

AI-Based Autonomous UAVs for Low-Light Object Recognition and Obstacle Avoidance Using LiDAR and Night-Vision Sensor Fusion

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Publication Date: 2026/10/21

Abstract: Flying autonomously in poor lighting is hard for unmanned aerial vehicles (UAVs) because obstacles must be both located and understood with little visible light. This survey examines twenty works on vision-based avoidance, LiDAR ranging, multi-modal perception, embedded deep learning, flight-controller and companion-computer design, and low-light or infrared detection. Cameras supply object semantics but degrade in darkness and give no direct range; LiDAR gives dependable distance but cannot name what it detects. Fusing the two compensates for each weakness, while compact neural detectors make onboard recognition increasingly feasible. Drawing on these findings, we propose a quadrotor architecture built around a Pixhawk flight controller and a Raspberry Pi companion computer with a night-vision camera, LiDAR, GPS and a telemetry link. The Raspberry Pi handles image-based classification; the Pixhawk keeps exclusive charge of stabilization and motor control. The design targets low-light surveillance and semi-autonomous navigation, and we outline the metrics needed to validate it: detection accuracy, ranging error, end-to-end latency, energy use and endurance.

Keywords: UAV, Autonomous Drone, LiDAR, Night Vision, Object Detection, YOLO, Raspberry Pi, Pixhawk, Sensor Fusion, Obstacle Avoidance.

How to Cite: Dr. A. S. Shirkande; Dnyaneshwari Kale; Sonali Deokar; Yash Jagtap (2026) AI-Based Autonomous UAVs for Low-Light Object Recognition and Obstacle Avoidance Using LiDAR and Night-Vision Sensor Fusion.

International Journal of Innovative Science and Research Technology, 11(10), 1045-1049.

<https://doi.org/10.38124/ijisrt/26oct723>

I. INTRODUCTION

UAVs are shifting from pilot-driven aircraft to platforms that perceive their surroundings, estimate their own state and adjust their trajectory without constant human input. Typical uses include surveillance, infrastructure inspection, agriculture, damage assessment and search and rescue. Two questions must be answered in flight: does an object endanger the planned path, and what is that object?

Cameras are a natural answer to the second question, since a trained detector can separate people, animals, vehicles and vegetation. However, image quality falls with scene brightness and contrast, so darkness, shadow and haze all hurt detection. Night-vision and infrared-assisted cameras widen the usable range of conditions, yet they still do not return metric distance.

LiDAR fills that gap by timing reflected laser pulses, which yields range that depends little on ambient light. Its weakness is the mirror image of the camera's: a return reveals that something exists and how far away it lies, not whether it is a person, a tree or a car. This complementarity motivates pairing LiDAR with learned visual recognition.

Recent work has accordingly turned to multi-sensor perception, embedded deep learning and companion-computer designs in which a dedicated autopilot keeps flight-critical loops separate from heavier computation. We adopt that separation in our proposed platform. Rather than catalogue avoidance methods, this survey compares the sensing and computing options that matter most for a UAV that must recognize objects and stay safe in low light. The main contributions are: 1) a synthesis of twenty sources organized by theme, 2) identification of technical and validation gaps, and 3) a project-level system architecture with a decision flow and an evaluation plan.

II. TECHNICAL BACKGROUND

➤ Flight Control

A flight controller closes the attitude loops and drives the actuators. Pixhawk-class hardware running PX4 or ArduPilot also provides sensor ports, failsafes and telemetry. Tasks that are heavy or flexible, such as neural inference and mission logic, are normally delegated to a separate companion computer [5], [7].

➤ *LiDAR Perception*

A LiDAR infers distance from the round-trip time of an emitted laser pulse. For avoidance, the output is typically a set of ranges or a point cloud that is filtered to find free space and nearby obstacles [3]. Although operation in darkness is a strength, performance still varies with target reflectivity, atmosphere, field of view, mounting and processing load.

➤ *Vision and Low-Light Sensing*

A visual detector converts pixels into a class label, a confidence score and an image location. YOLO-family models suit real-time use because they cast detection as one network pass [6]. When light is scarce, image quality becomes a system-level limit; night-vision and thermal imaging are two ways to retain useful content [1], [15].

➤ *Sensor Fusion*

Fusion can be applied to raw data, features, decisions or semantic maps. A LiDAR–camera pair links metric range to visual meaning, while GPS and inertial sensing support navigation. Our design uses a simple decision-level association: the Raspberry Pi names the object, and LiDAR supplies proximity to the control side.

➤ *Companion-Computer Architecture*

Keeping stabilization and actuator timing on the Pixhawk, and placing flexible processing on the Raspberry Pi, prevents variable inference time from entering the control loop. The two boards communicate over a UART link using MAVLink messages [8], [19].

III. REVIEW METHODOLOGY

The review covers five themes: low-light visual detection, LiDAR obstacle perception, camera–LiDAR and other multi-modal fusion, deep-learning UAV detection, and Pixhawk/companion-computer systems. The initial project sources were extended with ten further peer-reviewed or publisher-indexed works. Preference went to studies directly relevant to UAV perception, avoidance, embedded AI or flight-control integration. All summaries are written in the authors' own words, and the system figure is an original drawing. Bibliographic details and DOIs are listed where available.

IV. LITERATURE REVIEW

➤ *Low-Light and Infrared Detection*

Kumar et al. detect humans in darkness with a Raspberry Pi and night-vision sensing, showing that inexpensive embedded night surveillance is feasible [1]. Their scope excludes ranging, multi-class recognition and flight control. Jiang et al. evaluate YOLO models on UAV thermal imagery and report that infrared data can support real-time detection of

people and vehicles [15]. Because a night-vision camera is not a thermal camera, the two must not be conflated. Tan et al. refine YOLOv4 for small targets against cluttered backgrounds in aerial images [16], which is relevant when tuning a model for a low-power board.

➤ *Vision-Based Avoidance*

Sarmalkar et al. use camera input to detect obstacles and guide manoeuvres for autonomous aircraft [2]; the approach inherits the dependence of vision on environmental conditions and has no independent range channel. Wang et al. pair deep-learning detection with RGB-D data and let the recognized obstacle attributes shape the avoidance strategy [12].

➤ *LiDAR and Multi-Modal Fusion*

Ramasamy et al. establish active ranging as an effective way to warn of hazards along the flight path, while noting that range alone cannot classify objects [3]. Ma et al. fuse LiDAR with a visible-light camera for static and dynamic obstacles at low altitude [11], and Liang et al. close the loop from LiDAR perception through an avoidance algorithm to motion control [13]. Bultmann et al. run multi-modal semantic fusion onboard, combining LiDAR with RGB and thermal data [14]; their platform is considerably more capable than a student-scale system. Our work follows the same principle but emphasizes low-light imaging with lightweight embedded detection.

➤ *Autopilot and Companion-Computer Systems*

Meier et al. introduced Pixhawk as a micro aerial vehicle platform supporting autonomous flight with onboard computation [5]. PX4 and MAVLink supply the software stack and message protocol for linking a companion computer to the autopilot [7], [8]. Pedro et al. integrate range sensors, a Pixhawk 6X and a Raspberry Pi CM4 on a small fixed-wing sense-and-avoid platform [4], and Abro et al. present a modular Pixhawk–Raspberry Pi framework over MAVLink [19]. Zhu et al. report a sensor-fusion navigation and avoidance system on an ArduPilot-based orchard robot [18]; although not an aerial platform, it supports the serial autopilot–computer pattern. Hardware references for the compute board and GPS receiver are in [9] and [10]. The Raspberry Pi is accessible and flexible, but model size, frame rate and power draw must fit its resources; GPS supports waypoint navigation but is not an obstacle sensor.

➤ *Surveys*

Butt et al. review perception sensors, techniques and hardware for low-altitude UAV avoidance and conclude that performance emerges from the interplay of sensors, algorithms and hardware [17]. Alkhatib et al. survey static and dynamic obstacle detection and avoidance and stress safe path planning [20]. Both support the view that perception, decision and control must be designed together.

Table 1 Sensing Modalities in the Reviewed Literature

Modality	Strength	Limitation	Refs.
Visible camera + CNN	Semantic labels	Needs light; no direct range	[2], [6], [16]
Night-vision camera	Extends low-light imaging	Still no range; not thermal	[1]
Thermal infrared	Night person/vehicle detection	Cost; different image domain	[15]
RGB-D camera	Semantics plus depth	Bounded by depth-sensor range	[12]

LiDAR	Direct geometric range	No object identity	[3], [13]
LiDAR–camera fusion	Range plus semantics	Calibration and compute load	[11], [14]

➤ Comparative Analysis and Research Gap

Four trade-offs recur across the sources. LiDAR gives strong geometry but little semantics. Camera-based AI gives labels but is illumination-sensitive and lacks range unless paired with a range or depth source. Thermal and infrared sensing improves night performance but can add cost and a different image domain. Finally, more onboard intelligence demands more computation and power.

The gap addressed here is therefore integration, not a new sensor or detector: combining night-vision imaging for recognition, LiDAR for distance, a Raspberry Pi for inference and a Pixhawk for flight-critical control in one low-light platform. This is a system-level contribution that must be verified experimentally rather than presented as an algorithmic advance.

A second gap concerns validation. Many demonstrations rely on simulation, controlled settings or specialized hardware. A student-scale prototype should report detection precision

and recall, minimum detectable range, inference and communication latency, false detections in darkness, power consumption and endurance; without them, claims of real-time or autonomous operation remain qualitative.

➤ Proposed System Architecture

The proposed quadrotor comprises sensing, AI-processing, flight-control, actuation and communication subsystems (Fig. 1). The night-vision camera sends frames to the Raspberry Pi over CSI or USB; the Pi preprocesses them and runs a YOLO-based detector that outputs a class label, confidence and image position for humans, animals, trees and vehicles.

LiDAR forms a separate distance channel to the flight-control side, so proximity can be judged independently of the camera result. GPS provides global position and waypoints. The Pixhawk runs the control loops, stabilizes the airframe and issues PWM signals to four ESCs that drive four BLDC motors.

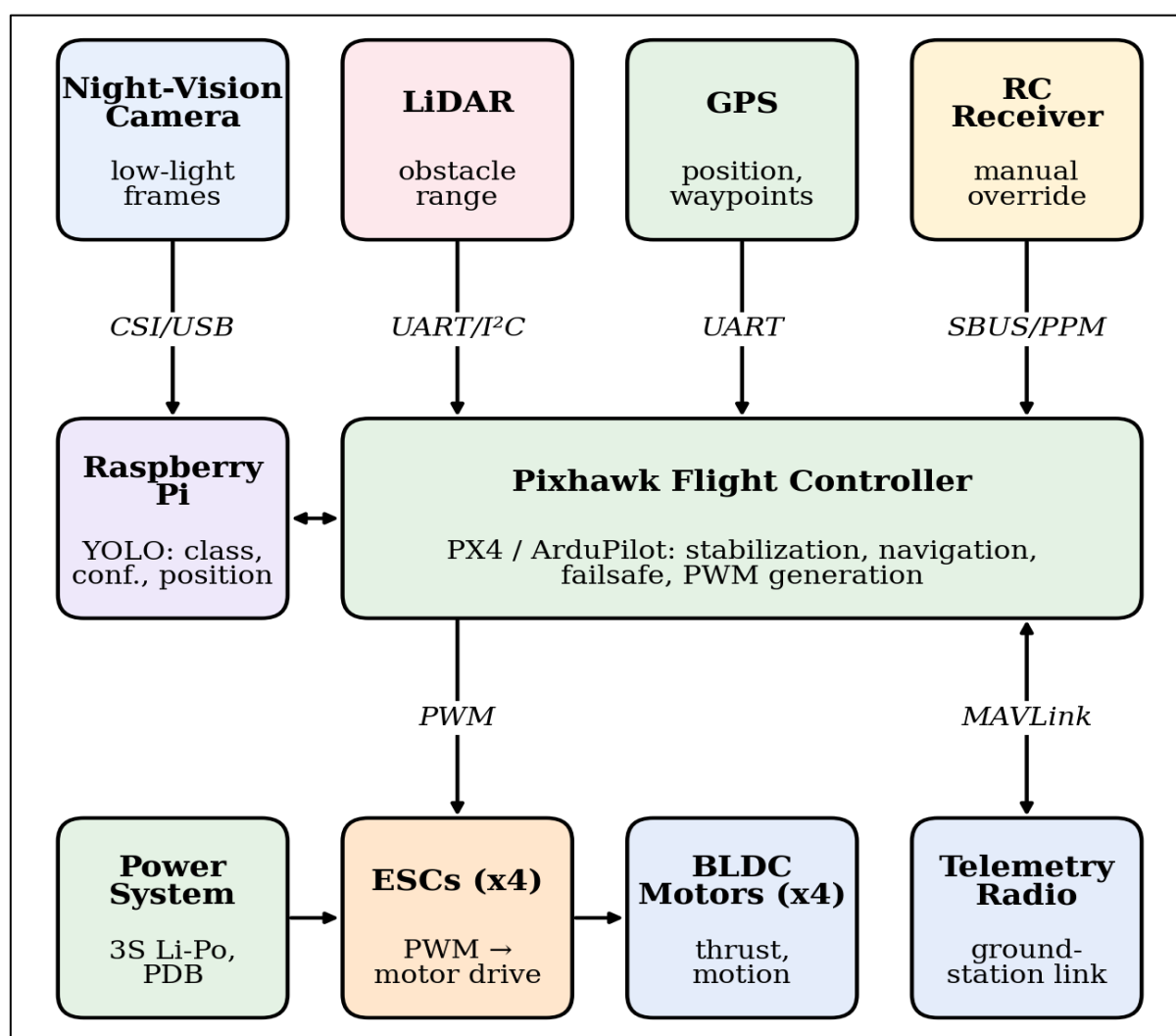


Fig 1 Block Diagram of the Proposed UAV Architecture. The Raspberry Pi–Pixhawk Link is UART/MAVLink; the Power System Feeds the ESCs.

The two computers exchange high-level data over UART with MAVLink [8]. A telemetry radio links the aircraft to a ground station for monitoring position, status, detections and warnings, and an RC receiver remains available for manual control or safety override. The central design choice is to keep AI inference out of the time-critical control loop, so the aircraft tolerates variable processing time.

➤ *Data and Decision Flow*

Each cycle begins with image capture and LiDAR ranging. The Raspberry Pi returns an object class and confidence for the frame while LiDAR independently reports distance, and the control logic associates the two. For example, a detected human may trigger an operator alert, whereas a tree or vehicle inside the safety boundary may trigger an avoidance response.

The distance threshold should be configurable rather than fixed, because the safe value depends on speed, braking capability, sensor update rate, processing latency, field of view and environment. It should be tuned experimentally and reported together with measured response time.

The ground station is for monitoring and is not the sole safety mechanism. The vehicle must keep onboard sensing and control so that a lost link does not prevent stable flight or basic failsafe behaviour.

➤ *Critical Observations*

- Neither sensor alone suffices: LiDAR answers “how far,” vision answers “what,” and each is weak at the other’s question.
- Low light is first a sensing problem and only second a modelling problem; a better detector cannot recover information the image lacks.
- Correct classification does not guarantee safe avoidance, because a correctly labelled tree may still be ranged inaccurately or reacted to too late.
- A Raspberry Pi is a practical development board, not a guarantee of real-time inference; frame rate, latency and memory must be benchmarked on the exact board and camera.
- Integration introduces failure modes absent from isolated demonstrations, including serial dropouts, timestamp mismatch, calibration error, vibration, power transients and processor overload.
- Claims should match what the prototype demonstrates; a system limited to alerts or reactive avoidance should be called semi-autonomous.
- The most valuable contribution will be quantitative evaluation by object class, in darkness, with measured range error, end-to-end latency, avoidance success, false-alarm rate, power draw and flight time.

V. CONCLUSION AND FUTURE WORK

This survey reviewed twenty sources on UAV obstacle detection, low-light perception, AI-based recognition, sensor fusion and Pixhawk/companion-computer systems. The evidence shows that LiDAR contributes geometry while vision contributes semantics, and that darkness remains the main obstacle for conventional cameras. The proposed architecture combines a Pixhawk, Raspberry Pi, night-vision camera, LiDAR, GPS, telemetry, ESCs and BLDC motors, and separates AI processing from flight-critical control to support safer semi-autonomous navigation.

Future work includes prototype integration, sensor calibration, dataset preparation, model optimization, flight testing and quantitative evaluation. Further directions are target tracking, improved low-light enhancement, LiDAR–camera calibration, lighter networks, onboard logging, dynamic-obstacle handling and advanced path planning. Each should be validated experimentally before stronger claims of autonomy or safety are made.

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