



Artificial Intelligence- Powered Smart Safety Cap for Farm Workers Using Artificial Intelligence, IoT and Wearable Sensors: A Review

Khade Pranjal Dilip, Dr.Anand. A. Khatri, Prof. Bangar Abhishek, Prof. S.B.Bhosale

Dept. of Computer Engineering Jaihind College of Engineering, Pune, India

Abstract. Farm workers operating in sugarcane fields, forests, tea plantations, and other areas with thick vegetation may encounter hazardous animals and insects that are difficult to notice before approaching them. Conventional precautions, including sticks, torches, protective footwear, and visual observation, offer limited capability for identifying concealed threats in advance. Delays in communication and access to medical assistance can further increase the risks associated with such incidents. Recent progress in Artificial Intelligence (AI), computer vision, thermal imaging, edge computing, Global Positioning System (GPS) technology, and the Internet of Things (IoT) provides opportunities to develop wearable systems for improved agricultural safety. This paper presents a focused narrative review of research relevant to an AI-enabled safety cap, covering animal recognition, snake detection, thermal-based wildlife monitoring, edge deployment, and IoT- supported alert systems. The reviewed approaches are discussed across three areas: sensing methods, including visible-light cameras, thermal sensors, and supplementary positioning or motion sensors; deep-learning techniques, including YOLO -based detectors, transformer architectures, lightweight models, and object tracking; and system designs combining local processing, offline data handling, and cloud connectivity. Published results indicate that some animal and snake detection models achieve approximately 92–98% on selected evaluation metrics, while one thermal wildlife detection approach reports 89.1% mAP50 with approximately 1.45 million parameters. Certain lightweight YOLOv8 models have also demonstrated processing rates of around 52–65 frames per second on Jetson -class hardware, although performance may vary across devices and experimental settings. Despite these advances, much of the existing research relies on fixed cameras, aerial platforms, or controlled datasets. Limitations include restricted species coverage, insufficiently documented datasets partitioning, and limited evaluation under real agricultural conditions. The reviewed evidence does not establish the field performance of an integrated, multi-camera, head-worn safety device incorporating behaviour analysis, battery endurance assessment, and emergency alert testing. To address these gaps, this paper outlines a conceptual worker-to-cloud architecture combining visual and thermal sensing, edge-based inference, multi modal warnings, optional GPS-enabled SOS communication, and systematic field evaluation. The review also identifies research priorities for developing a practical and reliable wearable safety solution for agricultural workers.



Keywords: Smart Safety Cap, Farm Worker Safety, Animal Detection, Thermal Imaging, Edge AI, Internet of Things

I. Introduction

Agriculture is a major source of employment for a significant portion of India's population. However, workers in fields such as sugarcane, forest edges, and plantations often come into contact with animals that hide within crops and grass. Snakebites, in particular, have led to a high number of deaths in India, with about 1.2 million estimated deaths between 2000 and 2019, averaging around 58,000 per year. Most of these incidents occurred in rural homes. Despite this, workers still rely on tools like sticks, torches, protective footwear, and their own observation to detect dangers, which do not offer early warnings or automatic alerts. Additionally, rescue efforts are delayed when the exact location of an injured worker is not known. Recent advancements in real-time object detection, specifically the YOLO family of one-stage detectors, have made camera-based detection fast enough for use directly on devices.

Farm security systems already use such detectors in combination with IoT alerts. For instance, an ESP32-CAM node running YOLOv8 can trigger a buzzer and send notifications to the cloud. There are also systems that integrate laser sensors, cameras, and compact networks using TinyML frameworks. Today, dedicated models focus on detecting snakes with high precision. For a head-worn safety cap, three key areas are converging: multi-camera and thermal sensors to monitor the worker's surroundings, lightweight AI models that run locally on the device, and IoT connectivity that enables GPS and SOS alerts to be sent to family members or emergency contacts. This review brings these developments together, assesses the current level of evidence for using such systems in real-world settings, and suggests a conceptual framework to address the identified limitations.

II. Review Methodology

A focused search of publisher platforms (MDPI, Springer Nature, IEEE, Elsevier), PubMed Central, the arXiv repository and Crossref metadata was carried out with combinations of the terms snake detection, animal intrusion, thermal wildlife detection, YOLO, edge AI, TinyML, Jetson, IoT and wearable, prioritising 2020–2026 publications. Studies were included when they reported animal- or snake-specific detection, thermal sensing or edge deployment with a stated method and quantitative outcome; reviews were used for context only. Reference details were cross-checked against publisher, DOI, repository or citing-paper records, and where only an abstract was accessible, results are reported as stated there. Several sources are preprints. Direct logged querying of Scopus and Web of Science was not carried out, so the review is narrative rather than systematic, and study counts are not reported.

III. Sensing Technologies for Farm Worker Safety

1. Visible-Light and Multi-Camera Sensing

Visible-light cameras are the main sensor in farm animal-detection systems. A low-cost ESP32-CAM node running a tuned YOLOv8 model reached a mean average precision (mAP) of 92.44 % and a sensitivity of 96.65 % on an unseen test set and



then triggered a buzzer and a cloud notification [4]. A TinyML intrusion framework paired a laser detection system with an AI camera and a lightweight classifier, and pruning and quantisation reduced the model file to as little as 1.63 MB [5]. Both are fixed or rover-mounted systems that protect crops or land; neither is worn by the person at risk. A cap must instead cover the path ahead, the ground near the feet and the left, right and rear sides, because small creatures such as snakes and scorpions lie low in grass while larger animals can approach from any direction. None of the reviewed studies evaluates such a head-worn camera array, so its coverage, motion blur from head movement and power demand remain unmeasured.

2. Thermal Infrared Imaging

Thermal infrared (TIR) cameras sense emitted heat and so work without visible light, which is why they are used for nocturnal wildlife monitoring. TIR images are single-channel, low in resolution and noisy, and targets can be blurred or overlapping [7]. BIRDSAI provides 48 aerial TIR videos of humans and animals recorded at night in African protected areas, with heat reflections, camera rotation and motion blur as typical difficulties [8]. Most published TIR detection work comes from drones, including a synthesis of the opportunities and constraints of automated wildlife detection by drones [9] and a feasibility analysis of real-time detection from UAV-derived thermal and RGB images [10]. A caution for the cap is that thermal contrast depends on the temperature difference between an animal and its surroundings: warm-bodied mammals such as boars, monkeys and dogs should stand out, whereas snakes and scorpions at ambient temperature may not, so thermal imaging is expected to complement rather than replace the downward visible-light camera. This expectation is a design inference, not a result reported in the reviewed studies.

3. Supplementary Sensing, Alerts and Positioning

Beyond imaging, a safety device needs range or motion sensing, positioning and human-readable alerts. The laser-assisted framework in [5] shows how a non-imaging sensor can support classification, and the buzzer in [4] shows a simple local alert. GPS tracking, a manual SOS button and voice, vibration and buzzer feedback are standard IoT components, but the reviewed studies evaluate alerting for farm or crop protection rather than for a worker wearing the device, so detection-to-alert latency, audibility in noisy fields and SOS reliability remain open questions.

IV. Machine Learning and Deep Learning Methods

1. Detector Families

Two-stage detectors such as the R-CNN family are accurate but computationally heavy, whereas one-stage detectors such as SSD and YOLO treat detection as a single regression step and run in real time [2], [7]. The YOLO family has evolved from the original model through YOLOv8, YOLO-NAS and transformer variants, and its nano and small versions are the usual choice for constrained hardware [3]. Lightweight designs based on depthwise separable convolutions reduce computation further [11]. The cost of heavy models is visible in thermal wildlife detection: on BIRDSAI, ALSS-YOLO reached 89.1 % mAP50 with 1.452 million parameters at 223.7 frames per second on a desktop GPU, while CE-RetinaNet reached 91.8 % with 55.8 million parameters at 6.1 frames per second [7].

2. Snake and Small-Animal Detection

Snakes are the hardest target for a cap because they are camouflaged, low to the ground and numerous in species. Snake-DETR, built on RT-DETR with a lightweight group-shuffle convolution encoder, reached 97.66 % accuracy,



93.92 % recall and 95.23 % mAP@0.5 on a custom 27-species dataset at 43.5 frames per second and was described as suitable for edge deployment [6]. An earlier study applied transfer learning to Australian snake images and built an iOS application with an on-device (offline) version and an online version [12], the same offline-first principle that a cap in low-connectivity fields requires. Both studies use custom image sets, and neither reports evaluation from a head-worn viewpoint.

3. Behaviour Analysis and Tracking

Deciding whether an animal is approaching, moving away or showing aggression needs more than a single-frame label. The dominant approach is tracking-by-detection, in which a tracker links detector outputs across frames; ByteTrack, for example, associates every detection box, including low-confidence ones, to keep identities through partial occlusion [13]. From such tracks, approach and retreat could be inferred from changes in box size and position over time, but this is a design approach: the reviewed animal-detection studies classify species and presence and do not validate behaviour or aggression labels, so behaviour analysis for the cap is at an early research stage.

4. Validation Practice

Frames taken from the same video, site or session are highly correlated, so a random split of frames between training and test sets can leak information and inflate reported accuracy [14]. Aerial TIR datasets such as BIRDSAI are built from continuous videos [8]. The farm and snake studies report scores on unseen or independent test sets, but the accessible abstracts do not state whether splits were made by video, scene or site [4]–[6]. Splitting by field, session or worker is therefore recommended for any cap dataset.

V. IoT Integration and Edge Deployment

The reviewed IoT-based systems adopt different strategies for processing data and delivering alerts. In [4], detected hazards trigger a buzzer and cloud-connected notifications to nearby farmers. The system described in [5] combines remotely managed TinyML models with resource-limited edge devices and an IoT-enabled rover, whereas the approach in [12] supports on-device execution through a mobile phone, allowing operation without a continuous internet connection. Experiments involving resource-constrained hardware highlight important considerations for deploying AI on a wearable safety cap. In a drone-based detection system, YOLOv8n achieved 52 FPS on a Jetson Orin NX, increasing to 65 FPS after INT8 quantisation. However, the Raspberry Pi 5 could not provide the processing speed required for real-time operation in that experiment. Cloud-based inference also introduced additional communication delays, limiting its suitability for time-critical detection [15]. Another evaluation comparing YOLOv8, EfficientDet-Lite, and SSD across Raspberry Pi and Jetson Orin Nano platforms found that the Jetson Orin Nano offered faster and more energy-efficient request processing, although its idle power consumption was comparatively high. The results also indicated that models with lower mAP could offer advantages in processing speed and energy efficiency [16]. These findings suggest that selecting an appropriate balance between detection performance, processing speed, and power consumption is essential for wearable AI applications. Local inference can support faster alerts and reduce reliance on network availability, while cloud services remain useful for remote monitoring and analysis across multiple locations. Nevertheless, further investigation is required to assess continuous multi-camera operation on a wearable device, particularly in terms of battery endurance, heat generation, device weight, and reliable data synchronisation following extended



network interruptions. These factors remain important considerations when translating existing edge-AI approaches into a practical smart safety cap for agricultural workers.

VI. Comparative Analysis

Table I summarises representative primary studies. Reported values are not directly comparable because targets, datasets, hardware and validation schemes differ.

Table 1: Comparison of Representative AI-Based Animal Detection and Edge Safety Studies

Author, year	Objective	Sensing / method	Major reported findings	Limitations
Bondi et al., 2020 [8]	Thermal dataset for detection and tracking	Aerial TIR videos from fixed-wing drones	48 night-time videos of humans and animals in African protected areas	Aerial viewpoint; dataset only, no worn-device model
Yang and Sinnott, 2021 [12]	Detect and classify snakes on mobile devices	CNNs with transfer learning; iOS app	On-device (offline) and online versions implemented	Australian snakes; smartphone, not worn
Raiaan et al., 2023 [4]	Detect harmful and endangered animals on farms	ESP32-CAM; YOLOv8; cloud alert and buzzer	mAP 92.44 %; sensitivity 96.65 % on unseen test set	Fixed farm node; visible light only
Reddy et al., 2024 [5]	Animal intrusion detection and deterrence	TinyML EvoNet; laser + AI camera; IoT rover	Model file as small as 1.63 MB after pruning and quantisation	Crop-protection system; not worn
He et al., 2024 [7]	Wildlife detection in thermal images	ALSS-YOLO (lightweight YOLO)	mAP50 89.1 %; 1.452 M parameters; 223.7 FPS (RTX 3090)	UAV viewpoint; embedded tests listed as future work
Toosi et al., 2024 [16]	Benchmark detectors on edge devices	YOLOv8, EfficientDet-Lite, SSD; Raspberry Pi, Jetson Orin Nano	Orin Nano fastest and most energy-efficient; accuracy–energy trade-off	Generic objects; not animal-specific
Rey et al., 2025 [15]	Deploy YOLOv8 on constrained edge devices	YOLOv8n/s; Jetson Orin Nano/NX; Raspberry Pi 5	52 FPS (65 with INT8) on Orin NX; Pi 5 not real-time	Drone pipeline; not worn

VII. Proposed Conceptual Architecture

Fig. 1 presents a proposed conceptual architecture derived from the reviewed systems and from the design of the smart safety cap. The worker moves through crops, grass or forest where hidden animals may approach (layer 1). Five visible-light cameras (front, rear, left, right and downward), a thermal camera and supplementary motion or range sensors capture the surroundings, and a GPS module tracks position (layer 2), because no single sensor covers low-lying snakes, warm-bodied mammals and night conditions [4], [7]. An embedded acquisition unit timestamps, synchronises and preprocesses the streams (layer 3), and

an Edge AI processor runs lightweight detection, tracking-based behaviour analysis and threat scoring with a confidence value (layer 4) [6], [13], [15]. Warnings are given at once by voice, vibration and buzzer, an SOS button sends the location to registered contacts, and events are stored locally when there is no network (layer 5); this local alert path works without connectivity. Stored events are uploaded to a cloud database and dashboard when connectivity returns, where sightings are mapped to high-risk zones (layer 6) [4], [5]. A sampled subset of events is verified by field staff or experts, and models are retrained only after independent re-testing (layer 7), which addresses the dataset and validation weaknesses identified in the literature [8], [14].

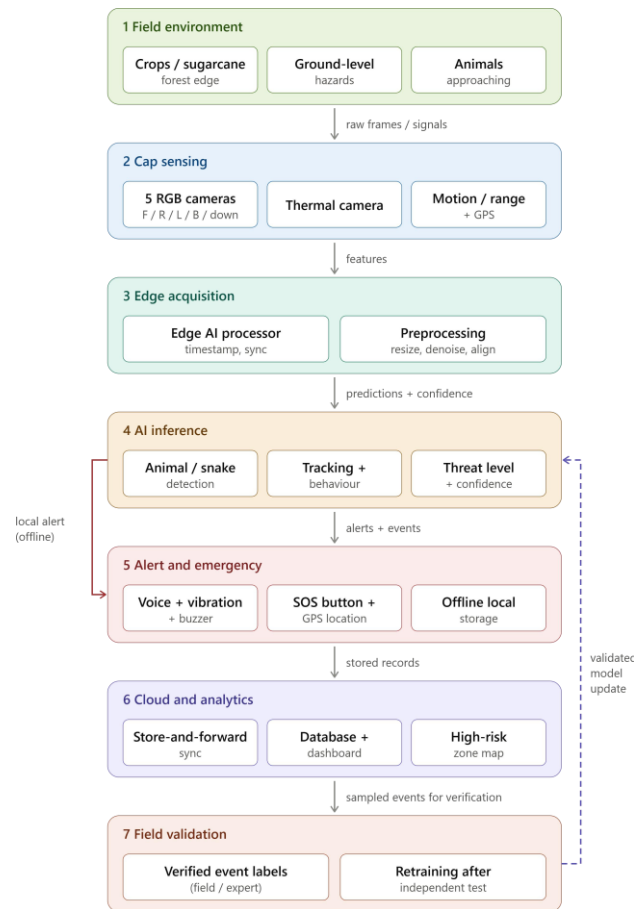


Fig.1. Proposed conceptual architecture for an AI-enabled smart safety cap for farm workers (conceptual, not experimentally validated)



VIII. Research Gaps and Future Directions

Gaps supported by the reviewed evidence. (i) No worn-device evidence: the reviewed detectors run on fixed nodes, rovers, drones, phones or desktop GPUs, and none reports a multi-camera head-worn trial [4]–[7], [12]. (ii) Dataset mismatch: thermal datasets are aerial and night-time [7], [8], and snake datasets are custom image collections [6], [12], so ground-level, head-height views of snakes and scorpions in crops and grass are scarce. (iii) Indirect embedded evidence: real-time results come from drone or generic benchmarks, and a Raspberry Pi 5 failed to meet real-time needs in one study [15], [16]. (iv) Behaviour and aggression labels are not validated in the reviewed animal-detection studies. (v) Weak validation reporting: random splits of correlated frames risk leakage, and the split scheme is often not stated [8], [14]. (vi) Power, heat, weight, comfort and detection-to-alert latency of continuous multi-sensor processing are not reported [15], [16].

Directions requiring investigation. Priorities include ground-level multi-camera datasets from real fields across seasons, regions and lighting with grouped train–test splits; paired thermal and visible-light datasets that test whether thermal imaging helps for snakes and scorpions as well as mammals; quantised nano-scale detectors profiled for latency, energy and temperature on candidate wearable hardware; field-validated behaviour and threat-level models; measurement of false alarms, alert audibility and worker response time; SOS and store-and-forward reliability under poor connectivity; and privacy and data governance for GPS and sighting data shared with cloud services.

IX. Conclusion

AI-enabled animal detection has progressed from desktop research models to lightweight detectors, snake-specific networks, thermal wildlife detectors and IoT-connected edge systems. Reported detection scores are high for specific tasks, and nano-scale models can run in real time on Jetson-class hardware, but the evidence base is dominated by fixed-camera, drone and laboratory studies with limited independent validation and no reported trial of a multi-camera head-worn device. Thermal imaging is expected to help most for warm-bodied animals, so visible-light coverage of the ground near the feet remains essential. Reliable deployment of a smart safety cap will require ground-level, multi-season datasets, grouped validation, field trials of power, latency and alert effectiveness, validated behaviour analysis and offline-first emergency communication, as reflected in the proposed conceptual architecture.

References

1. W. Suraweera, D. Warrell, R. Whitaker, G. R. Menon, R. Rodrigues, S. H. Fu, R. Begum, P. Sati, K. Piyasena, M. Bhatia, P. Brown, and P. Jha, “Trends in snakebite deaths in India from 2000 to 2019 in a nationally representative mortality study,” *eLife*, vol. 9, Art. no. e54076, 2020, doi: 10.7554/eLife.54076.
2. J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You only look once: Unified, real-time object detection,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2016, doi: 10.1109/CVPR.2016.91.
3. J. Terven, D.-M. Córdova-Esparza, and J.-A. Romero-González, “A comprehensive review of YOLO architectures in computer vision: From YOLOv1 to YOLOv8 and YOLO-NAS,” *Mach. Learn. Knowl. Extr.*, vol. 5, no. 4, pp. 1680–1716, 2023, doi: 10.3390/make5040083.



4. M. A. K. Raiaan, N. M. Fahad, S. Chowdhury, D. Sutradhar, S. S. Mihad, and M. M. Islam, "IoT-based object-detection system to safeguard endangered animals and bolster agricultural farm security," *Future Internet*, vol. 15, no. 12, Art. no. 372, 2023, doi: 10.3390/fi15120372.
5. K. V. Reddy, B. S. K. Reddy, V. Goutham, M. Mahesh, J. S. Nisha, G. Palanisamy, M. Golla, S. Purushothaman, K. R. Reddy, et al., "Edge AI in sustainable farming: Deep learning-driven IoT framework to safeguard crops from wildlife threats," *IEEE Access*, vol. 12, 2024, doi: 10.1109/ACCESS.2024.3406585.
6. H. Wang, S. Zhang, C. Zhang, Z. Liu, Q. Huang, X. Ma, and Y. Jiang, "Snake-DETR: A lightweight and efficient model for fine-grained snake detection in complex natural environments," *Sci. Rep.*, vol. 15, no. 1, 2025, doi: 10.1038/s41598-024-84328-w.
7. A. He, X. Li, X. Wu, C. Su, J. Chen, S. Xu, and X. Guo, "ALSS-YOLO: An adaptive lightweight channel split and shuffling network for TIR wildlife detection in UAV imagery," *arXiv:2409.06259*, 2024.
8. E. Bondi, R. Jain, P. Aggrawal, S. Anand, R. Hannaford, A. Kapoor, J. Piavis, S. Shah, L. Joppa, B. Dilkina, and M. Tambe, "BIRDSAI: A dataset for detection and tracking in aerial thermal infrared videos," in *Proc. IEEE Winter Conf. Appl. Comput. Vis. (WACV)*, 2020, doi: 10.1109/WACV45572.2020.9093284.
9. E. Corcoran, M. Winsen, A. Sudholz, and G. Hamilton, "Automated detection of wildlife using drones: Synthesis, opportunities and constraints," *Methods Ecol. Evol.*, vol. 12, no. 6, pp. 1103–1114, 2021.
10. S. Lee, Y. Song, and S.-H. Kil, "Feasibility analyses of real-time detection of wildlife using UAV-derived thermal and RGB images," *Remote Sens.*, vol. 13, no. 11, Art. no. 2169, 2021.
11. A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, "MobileNets: Efficient convolutional neural networks for mobile vision applications," *arXiv:1704.04861*, 2017.
12. Z. Yang and R. Sinnott, "Snake detection and classification using deep learning," in *Proc. 54th Hawaii Int. Conf. Syst. Sci. (HICSS)*, 2021.
13. Y. Zhang, P. Sun, Y. Jiang, D. Yu, F. Weng, Z. Yuan, P. Luo, W. Liu, and X. Wang, "ByteTrack: Multi-object tracking by associating every detection box," in *Proc. Eur. Conf. Comput. Vis. (ECCV)*, 2022, *arXiv:2110.06864*.
14. S. Kapoor and A. Narayanan, "Leakage and the reproducibility crisis in machine-learning-based science," *Patterns*, vol. 4, no. 9, Art. no. 100804, 2023, doi: 10.1016/j.patter.2023.100804.
15. L. Rey et al., "A performance analysis of You Only Look Once models for deployment on constrained computational edge devices in drone applications," *arXiv:2502.15737*, 2025.
16. D. K. Toosi et al., "Benchmarking deep learning models for object detection on edge computing devices," *arXiv:2409.16808*, 2024.