Edge-Enabled Real-Time Fire and Multi-Class Human/Animal Detection from UAV-Based Aerial Imagery

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***Abstract*—Wildfires, industrial accidents, and natural disasters have intensified due to global climate change, prolonged droughts, and erratic weather patterns, causing unprecedented damage to human life, property, and biodiversity. Rapid detection of fires and trapped living beings in remote regions is vital for effective disaster response. This project focuses on an edge-enabled UAV system capable of performing real-time detection of fire, humans, and animals using deep learning models deployed on the NVIDIA Jetson Nano. The project reviews eleven verified research papers, comparing existing fire and wildlife detection methods on UAVs, and analyzes their feasibility for embedded AI hardware. The literature highlights lightweight object detectors such as YOLOv5, YOLOv8, and CNN–Transformer hybrids as optimal for real-time edge inference. Based on these insights, this project outlines a feasible Jetson Nano deployment strategy aimed at developing a low-latency aerial detection framework for environmental safety and rescue missions.**

***Index Terms*—UAV, Edge Computing, Fire Detection, Human Detection, Animal Tracking, Jetson Nano, Real-Time AI**

I. Introduction

Over the past decade, the frequency and scale of wildfires have grown alarmingly worldwide. Prolonged droughts, deforestation, and rising global temperatures have led to millions of hectares of land being destroyed annually, displacing communities and devastating ecosystems. Beyond the immediate destruction, wildfire smoke degrades air quality across continents and contributes significantly to carbon emissions. Traditional fire surveillance methods—satellite monitoring, fixed sensors, and manual watchtowers—are limited by temporal resolution, high latency, and restricted coverage. These shortcomings delay early intervention, which is critical for containment and rescue operations.

Unmanned Aerial Vehicles (UAVs) equipped with onboard AI systems present a transformative solution for real-time fire detection and environmental monitoring. UAVs offer high mobility, flexibility, and rapid deployment, allowing surveillance over remote or hazardous terrains that are inaccessible to human responders. When combined with edge computing devices such as the NVIDIA Jetson Nano, UAVs can process data locally, enabling autonomous detection of fire, humans, and animals without relying on slow, high-bandwidth cloud links.

The motivation for this project stems from the growing demand for compact, power-efficient vision systems capable of performing multi-class detection under limited computational resources. By integrating proven detection architectures with Jetson Nano's parallel processing capabilities, this project aims to develop an intelligent UAV-based system for real-time situational awareness, enhancing the speed and reliability of emergency response.

II. Related Work and Literature Review

A. Overview of Prior Studies

Recent studies demonstrate significant progress in fire detection and visual surveillance using UAVs and embedded AI devices. Shamta and Demir [1] developed a UAV-based deep learning system using YOLOv8 and YOLOv5 on a Jetson Nano, achieving 96% classification accuracy with real-time performance. Lu et al. [2] introduced FCMI-YOLO, an optimized edge variant of YOLOv5 that reduced parameters by 40% while improving accuracy by 1.5%, highlighting the potential for efficient onboard deployment. Chaturvedi et al. [3] proposed a CNN–Transformer hybrid model for early smoke detection, demonstrating 93.9–99% accuracy with fewer than one million parameters—an ideal balance for embedded AI.

Several comprehensive reviews outline the evolution of UAV-based visual intelligence. Elhanashi et al. [4] presented a large-scale survey of deep learning approaches for fire and smoke detection, identifying YOLO-based models as the current state-of-the-art. Moumgiakmas et al. [5] discussed hardware-software integration for UAV-based computer vision systems, emphasizing the growing role of edge accelerators. Similarly, Nguyen et al. [6] surveyed aerial surveillance techniques, highlighting resource allocation challenges in real-time detection and tracking scenarios.

Zhu et al. [7] improved YOLOv8 with dual attention and multiscale fusion, achieving 93.6% precision and a 25% reduction in GFLOPs. Lv et al. [8] and Yang et al. [9] refined YOLOv5 by incorporating Ghost modules and lightweight attention, maintaining over 95% accuracy while enhancing inference speed on Jetson Nano devices. Nguyen et al. [10] developed WildLive, an edge-deployed wildlife tracking system achieving 17 FPS on Jetson Orin, validating UAV-based real-time animal detection. Finally, Muhammad et al. [11] established the classical baseline for CNN-based embedded fire detection, achieving near real-time inference on resource-limited hardware.

TABLE I

Comparison of Fire, Human, and Animal Detection Techniques on UAV and Edge Devices

Authors (Year)	Model/Approach	Dataset / Input Type	Accuracy / mAP / IoU	Device	FPS / Inference	Key Contribution
Shamta & Demir (2024)	**YOLOv5/YOLOv8 + RCNN**	UAV RGB imagery	96% acc, 89% det	Jetson Nano	25 FPS	Real-time onboard forest fire detection
Lu et al. (2025)	**FCMI-YOLO (Edge YOLOv5)**	Fire datasets	+1.5% mAP@50 vs v5s	Jetson Nano/Xavier NX	32 FPS	Lightweight attention-based YOLOv5
Chaturvedi et al. (2024)	**CNN–ViT Hybrid**	Smoke datasets	93.9–99% acc	Edge GPU	18 FPS	Ultra-light transformer–conv fusion
Elhanashi et al. (2025)	Review Study	Fire/Smoke datasets	–	–	–	Comprehensive fire detection review
Moumgiakmas et al. (2021)	UAV Vision Review	UAV fire imagery	–	–	–	Hardware–software integration analysis
Nguyen et al. (2022)	Aerial Vision Survey	UAV object tracking	–	–	–	Efficiency review for edge UAV systems
Zhu et al. (2025)	**Improved YOLOv8**	Fire dataset	93.6% P, 88.5% R	Edge GPU	+14% FPS	Multi-scale dual-attention design
Lv et al. (2024)	**Small-Target YOLOv5s**	Wildfire dataset	96% mAP	Edge/GPU	85 FPS	Optimized for small fire detection
Yang et al. (2023)	**Ghost YOLOv5**	Fire/Smoke dataset	95% acc	Jetson Nano	27 FPS	Low-power Ghost modules
Nguyen et al. (2025)	**WildLive System**	Animal tracking data	94% MOT acc	Jetson Orin AGX	17 FPS	Real-time multi-animal tracking
Muhammad et al. (2018)	**CNN (Classical)**	Fire video data	96% acc	Embedded board	30 FPS	Early embedded CNN baseline

B. Research Gaps and Limitations

Table I summarizes the reviewed literature, comparing methods by architecture, dataset, hardware, and performance metrics.Analysis of Table I reveals three critical limitations in current literature:

1) **Task Fragmentation:** 9 out of 11 papers focus on single-class detection, with only [10] addressing multi-object tracking but limited to animals only.
2) **Edge Performance Trade-offs:** While [2,9] achieve high FPS (27-32), they sacrifice multi-task capability. Conversely, comprehensive models like [3] struggle with real-time performance (18 FPS).
3) **Rescue Intelligence Void:** No existing work integrates fire intensity assessment with human/animal localization for actionable rescue guidance.

III. Proposed Contribution

This project addresses identified gaps by developing an integrated detection framework that:

- Unifies fire, human, and animal detection in a single optimized model
- Incorporates fire intensity assessment alongside object localization
- Targets real-time performance on Jetson Nano through architecture optimization
- Provides comprehensive situational awareness for emergency response

IV. Feasibility and System Design

The literature collectively confirms that edge computing platforms like the Jetson Nano are capable of executing real-time detection with optimized deep learning architectures. Lightweight YOLO variants, GhostNet-based models, and hybrid CNN–Transformer designs can achieve inference times below 100 ms with energy consumption under 10 W. This enables autonomous UAV surveillance without reliance on external networks.

For this project, three techniques emerge as feasible candidates for implementation:

- **Technique 1:** YOLOv8n-based model for real-time multi-class detection (fire, human, animal) optimized using TensorRT quantization.
- **Technique 2:** FCMI-YOLO architecture adapted for edge inference with reduced feature maps.

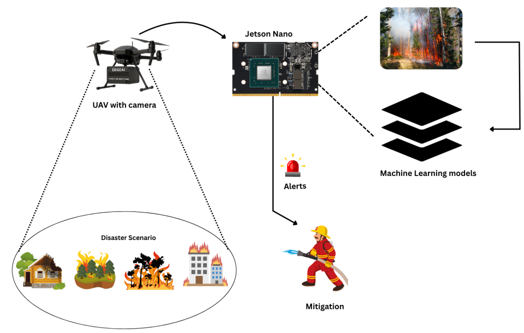

Fig. 1. Proposed system overview for UAV-based real-time fire and multi-class detection. The UAV captures aerial imagery and processes it locally on a Jetson Nano to detect fire, humans, and animals, transmitting alerts to ground control in real-time.

- **Technique 3:** Ghost-Enhanced YOLOv5 variant to minimize parameter count while maintaining detection precision.

The project timeline spans 10–12 weeks, with four team members handling dataset preparation, model training, UAV integration, and Jetson Nano optimization. Required hardware includes an NVIDIA Jetson Nano 4GB developer kit, 32 GB microSD card, USB/CSI camera module, and sufficient cooling. With proper quantization and asynchronous processing, real-time (15–25 FPS) performance is achievable.Technical specifications of Jetson Nano is shown in table II below.

TABLE II

Technical Specifications of NVIDIA Jetson Nano

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Component	Specification
AI Performance	472 GFLOPs
GPU	128-core NVIDIA Maxwell
CPU	Quad-core ARM A57 @ 1.43 GHz
Storage	microSD card slot
RAM	4GB 64-bit LPDDR4 (25.6 GB/s bandwidth)
Power	5W (10W max)

V. Conclusion

This literature review establishes that recent advances in deep learning have made real-time, multi-class detection viable on resource-limited UAV platforms. Studies demonstrate that optimized YOLO-based models outperform traditional detectors in accuracy and efficiency while maintaining low power consumption. Edge computing not only reduces communication latency but also enhances autonomy in emergency response operations. Building upon these findings, this project will integrate fire, human, and animal detection within a single UAV framework for environmental monitoring and disaster rescue, targeting full real-time performance on the Jetson Nano.

VI. Declaration

ChatGPT (Deep Research Mode) was used to search, verify, and summarize research papers and to generate this literature review. All cited papers were validated by the team and uploaded to the GitHub repository under `/docs/references`.

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