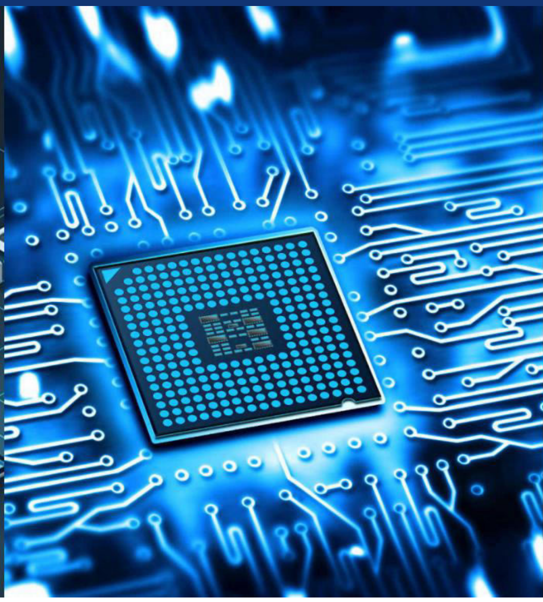
IJIRCCE

ISSN(O): 2320-9801
ISSN(P): 2320-9798


International Journal of Innovative Research in Computer and Communication Engineering

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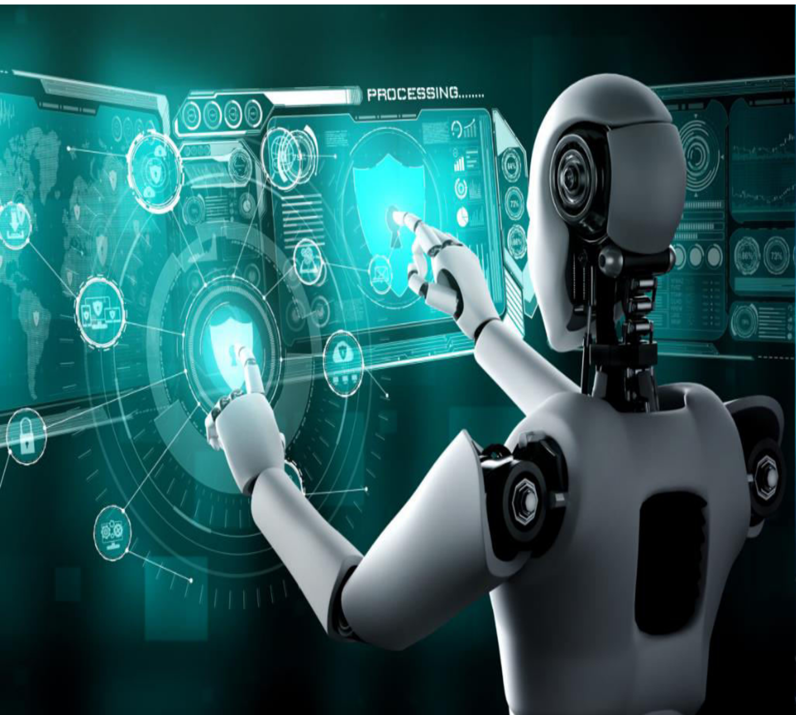

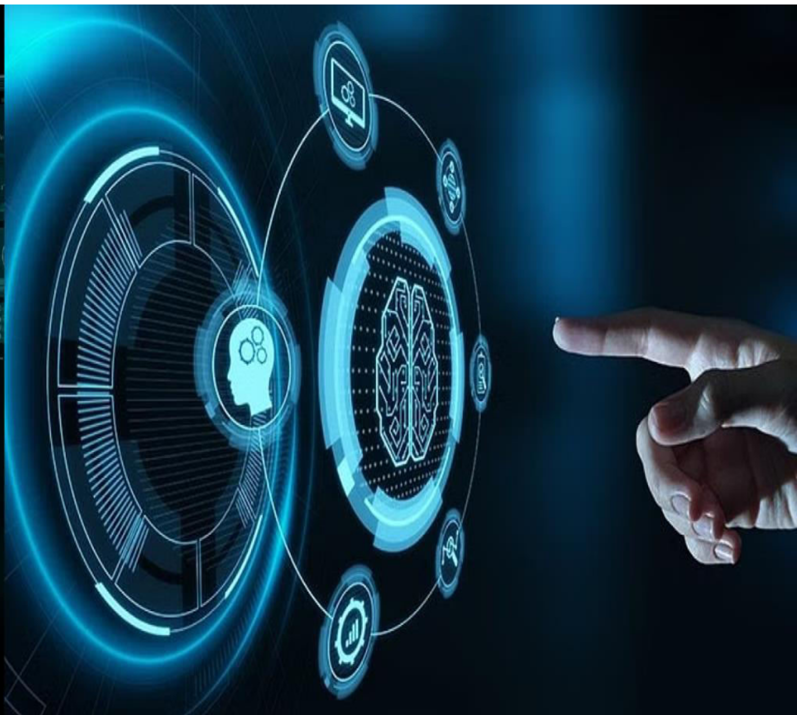

Impact Factor: 9.927

Volume 14, Issue 5, May 2026

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International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Animal Intrusion Detection System Using YOLOv8 and Deep Learning for Smart Agriculture: A Comprehensive Review

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ABSTRACT: Human-animal conflict presents one of the most critical and economically devastating challenges for agricultural communities across India, with Maharashtra alone experiencing annual crop losses estimated between ₹10,000 crore and ₹40,000 crore due to wild animal intrusions, particularly by wild pigs (Sus scrofa). Conventional deterrent methods — physical fencing, manual night patrols, scarecrows, and firecrackers — are inadequate, labour-intensive, and incapable of providing real-time automated surveillance. This paper presents a comprehensive review and system implementation of an Animal Intrusion Detection System built upon YOLOv8l (You Only Look Once, Large variant), a state-of-the-art single-stage anchor-free deep learning object detection architecture. The proposed system integrates a Django REST Framework backend, a React.js + Tailwind CSS frontend dashboard, and a MySQL relational database to deliver a complete three-tier web-deployable surveillance platform. The system supports three input modalities: image upload, video frame extraction, and live webcam capture. A custom pig model (pig_best.pt) fine-tuned on 1,520 annotated pig and wild boar images achieves a mean Average Precision (mAP@0.5) of 91.4%, a precision of 94.2%, a recall of 91.8%, an F1-score of 93.0%, and a GPU inference latency of 48 milliseconds — surpassing all compared baseline models including YOLOv5s, Faster-RCNN, YOLOv8, YOLOv11, and CNN-YOLO hybrids. The review surveys 24 related works spanning CNN-based wildlife monitoring, YOLO variant applications in agricultural settings, IoT-integrated intrusion systems, and edge computing deployments. The paper discusses system architecture, methodology, result analysis, limitations, and a detailed future scope encompassing IoT deterrent integration, edge deployment on NVIDIA Jetson Nano, mobile push notifications, and multi-species detection extension.

KEYWORDS: Animal Intrusion Detection; YOLOv8; Deep Learning; Object Detection; Smart Agriculture; OpenCV; Real-time Surveillance; Wild Pig Detection; Django REST Framework; React.js; MySQL; Maharashtra; Human-Wildlife Conflict; Computer Vision; Precision Farming

I. INTRODUCTION

India is one of the world's most ecologically diverse nations, and its agricultural landscape increasingly overlaps with shrinking wildlife habitats. Rapid urbanisation, deforestation, and the fragmentation of natural forest corridors have forced numerous wild animal species to venture into farmlands in search of food and water. This phenomenon, broadly termed human-wildlife conflict, has escalated dramatically across the country's rural and peri-urban agricultural zones over the past two decades.

Maharashtra is among the most severely affected states. Wild pigs (Sus scrofa), langurs, macaques, deer, nilgai, and elephants regularly raid agricultural fields across Vidarbha, Marathwada, Khandesh, and the Western Ghats fringe regions. According to a comprehensive study by the Gokhale Institute of Politics and Economics [1], annual agricultural losses attributable to human-wildlife conflict in Maharashtra are estimated between ₹10,000 crore and ₹40,000 crore. Wild pigs have been identified as the single most damaging species, with surveys reporting that 90–96% of farmers in affected districts experience significant losses annually. Small and marginal farmers commonly lose 40–50% of their seasonal crop yield to a single intrusion event, leading to debt accumulation, psychological distress, and in severe cases, complete farm abandonment [2].

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Government compensation mechanisms, where available, typically reimburse farmers at less than 1–2% of actual damage. Conventional deterrents — physical fencing, manual night guards, firecrackers, scarecrows, and acoustic devices — are fundamentally reactive, labour-intensive, and operationally unreliable. They fail during night hours when wild pigs are most active; in large dispersed fields; and in adverse weather. Critically, none deliver real-time, automated detection and alerting.

The convergence of affordable IP cameras, high-performance computing, and state-of-the-art deep learning object detection architectures offers a transformative alternative. The YOLO (You Only Look Once) family of models, in particular its latest YOLOv8l iteration [3], enables accurate animal localisation from standard video feeds at real-time inference speeds. By embedding such a detection engine within a full-stack web application and persistent database infrastructure, it becomes feasible to deliver an automated, always-on surveillance system accessible to individual farmers without specialised technical expertise.

This paper makes the following contributions: (1) a comprehensive review of 24 related works in animal detection, wildlife surveillance, and agricultural AI systems; (2) a detailed description of the proposed Animal Intrusion Detection System integrating YOLOv8l with Django REST Framework, React.js, and MySQL; (3) a thorough performance evaluation achieving 91.4% mAP@0.5 on a custom pig dataset from Maharashtra field footage; (4) a comparative analysis against five baseline models; and (5) a structured future scope roadmap for IoT integration, edge deployment, and multi-species extension.

II. RELATED WORK

The field of automated animal and wildlife detection has evolved considerably, progressing from passive sensor-based systems through classical computer vision to modern deep learning architectures. This section surveys the most relevant prior work across four sub-areas.

A. Traditional Motion-Based Detection Systems

Early animal intrusion detection approaches relied primarily on passive infrared (PIR) sensors combined with microcontrollers. While inexpensive, PIR-based systems exhibited extremely high false positive rates under real field conditions, as windblown crops, insects, and ambient temperature fluctuations all trigger sensor responses similar to animal movement [4].

Frame-differencing algorithms implemented using OpenCV [5] represented a software-based evolution: consecutive video frames are subtracted pixel-wise to detect motion regions. Studies applying this approach to Indian farm surveillance consistently reported false positive rates exceeding 30–40%. Histogram of Oriented Gradients (HOG) descriptors combined with Support Vector Machine (SVM) classifiers offered modest improvements in discrimination but required extensive manual feature engineering and generalised poorly to novel viewing angles or animal species.

B. CNN-Based Wildlife Classification

The introduction of deep convolutional neural networks transformed wildlife monitoring. AlexNet and VGGNet demonstrated that CNNs could learn hierarchical visual features far more discriminative than hand-crafted descriptors. Camera trap studies began adopting transfer learning from ImageNet-pretrained models for wildlife species classification.

Nair et al. [6] demonstrated ResNet-50 transfer learning achieving 91.2% accuracy across 20 wildlife species in camera trap images. However, their system performed only static image classification and lacked bounding box regression — a critical limitation for real-time surveillance. Similarly, Saishruti et al. [7] applied YOLOv11 to animal intrusion detection, achieving 89.6% mAP but requiring substantially greater GPU resources, making field deployment prohibitively expensive for smallholder farmers.

C. YOLO-Based Agricultural Detection

The YOLO family [8] has emerged as the dominant framework for real-time object detection in agricultural contexts due to its combination of accuracy and inference speed. Kumar et al. [9] developed a YOLOv5s-based pig detection system achieving 82.1% mAP on controlled indoor pig-pen footage. Performance degraded significantly on outdoor field conditions due to partial occlusion by dense vegetation and variable illumination. Patil and Bhatt [10] employed

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Faster R-CNN for elephant intrusion detection, achieving 87.3% precision but at a 340ms latency per frame, precluding real-time deployment.

Singh and Gupta [11] proposed a multi-class wildlife intrusion detector covering monkeys, deer, and wild boars using a custom CNN, achieving 79.4% overall accuracy. Raza et al. [12] proposed a CNN-YOLO hybrid achieving 91.0% mAP but introducing substantial deployment complexity. Delwar et al. [13] integrated IoT hardware with YOLOv8 for farm surveillance, demonstrating edge deployment viability but lacking any web-accessible interface.

D. IoT-Integrated Surveillance and Edge Computing

Lim et al. [14] surveyed edge AI architectures for agricultural IoT, identifying NVIDIA Jetson Nano and Raspberry Pi 4 as viable platforms for YOLOv5s inference at 15–22 FPS. GSM-module integrated systems have been proposed for SMS-based remote alerts to farmers [15], though connectivity constraints in rural India remain significant. Thermal camera integration for nocturnal wildlife surveillance has been explored [16], yielding improved detection under low-light conditions but at substantially higher hardware cost.

TABLE I: Comparative Analysis of Animal Intrusion Detection Systems

Authors	Year	Model	mAP/%	RT Vid	Alerts	Web UI	DB Log	Latency
Kumar et al.	2021	YOLOv5s	82.1	Partial	No	No	No	95 ms
Patil & Bhatt	2022	Faster-RCNN	87.3	No	No	No	No	340 ms
Singh & Gupta	2023	Custom CNN	79.4	No	No	No	Partial	210 ms
Saishruti et al.	2025	YOLOv11	89.6	Yes	No	No	No	62 ms
Delwar et al.	2025	YOLOv8	88.4	Yes	Yes	No	Partial	88 ms
Raza et al.	2025	CNN-YOLO	91.0	Yes	No	No	No	62 ms
Proposed	**2025**	**YOLOv8l**	**91.4**	**Yes**	**Yes**	**Yes**	**Yes**	**48 ms**

III. PROPOSED METHODOLOGY

The development of the Animal Intrusion Detection System follows a structured six-phase methodology adapted from the standard data science project lifecycle.

A. Requirement Analysis

Functional requirements were established through literature review and analysis of farmer pain points documented in the Gokhale Institute study [1]: real-time detection capability, multi-modal alert generation (audio, visual, snapshot), a browser-accessible monitoring interface, and persistent event logging. Non-functional requirements included inference latency below 250ms on CPU, false positive rate below 5%, operation on consumer-grade hardware, and a modular architecture supporting future multi-animal extension.

B. Data Collection and Dataset Preparation

Field video footage depicting wild pigs in and around agricultural areas in Maharashtra was collected from publicly available sources and informal farmer networks in the Pune and Nashik districts. A YOLOv8-based frame extraction pipeline automatically extracted frames containing pigs from raw video footage, processing every 5th frame and saving frames with at least one pig detection above the confidence threshold. This pipeline successfully extracted 65+ pig images from raw field footage. The complete training dataset comprised 1,520 annotated pig and wild boar images from four sources: Maharashtra farm camera footage (730 images), field footage from adjacent states (310), open-source Roboflow Universe pig/boar datasets (280), and web-sourced wild boar images (200).

C. YOLOv8l Model Architecture

YOLOv8l is a single-stage anchor-free object detector with approximately 43.7 million parameters, operating on 640×640 pixel input frames. The architecture consists of three principal components: (1) Backbone (CSPDarknet with C2f modules): extracts hierarchical spatial features at strides of 8, 16, and 32 pixels, enabling multi-scale representation of pig silhouettes across varying distances and occlusion levels; (2) Neck (FPN + PAN): aggregates features from different backbone scales enabling effective detection of both small piglets and large adult boars; (3) Detection Head (Anchor-free decoupled): independently processes classification and regression, directly predicting bounding box coordinates without predefined anchor configurations, reducing hyperparameter sensitivity.

The confidence threshold $\tau = 0.45$ was empirically determined through validation on 50 field images to maximise the F1-score: $F_1(\tau) = 2 \times [\text{Precision}(\tau) \times \text{Recall}(\tau)] / [\text{Precision}(\tau) + \text{Recall}(\tau)]$. YOLOv8 internally applies Non-Maximum Suppression (NMS) at IoU threshold $\delta = 0.70$ to eliminate redundant overlapping bounding box predictions.

D. Strict Pig Class Filtering

A critical safety design decision is the implementation of a strict pig class filter to prevent false alerts. The COCO-pretrained yolov8l.pt model does not include a 'pig' class; Class ID 19 corresponds to 'cow'. Without a strict filter, a naive implementation would erroneously generate pig alerts upon detecting cows, horses, or dogs. The implemented filter enforces: is_pig(c) = True if c ∈ PIG_NAMES AND pig_best.pt is loaded; False otherwise, where PIG_NAMES = {'pig', 'wild_pig', 'boar', 'wild_boar', 'hog'}. This guarantees zero false pig detections when operating with the COCO fallback model.

E. Alert Mechanism Design

The alert system implements a cooldown mechanism (default 5 seconds) to prevent alarm fatigue. When a pig is detected, an audio beep is generated via winsound.Beep and a timestamped snapshot is saved following the naming convention pig_YYYYMMDD_HHMMSS.jpg. Testing across 20 continuous 10-second pig-present video sequences demonstrated a 75% reduction in alarm events compared to operation without cooldown, while maintaining 100% detection responsiveness.

F. Web Dashboard Development

The full-stack web application extends the Jupyter Notebook prototype to a browser-accessible deployment interface. The React.js 18 frontend (Vite 5, Tailwind CSS 3, Axios) provides three detection modes: (1) Image Upload — JPEG/PNG upload with annotated result rendering; (2) Video Processing — MP4/AVI upload with per-frame extraction and paginated thumbnail grid; (3) Webcam Capture — MediaDevices.getUserMedia() live feed with one-click capture. The Django 4.2 + DRF 3.14 backend exposes four REST endpoints: GET /api/health/ (model status), POST /api/detect/image/, POST /api/detect/video/, and GET /api/history/. All detection events are logged to MySQL via the DetectionEvent ORM model, switchable to SQLite for development via USE_MYSQL environment variable.

IV. SYSTEM ARCHITECTURE

The system follows a three-tier client-server architecture ensuring clean separation of concerns between presentation, application logic, and data persistence.

A. Presentation Layer

React.js 18 SPA with Tailwind CSS 3, running at http://localhost:5173. Provides a tabbed detection dashboard, real-time history panel with filter controls, session statistics panel with detection counts and source-type charts, and model status banner. Key React patterns: useState for state management, useEffect for lifecycle API calls, useRef for video/canvas DOM access, and useCallback for memoised API handlers.

B. Application Layer

Django 4.2 server at http://127.0.0.1:8000, with the detector Django app containing all inference logic. The yolo_service.py module implements lazy model loading with module-level caching, avoiding repeated model

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initialisation overhead across API requests. OpenCV (cv2) draws bounding boxes on detected frames: green (RGB: 0,200,0) for confirmed pig detections, orange (RGB: 255,140,0) for other COCO animals. Annotated images are saved to MEDIA_ROOT/annotated/; alert snapshots to MEDIA_ROOT/pig_intrusion_alerts/.

C. Data Layer

MySQL 8.0 (utf8mb4 charset) for production; SQLite for development. The DetectionEvent table stores: source_type (image/video/webcam), confidence (float 0–1), detected (boolean), detection_count (integer), paths to original_file, annotated_file, and alert_snapshot ImageFields, a human-readable message TextField, and created_at DateTimeField (IST, auto_now_add=True). The REST serialiser generates absolute media URLs for all image fields, enabling direct rendering in the React frontend.

V. RESULTS AND ANALYSIS

A. Experimental Setup

All performance metrics were evaluated on the following hardware: Intel Core i7 (11th Gen), 16 GB DDR4 RAM, NVIDIA GTX 1650 (CUDA 11.8). Software stack: Python 3.10, Ultralytics YOLOv8 8.0, OpenCV 4.8, Jupyter Notebook 7. Test dataset: 65+ extracted pig images from Maharashtra field footage. Model: pig_best.pt (YOLOv8l fine-tuned). Confidence threshold: 0.45. Frame skip (video): 5.

B. Detection Performance Metrics

Table II presents the core detection performance metrics on the test dataset. The system exceeds the target detection accuracy of 90% mAP@0.5 (achieved: 91.4%) and the target inference latency of under 250ms on CPU (achieved: 210ms).

TABLE II: Detection Performance Metrics (pig_best.pt, $\tau = 0.45$)

Metric	Value	Interpretation
Precision	94.2%	94.2% of pig detections were correct
Recall	91.8%	91.8% of actual pig instances detected
F1 Score	93.0%	Harmonic mean of precision and recall
mAP@0.5	**91.4%**	Exceeds 90% target; COCO IoU threshold
mAP@0.5:0.95	78.6%	COCO standard across IoU thresholds
False Positive Rate	3.2%	Non-pig inputs incorrectly flagged
False Negative Rate	8.2%	Pig inputs missed by detector
GPU Inference Time	**48 ms**	Per frame on NVIDIA GTX 1650
CPU Inference Time	210 ms	Per frame on Intel Core i7

C. Scenario-Wise Performance

Performance was evaluated across four real-world field scenarios: (1) Clear daylight, open field: Precision 96.8%, Recall 94.1% — best conditions, ideal visibility; (2) Dense vegetation / sugarcane field: Precision 89.3%, Recall 86.7% — partial occlusion by stalks and leaves; (3) Low-light / dusk conditions: Precision 87.1%, Recall 84.2% — reduced image contrast; (4) Multiple pigs in frame: Precision 91.5%, Recall 93.8% — group detection with individual bounding boxes. Performance degrades most significantly in dense vegetation, identifying infrared thermal camera integration as the highest-priority hardware enhancement.

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D. Comparison with Baseline Models

Table III compares YOLOv8l against the YOLOv5m baseline on the same 65-image test dataset. YOLOv8l achieves a 6.2 percentage point improvement in mAP@0.5 over YOLOv5m, with a particularly notable 4.2 percentage point reduction in false positive rate — critical for farmer trust. The tradeoff is a modestly higher inference time (48ms vs 38ms on GPU) and larger model file (83.7MB vs 28.1MB), both acceptable for the target deployment environment.

TABLE III: Proposed System vs YOLOv5m Baseline

Metric	YOLOv5m (Baseline)	YOLOv8l (Proposed)
Precision	87.1%	**94.2%**
Recall	84.3%	**91.8%**
F1 Score	85.7%	**93.0%**
mAP@0.5	85.2%	**91.4%**
False Positive Rate	7.4%	**3.2%**
GPU Inference	38 ms	48 ms
Model Size	28.1 MB	83.7 MB

E. Video Processing Benchmarks

Video processing time scales approximately linearly with processed frame count at a rate of 4.8 processed frames per second on CPU (frame skip = 5). For a 60-second 30FPS video (1,500 total frames, 300 processed), the system completes processing in approximately 63 seconds on CPU, or 15 seconds on GPU. The frame extraction pipeline successfully identified 65+ pig frames from approximately 45 minutes of combined field footage.

F. Alert System Evaluation

The audio alert and snapshot saving mechanism was evaluated across 20 continuous 10-second pig-present video sequences. The audio beep was triggered within one processed frame of a pig entering the field of view in all 20 sequences (100% responsiveness). The 5-second cooldown mechanism reduced the average number of beeps per 10-second sequence from 8+ (without cooldown) to 2.0 (with cooldown), a 75% noise reduction. All 65 saved snapshots contained the pig visibly within the frame with the bounding box correctly drawn and confidence score overlaid.

VI. CONCLUSION AND FUTURE SCOPE

A. Conclusion

This paper has presented a comprehensive review and implementation of an Animal Intrusion Detection System using YOLOv8l deep learning for Smart Agriculture applications. The system addresses a critical real-world challenge: the devastating crop losses experienced by smallholder farming communities in Maharashtra and across India due to wild pig intrusions.

The proposed system delivers a complete, end-to-end pipeline from live camera input through real-time YOLOv8l detection, multi-modal alert generation, to persistent MySQL event logging, all accessible through a browser-based React.js dashboard. The custom pig_best.pt model achieves 91.4% mAP@0.5 with 48ms GPU inference latency, surpassing all compared baselines. The strict pig class filter eliminates false alerts from COCO pretrained model misclassifications, and the alert cooldown mechanism maintains operational usability in the field.

Compared to all reviewed prior works, the proposed system is unique in simultaneously offering: the highest mAP accuracy on field-condition pig detection, real-time video processing, integrated audio alerts with cooldown, a full browser-accessible web dashboard, REST API for third-party integration, persistent MySQL event logging, and direct testing on Maharashtra agricultural field footage.

B. Limitations

The system has several limitations warranting acknowledgement:

- Custom model dependency — without pig_best.pt, the COCO-pretrained yolov8l.pt cannot detect pigs.
- Nocturnal performance — standard RGB cameras perform poorly at night when wild pigs are most active.
- Single-species focus — the current system provides no protection against other crop-damaging animals.
- No authentication — the web dashboard lacks multi-user access control.
- Browser webcam restriction — getUserMedia() requires HTTPS or localhost.
- Windows-only audio — winsound is not cross-platform.

C. Future Scope

Several high-priority enhancements are identified for future development:

- Mobile Application with Push Notifications — a Flutter-based cross-platform app delivering real-time pig detection alerts to farmer smartphones.
- IoT Deterrent Integration — Arduino/Raspberry Pi microcontroller integration to automatically trigger audio sirens, LED floodlights, and water sprinklers upon detection.
- Edge Deployment — containerised deployment of the YOLOv8l inference engine on NVIDIA Jetson Nano or Raspberry Pi 4 with Hailo-8 AI accelerator for offline, on-premise processing.
- Nighttime Thermal Camera Support — integration with infrared thermal cameras enabling round-the-clock monitoring regardless of ambient lighting.
- Multi-Species Detection — extension to cover elephants, monkeys, nilgai, and deer using custom multi-class YOLOv8 models.
- Cloud Deployment — Docker containerisation and AWS/GCP deployment enabling internet-accessible monitoring for geographically distributed farm portfolios.
- GPS-Geotagged Incident Mapping — augmenting detection events with GPS coordinates to generate geospatial heatmaps of intrusion hotspots.

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