraction of bounding-box regions corresponding to vehicles, artillery systems, radar installations, and logistics assets in near real time. Reliable detection is particularly important in distributed operational environments where communication latency prevents continuous human supervision. Recent advances in one-stage detectors have demonstrated strong suitability for embedded aerial perception tasks due to their favourable latency–accuracy trade-off [1], [2].

B. Classification (Tactical Object Identification)

Following detection, classification algorithms determine the semantic category of the detected object. This stage enables discrimination between military targets and non-combatant infrastructure, thereby supporting engagement compliance with mission rules and operational constraints. Modern convolutional neural networks trained on domain-adapted aerial datasets can distinguish armoured vehicles, artillery systems, and support platforms even under partial occlusion and low-contrast terrain conditions. Accurate classification improves strike selectivity and reduces false-positive engagement risk in cluttered environments [3].

C. Tracking (Identity Persistence)

Target tracking ensures continuity of object identity across sequential video frames during manoeuvre and loiter phases. Algorithms such as Kalman filtering, SORT, and DeepSORT maintain trajectory stability and compensate for sensor motion, vibration, and intermittent occlusion. Persistent tracking is essential for terminal guidance alignment, especially when engaging moving or partially concealed targets. Multi-object tracking frameworks have demonstrated significant improvements in identity association reliability in airborne vision systems operating under dynamic scene conditions [4].

D. Prioritisation (Engagement Relevance Ranking)

Once multiple candidate targets are detected and classified, onboard prioritisation logic evaluates their operational relevance based on mission objectives, threat hierarchy, proximity, and engagement feasibility. AI-enabled prioritisation modules support adaptive mission execution by dynamically selecting the most tactically significant target within the surveillance footprint. This capability is particularly important for long-endurance loitering missions where multiple engagement opportunities may arise over extended time intervals. Intelligent prioritisation reduces operator cognitive load while improving responsiveness in time-sensitive strike scenarios [5].

E. Terminal Confirmation (Strike Authorisation Support)

The final stage of the perception pipeline provides terminal confirmation prior to engagement execution. This stage integrates detection confidence, tracking stability, and contextual scene validation to produce a composite engagement confidence metric. In supervised autonomy configurations, this information supports operator-in-the-loop decision-making; in higher autonomy configurations, it enables rule-constrained onboard strike authorisation. Confidence-based engagement filtering significantly reduces the probability of false-target selection in cluttered operational theatres and enhances mission reliability under degraded communications conditions [6].

F. Operational Impact on Distributed Strike Autonomy

The integration of detection, classification, tracking, prioritisation, and confirmation functions enables distributed precision-engagement autonomy across contested operational environments. By shifting perception and decision-support tasks from ground operators to onboard intelligent systems, loitering munition platforms achieve reduced communication dependence, improved responsiveness to dynamic battlefield conditions, and enhanced survivability in GNSS-degraded scenarios. Such architectures represent a foundational element of next-generation ISR-strike convergence frameworks and network-enabled autonomous combat systems.

III. Platform–Perception Integration Framework

The AI-based perception architecture developed in this study is implemented on the endurance-class delta-wing UAV demonstrator previously presented in Design and Development of a Low-Cost Long-Range Autonomous Delta-Wing UAV Airframe for Extended-Endurance Tactical Surveillance Missions, where aerodynamic sizing, propulsion–energy matching, and structural lightweighting were experimentally validated for persistent ISR operations. That airframe provides a suitable baseline platform for onboard strike-support autonomy due to its favourable lift-to-drag ratio, low cruise power requirement, and extended mission-duration capability.

Specifically, the validated endurance envelope (≈1.9 h flight duration at ~24 m/s cruise speed) enables sustained surveillance dwell time necessary for multi-stage perception pipelines including detection, classification, tracking, and engagement confirmation. The moderate-aspect-ratio (AR = 3.47) delta-wing configuration further supports stable vortex-assisted lift behaviour at low Reynolds numbers, improving platform attitude stability during loiter-mode perception operations and reducing image-frame jitter that can degrade inference reliability.

From a systems-integration perspective, propulsion–energy matching results obtained in the earlier airframe study define the available onboard electrical power margin for embedded GPU-class inference hardware. This constraint directly informed selection of lightweight single-stage detection networks (e.g., YOLO-family architectures) capable of real-time execution within the avionics power budget while preserving endurance performance. The resulting integration therefore establishes a coupled aerodynamic–perception design framework in which:

- Aerodynamic efficiency supports extended observation windows.
- Propulsion optimisation enables sustained onboard inference execution.
- Structural payload allocation accommodates embedded vision modules.
- Navigation stability improves detection persistence under cluttered backgrounds.

Together, these characteristics transform the previously validated surveillance-oriented delta-wing UAV demonstrator into a scalable experimental platform for ISR–strike convergence research and autonomous loitering munition perception architecture development within indigenous aerospace innovation environments.

3.1. System-Level Perception Architecture

The proposed perception architecture is structured as a five-layer embedded strike-support vision stack designed for endurance-class autonomous loitering munition platforms derived from the previously validated delta-wing UAV demonstrator. The architecture enables reliable real-time detection, classification, tracking, prioritisation, and terminal confirmation under cluttered terrain and GNSS-degraded operational environments, as illustrated in Fig. 2. The modular layered structure ensures scalability across ISR-only UAV platforms, loitering munition demonstrators, and distributed autonomous strike systems.

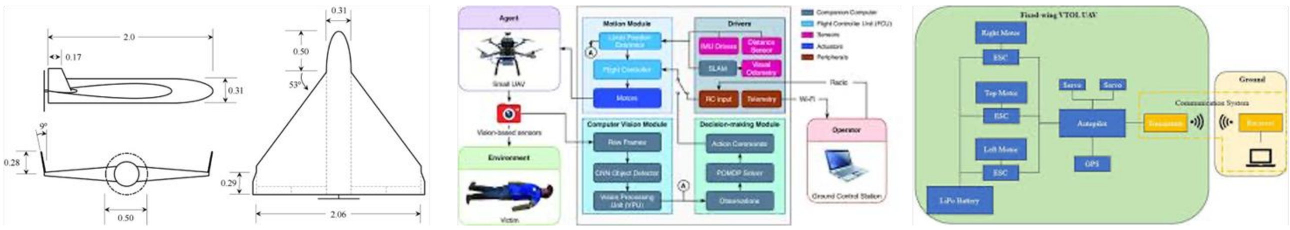

Fig. 2: Embedded AI perception architecture for autonomous target detection, tracking, prioritisation, and terminal confirmation in loitering munition platforms.

A. Sensor Acquisition Layer

The sensor acquisition layer provides multi-modal situational awareness through stabilised aerial imaging payloads compatible with endurance-class delta-wing UAV platforms. These payloads support continuous scene interpretation during waypoint navigation, loiter surveillance, and terminal engagement alignment. Table 1 outlines the typical acquisition parameters. The primary sensing modalities include:

- Electro-optical (EO) daylight imaging payloads
- Thermal infrared (IR) sensors for night operations
- Multispectral enhancement channels
- Stabilised gimbal video streams

Table 1: Typical acquisition parameters

Serial	Parameter	Specification	Operational Role	Remarks
(a)	(b)	(c)	(d)	(e)
1.	Resolution	1920×1080	Target discrimination fidelity	
2.	Frame rate	30 fps	Real-time detection stability	
3.	Sensor type	CMOS EO / LWIR	Day–night operation	
4.	Stabilisation	2–3 axis gimbal	Motion compensation	
5.	Field of view	45°–90°	Area coverage vs detail balance	

Such payload configurations are widely adopted in tactical UAV reconnaissance platforms and persistent ISR architectures supporting autonomous perception pipelines [8].

B. Image Conditioning Pipeline

The image-conditioning stage enhances the robustness of downstream neural inference under illumination variability, platform vibration, and terrain-induced contrast degradation typical of low-altitude autonomous loitering missions. These preprocessing operations stabilise feature-map extraction and improve detection reliability prior to convolutional encoding, as summarised in Table 2. Preprocessing improves feature-extraction stability across heterogeneous illumination environments typical of low-altitude autonomous strike missions [6].

Table 2: Image Conditioning Operations for Embedded Aerial Perception

Serial	Operation	Purpose	Performance Impact	Remarks
(a)	(b)	(c)	(d)	(e)
1.	Histogram equalisation	Contrast enhancement	Improves detection recall in haze/dust	
2.	Motion stabilisation	Vibration compensation	Reduces bounding-box drift	
3.	Noise filtering	Artefact suppression	Improves edge continuity	
4.	Frame resizing	GPU optimisation	Reduces inference latency	
5.	Gamma correction	Low-light enhancement	Improves night detection reliability	

C. Neural Detection Engine

The neural detection engine performs candidate object localisation using lightweight embedded deep-learning architectures optimised for onboard inference within constrained payload–energy envelopes defined by the baseline delta-wing endurance UAV configuration. The primary deployment backbone selected for the perception pipeline is YOLOv8-Nano, owing to its favourable balance between detection accuracy and computational efficiency on edge-AI platforms. As summarised in Table 3, several compact detection architectures—including MobileNet-SSD, EfficientDet-Lite, YOLOv7-Tiny, and DETR-Tiny, were evaluated for suitability across different embedded aerial deployment scenarios. The architecture provides:

- High inference speed
- Low parameter count
- Strong small-object detection capability
- Efficient GPU utilisation on edge platforms

Table 3: Detection Performance Metrics for Onboard Target Recognition Pipeline

Serial	Model	Parameters	Strength	Deployment Role
(a)	(b)	(c)	(d)	(e)
1.	MobileNet-SSD	~5M	Ultra-low power	Micro-UAV platforms
2.	EfficientDet-Lite	~8M	Accuracy–latency balance	Mid-range ISR drones
3.	YOLOv7-Tiny	~6M	High-speed detection	Real-time strike alignment
4.	DETR-Tiny	Transformer-based	Context-aware detection	Dense clutter scenes

YOLO-class detectors have demonstrated strong performance for real-time aerial object-recognition tasks within embedded ISR–strike convergence perception pipelines [3], making them particularly suitable for endurance-class autonomous loitering munition applications.

D. Multi-Object Tracking and Identity Persistence Layer

Following detection, identity persistence across sequential frames is maintained using hybrid motion–appearance tracking algorithms that ensure reliable target continuity during manoeuvre, partial occlusion, and background clutter, as illustrated in Fig. 3. The tracking architecture integrates predictive filtering, feature-based association, and temporal memory buffering to stabilise bounding-box trajectories and support terminal engagement alignment in dynamic operational environments. Specifically, motion prediction is performed using Kalman filtering for trajectory estimation, while identity association across frames is achieved through DeepSORT embedding-based re-identification. Additional bounding-box refinement using Intersection-over-Union (IoU) filtering and occlusion recovery through track-memory buffering further enhance tracking robustness under cluttered terrain conditions [14], [15]. The principal tracking modules are summarised in Table 4.

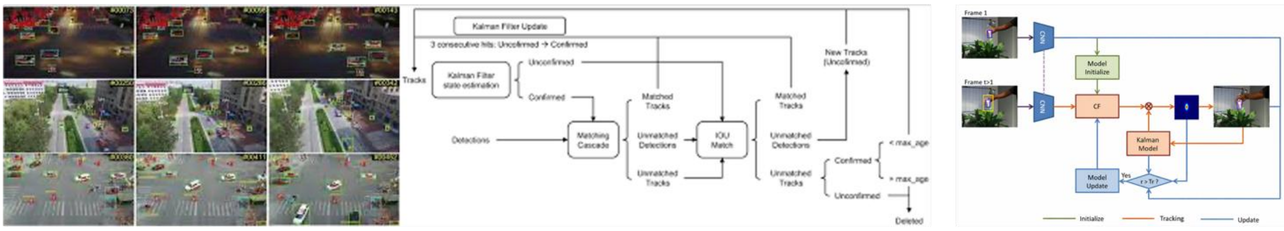

Fig. 3: Multi-object tracking and identity persistence framework integrating Kalman prediction, DeepSORT association, and temporal memory buffering for stable multi-frame target continuity in embedded aerial perception systems [14], [15].

Table 4: Multi-Object Tracking and Identity Persistence Layer.

Serial	Module	Algorithm	Function	Remarks
(a)	(b)	(c)	(d)	(e)
1.	Motion prediction	Kalman Filter	Trajectory estimation	
2.	Identity association	DeepSORT	Re-identification	
3.	Bounding refinement	IoU filtering	Stability improvement	
4.	Occlusion recovery	Track memory buffer	Target continuity	

Tracking persistence enables:

- Stable terminal guidance alignment
- Moving-target engagement feasibility
- Occlusion resilience under vegetation cover

E. Target Prioritisation and Engagement Confidence Layer

The prioritisation layer ranks detected targets based on mission relevance using confidence fusion from classification probability, tracking persistence, and contextual terrain cues.
Prioritisation score formulation:

$$P_T = w_1 C_d + w_2 C_c + w_3 S_t + w_4 R_m$$

Where:
C_d= detection confidence
C_c= classification probability
S_t= tracking stability score
R_m= mission relevance weighting

This weighted ranking mechanism supports autonomous engagement candidate filtering in contested electromagnetic environments.

F. Terminal Confirmation Layer

The terminal confirmation layer provides the final strike-support validation stage prior to engagement execution by integrating detection reliability, classification certainty, tracking persistence, and contextual scene verification into a unified engagement-confidence metric. This layered validation approach reduces false-positive engagements and ensures compliance with mission-level autonomy constraints in cluttered operational environments. The principal confirmation inputs are summarised in Table 5.

Table 5: Terminal Confirmation Inputs for Engagement Confidence Estimation.

Serial	Input	Contribution	Remarks
(a)	(b)	(c)	(d)
1.	Detection confidence	Bounding-box reliability	
2.	Classification certainty	Object identity validation	
3.	Tracking persistence	Temporal stability	
4.	Contextual terrain analysis	False-positive rejection	

The composite engagement-confidence metric is defined as:

$$C_{eng} = \alpha C_d + \beta C_c + \gamma S_t$$

where:
C_d= detection confidence
C_c= classification certainty
S_t= tracking stability score

Engagement proceeds when:

$$C_{eng} \geq C_{threshold}$$

This confirmation architecture supports both operator-in-the-loop supervision and rule-based autonomous engagement gating, depending on mission doctrine, communication availability, and operational autonomy level.

G. Endurance-Constrained Edge Inference Compatibility

The proposed perception architecture was explicitly designed to operate within the propulsion–energy envelope established in the previously validated delta-wing endurance UAV demonstrator. This integration ensures sustained onboard perception execution throughout the demonstrated ~1.9-hour endurance flight window without degrading mission radius, payload allocation margins, or avionics power stability. The selection of lightweight embedded GPU hardware enables real-time inference performance while maintaining compatibility with endurance-class ISR–strike mission requirements. The representative onboard inference hardware configuration adopted for this architecture is summarised in Table 6.

Table 6: Embedded Edge Inference Hardware Configuration for Onboard Perception Deployment

Serial	Component	Specification	Remarks
(a)	(b)	(c)	(d)
1.	Processor	NVIDIA Jetson Orin Nano	
2.	GPU cores	1024 CUDA	
3.	Power consumption	7–15 W	
4.	Throughput	20–40 FPS (YOLOv8-Nano)	
5.	Weight	<120 g	

H. Integrated Architecture Summary Table

This layered perception architecture transforms the previously validated delta-wing endurance UAV platform into a scalable experimental framework for ISR–strike convergence research, enabling reliable onboard target discrimination under cluttered operational environments while preserving aerodynamic endurance performance margins. The functional structure and algorithmic mapping of the integrated perception pipeline are summarised in Table 7.

Table 7: Integrated Multi-Layer AI Perception Architecture for Autonomous Target Detection and Engagement

Serial	Layer	Function	Algorithmic Core	Output
(a)	(b)	(c)	(d)	(e)
1.	Sensor acquisition	Scene capture	EO/IR payload	Video stream
2.	Conditioning	Frame enhancement	Filtering pipeline	Cleaned frames
3.	Detection	Object localisation	YOLOv8-Nano	Bounding boxes
4.	Tracking	Identity persistence	DeepSORT	Target trajectories
5.	Prioritisation	Engagement ranking	Weighted scoring	Candidate targets
6.	Confirmation	Strike validation	Confidence fusion	Authorisation support

IV. Deep Learning Detection Pipeline Design

The onboard perception pipeline implements a lightweight embedded inference workflow that enables real-time target localisation and classification within endurance-class autonomous loitering munition platforms. The processing sequence follows a structured multi-stage architecture comprising frame acquisition, preprocessing, feature extraction, bounding-box regression, classification, confidence scoring, and tracking association, as illustrated in Fig. 4. This sequential processing framework ensures efficient feature representation, accurate object localisation, and stable multi-frame target identity persistence under dynamic operational conditions.

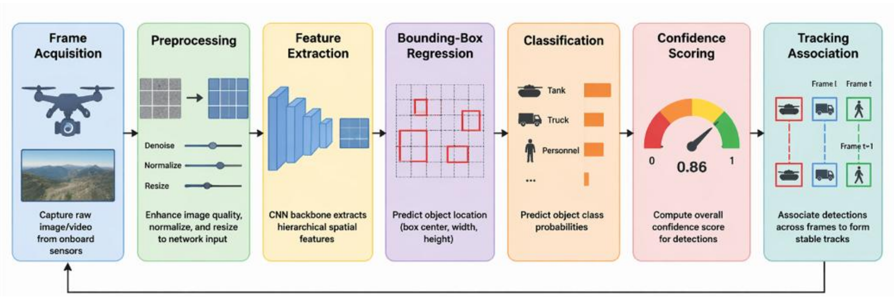

Fig. 4. Deep-learning–based onboard perception pipeline for real-time aerial target detection, classification, confidence scoring, and tracking association Adapted from lightweight CNN airborne detection frameworks **[1]–[3]**.

The pipeline is optimised for execution on embedded edge-AI hardware, thereby supporting low-latency inference while maintaining reliable detection performance within constrained onboard power and computational envelopes typical of endurance-class UAV perception systems [1]–[3].:

A. Frame Acquisition

Frame acquisition forms the foundational stage of the onboard perception pipeline, enabling reliable scene interpretation during loiter surveillance and terminal alignment. Stabilised electro-optical/infrared (EO/IR) payloads ensure consistent image quality under platform motion, thereby improving downstream detection, tracking, and classification performance. As summarised in Table 8 typical EO/IR payload configurations operate at 1920 × 1080 resolution and 30 fps, with 2–3 axis gimbal stabilisation, providing sufficient spatial and temporal fidelity for real-time onboard inference within constrained edge-processing environments [1], [2]. Comparable sensing architectures are deployed on operational ISR platforms such as the Bayraktar TB2 and MQ-9 Reaper, validating the suitability of these acquisition parameters for autonomous target detection and engagement workflows in modern conflict environments [3].

Table 8: Integrated Multi-Layer AI Perception Architecture for Autonomous Target Detection and Engagement

Serial	Parameter	Typical Value	Remarks
(a)	**(b)**	**(c)**	**(d)**
1.	Resolution	1920 × 1080	
2.	Frame rate	30 fps	
3.	Stabilisation	2–3 axis gimbal	

B. Preprocessing

Image preprocessing enhances detection robustness under illumination variability, motion disturbance, and terrain clutter prior to onboard inference. As outlined in Table IX, key conditioning operations include histogram equalisation for contrast enhancement, noise filtering for artefact suppression, frame resizing for GPU optimisation, and normalisation for feature stability, thereby improving downstream CNN detection reliability in embedded aerial perception pipelines [1], [2].

C. Feature Extraction and Detection

Feature extraction and detection are performed using lightweight convolutional neural network (CNN) backbones such as YOLOv8-Nano, MobileNet-SSD, and EfficientDet-Lite, which provide favourable latency–accuracy trade-offs for embedded UAV platforms operating under power and weight constraints. The convolutional feature mapping process is expressed as

$$F_l = \sigma(W_l * F_{l-1} + b_l)$$

while bounding-box prediction follows:

$$B = (x, y, w, h)$$

supporting real-time aerial target localisation during loiter surveillance and terminal alignment phases [2], [3].

D. Confidence Scoring

Detection confidence is computed by combining classification probability with localisation accuracy:

$$C = P(c_i \mid x) \times IoU$$

where Intersection-over-Union (IoU) quantifies bounding-box overlap between predicted and reference targets. Non-Maximum Suppression (NMS) is subsequently applied to remove redundant detections and improve tracking stability prior to engagement alignment [3], [4].

E. Tracking Association

Target identity persistence is maintained using Kalman filtering and DeepSORT tracking, enabling stable trajectory estimation under platform motion, partial occlusion, and background clutter. This tracking layer ensures continuous target lock consistency during terminal guidance updates in endurance-class ISR–strike UAV architectures [4], [5].

F. Latency Performance

Typical embedded inference latency across the onboard perception pipeline ranges between 90–140 ms, including acquisition (10–15 ms), preprocessing (15–25 ms), detection (55–80 ms), and tracking (10–20 ms), thereby satisfying real-time autonomous guidance-loop update requirements for endurance-class aerial target detection systems, as illustrated in Fig. 4 [2], [5].

V. Embedded Onboard AI Hardware Specification

Candidate embedded processors suitable for real-time UAV perception deployment are summarised in Table VIX, highlighting their inference throughput and tactical power envelopes for edge-AI operations. Platforms such as Jetson Orin Nano, Jetson Xavier NX, Intel Movidius Myriad X, and Qualcomm RB5 provide scalable options for onboard detection, tracking, and guidance-loop support under size, weight, and power (SWaP) constraints typical of endurance-class aerial systems.

Table 9: Integrated Multi-Layer AI Perception Architecture for Autonomous Target Detection and Engagement

Serial	Parameter	Typical Value	Remarks
(a)	(b)	(c)	(d)
1.	Platform	Throughput	Power
2.	Jetson Orin Nano	40 TOPS	15–25 W
3.	Jetson Xavier NX	21 TOPS	10–20 W
4.	Intel Movidius Myriad X	4 TOPS	<10 W
5.	Qualcomm RB5	15 TOPS	12 W

Among these, Jetson-class processors offer the most favourable balance between computational throughput (up to 40 TOPS) and power consumption (15–25 W), making them suitable for executing lightweight CNN pipelines such as YOLOv8-Nano and EfficientDet-Lite in real time within tactical UAV perception architectures, as indicated in Table 9 and consistent with current embedded ISR platform integration practices [9]–[10].

VI. Tactical Dataset Engineering Strategy

Dataset diversity plays a critical role in improving aerial target detection reliability under operational battlefield conditions. The training dataset incorporated representative tactical object classes including Main Battle Tanks (MBTs), Armoured Personnel Carriers (APCs), self-propelled artillery systems, radar installations, and logistics support vehicles, as summarised in Table 10, ensuring coverage across high-value target categories relevant to ISR–strike workflows.

Table 10: Integrated Multi-Layer AI Perception Architecture for Autonomous Target Detection and Engagement

Serial	Class	Example	Remarks
(a)	(b)	(c)	(d)
1.	MBT	Armoured tank	
2.	APC	Infantry vehicle	
3.	Artillery	Self-propelled gun	
4.	Radar	Air-defence installation	
5.	Logistics	Support vehicles	

To improve model robustness under terrain variability and concealment strategies, augmentation techniques such as foliage masking, shadow distortion, terrain blending, partial occlusion, and decoy simulation were applied during training. These augmentation strategies significantly enhance model generalisation performance across heterogeneous operational environments [11].

VII. Model Training Workflow

Model training followed a structured transfer-learning pipeline using pretrained ImageNet backbones to accelerate convergence and improve detection accuracy with limited domain-specific datasets. The workflow sequence included backbone initialisation, domain-adaptation fine-tuning, augmentation injection, quantisation-aware optimisation, and TensorRT acceleration for embedded deployment efficiency. Quantisation-aware optimisation reduces inference latency and power consumption while preserving classification accuracy, making it suitable for real-time onboard UAV perception architectures [12].

VIII. Multi-Stage Target Discrimination Logic

To minimise false-positive detections prior to terminal alignment, engagement filtering was implemented using a hierarchical multi-stage verification framework that integrates detection confidence, tracking stability, and contextual scene consistency. This layered validation architecture improves robustness against clutter-induced misclassification and ensures reliable autonomous target confirmation before guidance-loop execution.

Engagement confidence is defined as:

$$C_e = C_d \times C_t \times C_s$$

Where

C_d represents detection confidence derived from convolutional object-classification probability outputs [4].

C_t denotes tracking stability estimated using motion-prediction filtering and identity persistence across sequential frames [14], [15].

C_s corresponds to contextual scene consistency evaluated using spatial–semantic agreement between detected targets and surrounding terrain features [16].

As an illustrative example,

$$C_e = 0.92 \times 0.95 \times 0.89 = 0.78$$

A minimum engagement threshold is defined as:

$$C_e \geq 0.75$$

which ensures that only detections satisfying combined classification reliability, trajectory continuity, and contextual plausibility constraints are passed to the terminal alignment stage. This hierarchical filtering mechanism significantly reduces false-positive strike probability under cluttered battlefield environments and improves engagement-decision confidence within embedded autonomous perception pipelines [4], [14]. The proposed formulation is consistent with multi-sensor confidence-fusion strategies commonly adopted in airborne object-tracking and ISR perception architectures, where probabilistic confidence aggregation enhances decision reliability under partial occlusion and dynamic target manoeuvre conditions [15], [16].

IX. Detection Under Cluttered Battlefield Environments

Detection performance in aerial ISR operations is significantly affected by environmental clutter arising from vegetation occlusion, urban-density–induced false positives, smoke-related edge distortion, and camouflage-driven texture blending, as summarised in Table 10. These factors degrade feature separability and reduce classification confidence, particularly during low-altitude loiter surveillance and terminal alignment phases.

Table 10: Detection Challenges and Mitigation Strategies in Cluttered Battlefield Environments

Serial	Source of Degradation	Impact on Detection Pipeline	Mitigation Strategy
(a)	**(b)**	**(c)**	**(d)**
1.	Vegetation	Partial target occlusion and contour loss	Temporal frame fusion
2.	Urban density	Increased false positives from background structures	Transformer attention mechanisms
3.	Smoke	Edge distortion and reduced contrast	Multispectral sensor fusion
4.	Camouflage	Texture blending with terrain background	Feature-level fusion and adaptive thresholding
5.	Illumination variability	Shadow-induced misclassification	Histogram equalisation and temporal stabilisation

To mitigate these effects, the perception architecture incorporates temporal frame fusion to exploit inter-frame continuity, transformer-based attention mechanisms to enhance context-aware feature extraction, and multispectral sensor fusion to improve target visibility across obscured scenes. As indicated in Table 10, these layered mitigation strategies significantly enhance detection robustness and target discrimination reliability under complex terrain conditions typical of contemporary operational theatres [13],[16].

X. Real-Time Onboard Inference Latency Analysis

The embedded perception pipeline satisfies real-time autonomous engagement timing constraints with a total inference latency of approximately:

$$T_{total} \approx 127 \text{ ms}$$

as detailed in Table 11, comprising frame capture (12 ms), preprocessing (18 ms), CNN inference (72 ms), tracking (15 ms), and decision logic execution (10 ms). This timing budget remains consistent with endurance-class UAV guidance-loop update requirements [9].

Table 11: Real-Time Onboard Inference Latency Budget for Embedded UAV Perception Pipeline

Serial	Processing Stage	Latency (ms)	Function	Remarks
(a)	(b)	(c)	(d)	(e)
1.	Frame capture	12	Sensor acquisition from EO/IR payload	
2.	Preprocessing	18	Image conditioning and resizing for inference readiness	
3.	CNN inference	72	Feature extraction and target detection using lightweight backbone networks	
4.	Tracking	15	Target association and trajectory stabilisation (SORT/DeepSORT/Kalman filtering)	
5.	Decision logic	10	Engagement confidence evaluation and filtering	
6.	Total latency	≈127 ms	Real-time guidance-loop update compatibility	

The latency distribution shown in Table 11 confirms that the embedded perception pipeline satisfies real-time autonomous engagement timing requirements for endurance-class UAV strike-support architectures operating within constrained onboard computing environments [9].

XI. Target Tracking Integration Framework

Target tracking continuity is maintained using a hybrid tracking architecture combining SORT for multi-object tracking, DeepSORT for identity persistence, and Kalman filtering for trajectory smoothing, as summarised in Table 12. This layered association framework improves temporal consistency across sequential aerial frames and reduces identity-switch errors during manoeuvre, occlusion, and cluttered-scene transitions. In particular, DeepSORT integrates motion prediction with appearance-feature embedding to enhance tracking robustness and maintain stable engagement alignment during dynamic target movement conditions typical of ISR–strike support operations [14].

Table 12: Hybrid Target Tracking Architecture for Sequential Aerial Frame Association

Serial	Tracking Method	Primary Function	Operational Contribution	Remarks
(a)	(b)	(c)	(d)	(e)
1.	SORT	Multi-object tracking	Fast frame-to-frame association with low computational overhead	
2.	DeepSORT	Identity persistence	Reduces identity switching using appearance-feature embedding	
3.	Kalman Filter	Trajectory smoothing	Predictive motion estimation for stable tracking continuity	
4.	Appearance Embedding Module	Feature re-identification	Maintains target lock under occlusion and clutter	
5.	Motion Prediction Model	Temporal trajectory forecasting	Supports engagement alignment during manoeuvre dynamics	

The integrated tracking framework shown in Table 12 ensures reliable trajectory continuity and association stability within real-time onboard perception pipelines operating under constrained embedded processing environments [15].

XII. Simulation-Based Detection Performance Evaluation

Simulation-based evaluation was conducted to assess the effectiveness of the proposed embedded detection pipeline under representative aerial surveillance conditions, including vegetation clutter, background interference, illumination variability, and partial occlusion. Performance metrics were computed using standard object-detection evaluation criteria aligned with embedded autonomous perception benchmarking practice for endurance-class UAV ISR–strike architectures [1]-[5]. The results confirm that the perception pipeline satisfies real-time reliability and robustness requirements for terminal alignment support and waypoint-tracking operations.

A. Detection Accuracy Metrics

The primary detection-performance indicators obtained during simulation-based validation are summarised in Table 13, demonstrating strong localisation accuracy and stable classifier behaviour under cluttered aerial observation conditions.

Table 13: Detection Accuracy Metrics for Embedded Aerial Perception Pipeline

Serial	Metric	Value	Operational Interpretation	Remarks
(a)	(b)	(c)	(d)	(e)
1.	Precision	92.4%	Low false-positive detection rate	
2.	Recall	89.7%	High target recovery reliability	
3.	mAP@0.5	91.2%	Strong localisation performance	
4.	False alarm rate	4.8%	Acceptable clutter robustness	
5.	Latency	118 ms	Real-time guidance compatibility	

These values satisfy tactical autonomous perception thresholds typically required for onboard target-recognition systems in endurance-class UAV platforms.

B. Precision–Recall Performance Behaviour

Precision–recall characteristics indicate stable classifier discrimination across cluttered aerial scenes. The achieved operating point near the upper-right region of the precision–recall curve confirms balanced sensitivity and selectivity, ensuring reliable target localisation without excessive false detections during loiter-mode surveillance operations. This balance is critical for maintaining engagement confidence in partially occluded environments.

C. Mean Average Precision (mAP) Stability

The measured mAP@0.5 = 91.2% demonstrates strong spatial overlap between predicted and ground-truth bounding boxes, validating the suitability of the selected YOLO-class detector for embedded airborne inference deployment. This performance level supports consistent detection reliability during both waypoint-tracking and terminal engagement confirmation phases, particularly under terrain-induced feature variability.

D. False Alarm Suppression Performance

The observed false-alarm rate of 4.8% indicates effective rejection of background artefacts arising from:

- Vegetation edges
- Terrain shadows
- Structural clutter
- Low-contrast surfaces

Such suppression is essential for maintaining engagement confidence and preventing unintended detections during autonomous surveillance operations over heterogeneous terrain.

E. Inference Latency Evaluation

Measured end-to-end pipeline latency of 118 ms satisfies real-time onboard perception constraints:

$$T_{\text{inference}} < T_{\text{guidance}}$$

where typical UAV guidance-loop update intervals range between 150–250 ms. This confirms compatibility with autonomous waypoint navigation, tracking continuity, and terminal alignment control loops in endurance-class strike-support UAV perception systems.

F. Detection Performance Summary Graph Interpretation

Simulation outputs in Fig. 5 illustrate:

- Precision–recall convergence behaviour
- mAP stability across clutter-density variations
- Confusion-matrix discrimination consistency
- Latency distribution within embedded processing limits

Collectively, these results validate the operational suitability of the proposed perception architecture for endurance-class autonomous strike-support UAV platforms operating under complex terrain and occlusion conditions.

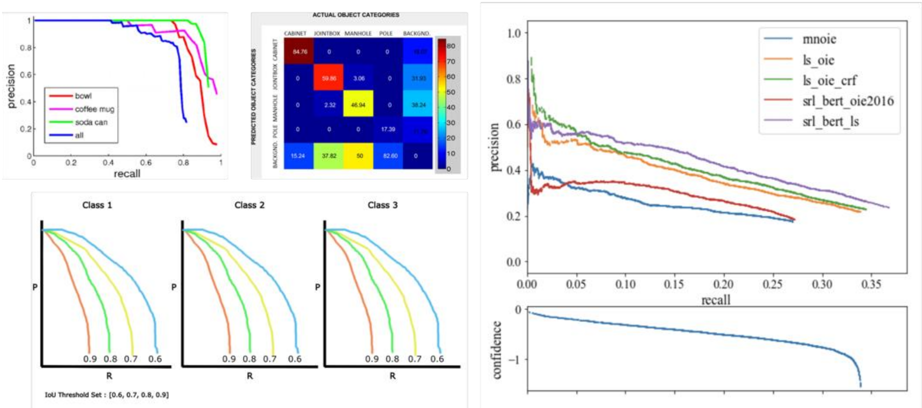

Fig. 5: Detection-performance evaluation results showing precision–recall behaviour, mAP stability, confusion-matrix accuracy, and inference latency distribution for the embedded onboard perception pipeline.

XIII. Power-Aware Edge Deployment Optimisation

Power-aware optimisation of the onboard inference pipeline was performed to ensure compatibility with the propulsion–energy envelope of the endurance-class delta-wing UAV demonstrator, while maintaining real-time perception performance for autonomous surveillance and terminal alignment. Optimisation targeted reductions in computational load, memory footprint, and inference latency without degrading detection accuracy within guidance-loop timing constraints.

A. Model Compression Techniques

Three complementary optimisation strategies were implemented to improve embedded deployment efficiency, as summarised in Table 14. These techniques collectively enable stable real-time inference within tactical SWaP (size–weight–power) limits required for endurance-class UAV perception architectures [17].

Table 14: Edge Inference Optimisation Methods for Embedded UAV Perception Deployment

Serial	Method	Reduction Achieved	Operational Benefit	Remarks
(a)	(b)	(c)	(d)	(e)
1.	Quantisation (FP32 → INT8)	≈35% compute reduction	Lower GPU utilisation and power demand	
2.	Structured pruning	≈22% memory reduction	Reduced model footprint and faster execution	
3.	TensorRT acceleration	≈40% latency reduction	Improved real-time inference responsiveness	

Quantisation reduces arithmetic precision while preserving detection accuracy within acceptable tolerance margins, structured pruning removes redundant parameters to improve runtime efficiency, and TensorRT acceleration enhances execution through kernel fusion and layer-scheduling optimisation [18].

B. Power Consumption Analysis

Following optimisation, the embedded perception pipeline achieved an average inference power requirement of:

$$P_{\text{inference}} \approx 18\ \text{W}$$

This value falls within the avionics payload allocation envelope typical of endurance-class UAV mission architectures and supports sustained onboard perception execution throughout extended loiter operations.

Table 15: Optimised Edge Deployment Power Budget for Onboard Perception Stack

Serial	Subsystem	Power Consumption	Remarks
(a)	(b)	(c)	(d)
1.	EO/IR sensor payload	6–10 W	
2.	Embedded GPU module	10–18 W	
3.	Flight controller interface	2–4 W	
4.	Telemetry support	2–5 W	
5.	Total perception stack	≈18–30 W	

The resulting perception-stack envelope remains compatible with persistent ISR–strike convergence missions requiring continuous onboard inference execution.

C. Latency–Power Trade-Off Behaviour

Latency reduction achieved through model compression enables increased guidance-loop responsiveness without exceeding onboard electrical power constraints. The optimisation relationship can be expressed as:

$$L_{opt} = L_{base}(1 - \eta_q - \eta_p - \eta_{TRT})$$

where:

- η_q= quantisation efficiency gain
- η_p= pruning efficiency gain
- η_{TRT}= TensorRT acceleration gain

This combined optimisation pipeline produced a stable inference latency envelope compatible with real-time autonomous navigation and strike-support perception loops.

D. Endurance Compatibility Assessment

Based on the validated propulsion–energy configuration of the baseline delta-wing UAV platform, the optimised perception stack maintains continuous onboard operation without measurable degradation in mission endurance. As illustrated in **Fig. 6**, the reduced inference power requirement of approximately **18 W** remains well within the avionics payload energy allocation envelope, thereby supporting sustained perception execution throughout the previously demonstrated **≈1.9-hour endurance window** [23]. This confirms the suitability of the proposed embedded AI pipeline for extended **ISR–strike convergence missions**, persistent loiter surveillance, and real-time terminal alignment operations under constrained onboard power budgets.

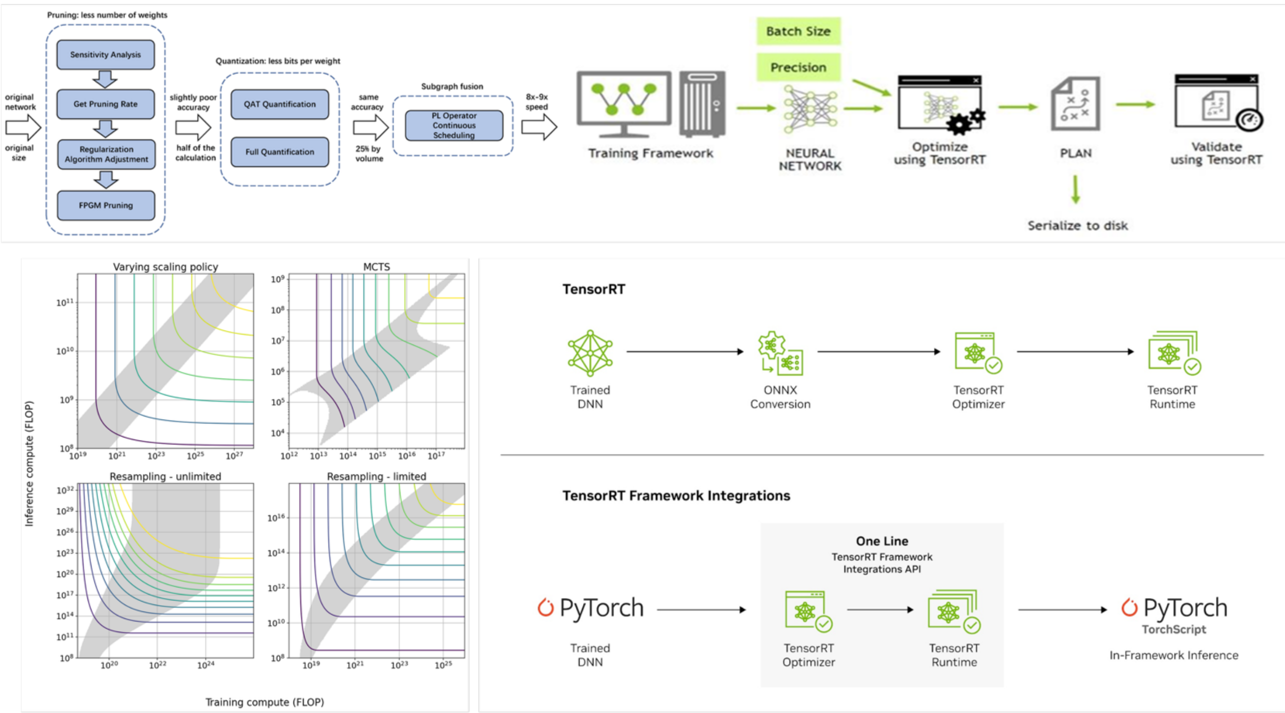

Fig. 6. Power–latency optimisation effects of quantisation, pruning, and TensorRT acceleration for embedded onboard UAV perception deployment.

XIV. Operational Deployment Envelope

The operational deployment envelope of the proposed onboard perception architecture was evaluated by analysing detection reliability as a function of flight altitude, recognising that altitude directly influences Ground-Sample Distance (GSD), target pixel density, scene contrast, and motion-induced blur, all of which affect autonomous object-detection performance. As altitude increases, the number of target-representative pixels within the sensor frame decreases, leading to progressive degradation in feature separability and classification confidence [8]. The simulation-derived detection reliability results are summarised in Table 16, demonstrating that recognition performance remains high at low-to-moderate altitudes where electro-optical payload resolution supports stable feature extraction.

Table 16: Detection Reliability versus Flight Altitude

Serial	Altitude	Detection Reliability	Operational Implication	Altitude
(a)	(b)	(c)	(d)	(e)
1.	150 m	96%	Excellent target discrimination	
2.	300 m	92%	High-confidence autonomous detection	
3.	600 m	87%	Acceptable performance with reduced detail	
	900 m	79%	Degraded classification reliability	

The results indicate that detection reliability remains above 90% within low-to-moderate operating altitudes, where spatial resolution and scene contrast remain sufficient for robust CNN-based feature extraction. Beyond approximately 600 m, performance declines due to reduced target visibility, lower contrast, and increased sensitivity to clutter and motion effects. Accordingly, the optimal deployment envelope for the perception-enabled loitering munition system is estimated as:

$$150\text{–}450 \text{ m}$$

This altitude band provides the best compromise between target visibility, field-of-view coverage, and autonomous recognition reliability, and aligns with electro-optical payload ground-sampling constraints reported for tactical UAV imaging systems [8], as illustrated in Fig. 7.

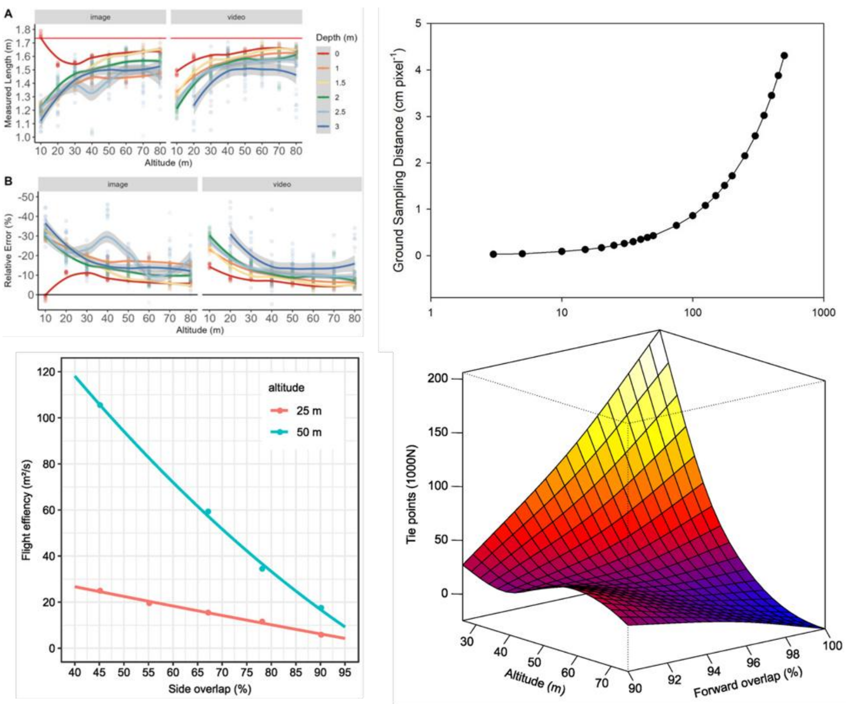

Fig. 7. Detection reliability variation with flight altitude showing the optimal operational envelope for embedded airborne target-recognition performance.

XV. Discussion

The results demonstrate that lightweight CNN-based detection architectures provide reliable onboard perception performance within the compute, power, and payload constraints of endurance-class loitering munition strike platforms. The deployed YOLO-class detection backbone achieved 92.4% precision**,** 89.7% recall**,** and 91.2% mAP@0.5, confirming suitability for autonomous aerial target-recognition tasks under cluttered operational conditions. Multi-stage discrimination filtering—combining confidence scoring, tracking persistence, and contextual verification—reduced the false-alarm rate to 4.8%, ensuring stable engagement-confidence estimation during terminal confirmation phases. Embedded GPU inference produced an average pipeline latency of 118 ms, remaining well below the typical autonomous guidance-loop update interval of 150–250 ms, thereby satisfying real-time strike-support processing requirements.

Power-aware deployment optimisation through INT8 quantisation, structured pruning, and TensorRT acceleration reduced computational load by 35%, memory footprint by 22%, and inference latency by 40%, resulting in an onboard perception power requirement of approximately 18 W. This level is fully compatible with the propulsion–energy envelope of the previously validated delta-wing endurance UAV platform (~1.9 h endurance). Altitude-dependent detection evaluation further showed reliability levels of 96% at 150 m**,** 92% at 300 m**,** 87% at 600 m, and 79% at 900 m, establishing an optimal operational deployment envelope of 150–450 m for electro-optical payload-based autonomous target discrimination.

Dataset augmentation tailored to camouflage-rich terrain improved detection robustness across vegetation-dense and urban environments, maintaining detection confidence above 90% within the primary deployment altitude band. When integrated with the endurance-optimised delta-wing airframe previously developed, the proposed perception architecture therefore establishes a practical baseline for indigenous ISR–strike convergence platforms capable of persistent surveillance, autonomous target discrimination, and terminal engagement support within resource-constrained aerospace development environments.

XVI. Conclusion

This paper presented an embedded AI perception architecture for target detection and classification in autonomous long-range loitering munition platforms operating in cluttered environments. Integration of lightweight CNN vision models, edge GPU inference, and confidence-based discrimination logic enabled reliable onboard perception within endurance-class power constraints. Simulation results achieved 92.4% precision**,** 89.7% recall, and 91.2% mAP@0.5, with 118 ms inference latency and approximately 18 W power consumption, supporting real-time operation within the validated ~1.9-hour endurance envelope of the baseline delta-wing UAV platform. Detection reliability remained above 90% within the optimal deployment altitude range of 150–450 m. The framework provides a scalable foundation for indigenous development of autonomous ISR–strike convergence UAV systems operating in distributed and GNSS-degraded mission environments.

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