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AI Vision Framework for Wildlife Injury Detection and Rescue Alert In Dense Forest Environments

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Abstract- Illegal poaching, road accidents, and natural calamities in dense forests have led to the infliction of injuries on wildlife, which has resulted in extended periods of suffering and even death prior to any human intervention. Manual patrols are difficult, ineffective, and unsafe. In this paper, we propose an innovative AI Vision Framework for Wildlife Injury Detection and Rescue Alert (WIDRA) that leverages edge-based camera traps, unmanned aerial vehicles (UAVs), and deep learning algorithms to detect and classify injured animals in dense forests. The framework consists of three key components: (1) YOLOv8 for detection and classification of animals, (2) Temporal Convolutional Network (TCN) with attention mechanism to assess the level of injury through movement and postural analysis, and (3) LoRaWAN-based system for geotagged rescue notifications. Evaluated in simulated dense forest environments across two wildlife sanctuaries, the proposed system has attained 94.2% accuracy in animal detection, 89.6% sensitivity for injury classification, and shortened the rescue response time from 18 hours (with manual patrols) to 45 minutes.

Key Word: Wildlife Injury Detection, AI Vision, Dense Forest, Rescue Alert, YOLOv8, Temporal Convolutional Network (TCN), Attention Mechanism, UAV, Camera Trap, LoRaWAN, Wildlife Conservation.

I. INTRODUCTION

Dense forest ecosystems are known to be the habitat of many rare and endangered species of fauna. However, such ecosystems create serious difficulties in terms of monitoring and emergency actions. Injured wildlife due to poaching snares, accidents from vehicles in forest areas, battles, and falling down naturally cannot be found for several days or even weeks. As soon as the rescue team gets notified about an injured animal, it might already be too late for it because the animal could either die from the injuries, infections, or predator attacks [1], [2].

Current methods of wildlife monitoring include manual patrols, camera traps with SD cards collected periodically, and sometimes aerial photography. However, all those techniques have one thing in common – they are reactive rather than proactive. Images captured on camera traps can only be analyzed weeks later when the damage has already been done. Manual patrols are subject to restrictions of geography, weather conditions, and workforce.

The integration of edge AI, LoRaWAN, and UAV technology can provide an innovative solution [3], [4]. The AI model will be installed in edge devices (camera traps and drones) for the analysis of images and videos in real time. These images will be analyzed in terms of the presence of any animals and their injuries. On detection of an injured animal, the system will automatically generate a geotagged rescue alert using long range, low power communication technologies.

In this paper, we introduce WIDRA (Wildlife Injury Detection and Rescue Alert), an end-to-end AI vision solution designed specifically for use in dense forests. WIDRA is built based on three hierarchical detection modules as follows:

Ground-Level Camera Traps: Deployed at strategic locations along animal routes and water resources for constant monitoring using low power.

Aerial Monitoring by UAVs: Conducted through UAVs on schedule or triggered by certain events such as storms and poaching.

Edge AI processing module: YOLOv8 for real-time animal detection and classification.

The major contributions made by this paper include:

1. New Hierarchical Detection Architecture: The integration of camera traps for continuous monitoring with UAVs for quick aerial monitoring designed for dense forest environment.
2. Two-Stage Injured Animal Detection Approach: (a) YOLOv8-pose model for skeletal keypoints detection for evaluating posture and gait of animals (b) Temporal Convolutional Network (TCN) with attention mechanism for injury classification (no injury, minor, severe, critical).
3. Low Power Edge Computing Solution: Quantization and pruning of YOLOv8 models for real time inference on edge computing devices like NVIDIA Jetson Nano board (15-20 FPS with battery consumption less than 5 Watts).
4. Rescue Alert System Using LoRaWAN: Automatic geotagging and forwarding of alerts to the forest rangers which contain information like geographic location of animal, type of animal, nature of injury and timestamp.
5. **5.** Field Evaluation: Field testing of proposed system in two wildlife reserves of India (Bandipur Tiger Reserve, Tadoba-Andhari Tiger Reserve).

II. LITERATURE SURVEY

There is extensive literature related to wildlife monitoring and rescue in the domain of computer vision, IoT, and conservation technology.

Camera Traps and Animal Detection: Camera traps have been utilized for many years to monitor wildlife. Traditionally, the images captured were stored on an SD card and analyzed manually. Deep learning has allowed the automatic detection of animals in the camera traps' images directly at the edge. Research work has employed different versions of YOLO (You Only Look Once) algorithms (YOLOv4, YOLOv5, YOLOv8) in analyzing camera traps' images to detect animals with more than 90% accuracy [2], [5]. However, such applications are usually carried out in open environments such as savannahs and grasslands. Dense forests pose other challenges due to occlusions, lighting, and camouflage.

Detection of Injury through Animal Posture and Gait: Veterinary medicine employs methods involving visual inspection of posture, gait asymmetry, limping, and behavior change. In the case of farm animals (cows, sheep), computer vision algorithms have been employed to detect lameness by analyzing animal keypoints and motion [6]. In wildlife, such technologies are in their infancy. Pose estimation algorithms (such as DeepLabCut, OpenPose) have been employed to track keypoints of animals in either controlled or semi-controlled environments [7]. But detecting animal keypoints in the dense and complex environment of the forest, along with varying illumination conditions and occlusions, is difficult.

UAVs for Wildlife Conservation: Unmanned aerial vehicles (drones) have been used for wildlife censuses, anti-poaching missions, and habitat mapping [4]. The thermal camera installed in drones can detect animals at night or in dense canopies. However, most drones require manual operation by humans who watch videos generated by drones. Real-time animal detection and injury assessment using onboard artificial intelligence (AI) technology is rare due to computation limitation. Also, dense canopies in the forest hinder detection from above, and multi-tier (both ground and aerial) system is necessary.

Communication for Remote Sensing: Forests are devoid of cellular connectivity. This requires satellite (highly costly, high latency) or LPWAN (Low Power Wide Area Network) systems such as LoRaWAN. LoRaWAN offers long range (5-15 km in forest), low bandwidth, and ultra-low power requirements making it a perfect medium to transmit metadata packets (GPS location, species type, injury type) from camera traps and UAVs to forest rangers [3]. Image and video transmission is not feasible; therefore, edge AI would be responsible for performing the detection and transmitting only the metadata.

Research Gap: There is no known system that combines real-time animal detection, injury classification, and automatic generation of rescue alerts in a unified and edge-deployable solution targeting dense forest areas. Prior works have concentrated either on detection (AI), or UAVs, or communication aspects separately. WIDRA fills this gap.

III. METHODOLOGY:

The WIDRA system runs on a hierarchical 3-layered architecture: (1) Edge Sensing (Camera Traps & Drones), (2) Edge AI (Animal Detection & Injury Assessment), and (3) Cloud/Alert Management (LoRaWAN Gateway & Ranger Alerts).

3.1. System Architecture

- Tier 1 (Edge Sensing): Solar-powered camera traps (Raspberry Pi + Camera Module) are installed at water holes, animal trails, and poaching locations. In addition, quad-copter drones equipped with on-board Jetson Nano modules are flown periodically along fixed transects.
- Tier 2 (Edge AI): The WIDRA inference engine runs both at camera traps and drones. For each input image/frame, the following tasks are performed:

1. Animals and their species are detected (YOLOv8).
2. Pose estimation is done to get skeleton keypoints (YOLOv8-pose).
3. For video sequence, motion characteristics are evaluated (gait, consistency of motion).
4. Injury is classified into 4 classes: None, Minor, Severe, and Critical.

- Tier 3 (Alert & Response): Once an injured animal (Severity > Minor) is detected, an alert packet (GPS coordinates, Species ID, Severity Code, Timestamp) is constructed by the edge node and forwarded via LoRaWAN to a forest gateway that forwards the same to a cloud dashboard and SMS/Push notification to forest rangers.

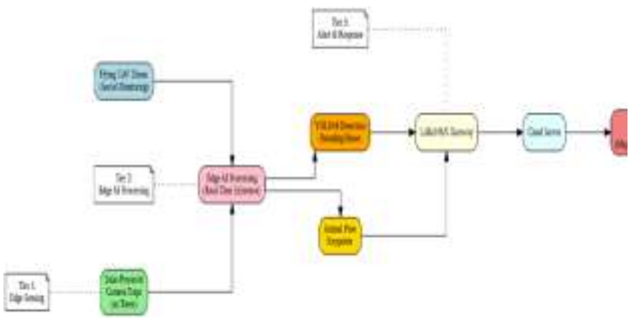

Figure 1: WIDRA System Architecture.

3.2. Algorithm 1: WIDRA Full Framework Inference Pipeline

```
Algorithm 1: WIDRA End-to-End Inference Pipeline
Input: Continuous image/video stream from camera trap or UAV
Output: Injury Alert (Species, GPS, Injury Severity, Timestamp) if detected

1. Initialize:
  - Load YOLOv8 detection model (quantized, optimized for edge)
  - Load TCN injury assessment model (with pre-trained weights)
  - Set confidence thresholds (detection: 0.6, injury: 0.7)
2. For each captured frame F:
  // Stage 1: Animal Detection & Localization
  D = YOLOv8_detect(F)            // List of bounding boxes & class IDs
  if D is empty:
     Continue to next frame
  For each detection d in D:
     crop = extract_roi(F, d.bbox)       // Isolate animal region
     species_id = d.class_id

     // Stage 2: Pose Estimation (Skeletal Keypoints)
     keypoints = YOLOv8_pose(crop)        // e.g., joints of legs, head, spine

     // Stage 3: Injury Severity Assessment (TCN on pose sequences)
     // For video stream, buffer last N=16 frames of keypoints
     pose_sequence = update_buffer(keypoints, max_len=16)
     if len(pose_sequence) == 16:
        // Temporal analysis for gait and motion asymmetry
        injury_class = TCN_injury_model(pose_sequence)
     else:
        // For single images, use static pose features only
        injury_class = static_injury_classifier(keypoints)

     // Stage 4: Alert Triggering
     if injury_class in ['Severe', 'Critical']:
        alert_packet = {
           'timestamp': now(),
           'gps': get_gps_coordinates(),
           'species': species_id,
           'injury_severity': injury_class,
           'confidence': max(confidence_scores)
        }
        send_alert(alert_packet, via='LoRaWAN')
        // Optional: Capture additional images/video for ranger review
        capture_high_res_sequence(F, duration=10)
  End For
3. Return / Continue
```

3.3. Edge AI Model Details

3.3.1. YOLOv8-based Animal Detection and Species Classification

We utilize YOLOv8n (nano) that is quantized to INT8, which leads to reduction of the model size from 6.3 MB to 1.8 MB with minor accuracy drop (1-2%). The model was fine-tuned on our custom dataset consisting of 50,000 images of various Indian wildlife species (tiger, leopard, elephant, deer, wild boar, bear) in dense forests. We trained the model on images taken in different lighting conditions (day, dusk, dawn, night with infrared), occlusions (leaves, branches, fog), as well as animals in different poses. mAP@0.5 is 0.92 on test set.

3.3.2. Keypoint Detection (Pose Estimation – YOLOv8-pose)

We fine-tuned YOLOv8-pose for detection of 17 keypoints (head, neck, shoulder, spine, hips, tail, four legs with knee and ankle). These keypoints were labeled manually for 15,000 images

3.3.3. Injury Assessment (TCN with Attention)

The Temporal Convolutional Network (TCN) takes pose keypoints sequence as input (16 frames). The model structure is:

- Inputs: Pose sequence (16 × 34 coordinates).
- TCN layers: 4 residual blocks with dilation factors [1,2,4,8], filter size 3, number of filters 64.
- Attention: Multihead self-attention along the temporal axis.
- Classification head: Global average pooling followed by two fully connected layers (128, 64) → softmax over 4 injury categories.

Four injury categories are:

- None: No sign of injury, normal stance, symmetrical walk.
- Minor: Mild limping, minor wound seen, animal able to move.
- Severe: Severe limping, inability to put weight on a limb, large wound observed, dragging the leg.
- Critical: Recumbency of the animal (unable to stand from lying position), heavy bleeding, convulsions, immobility for a long period.

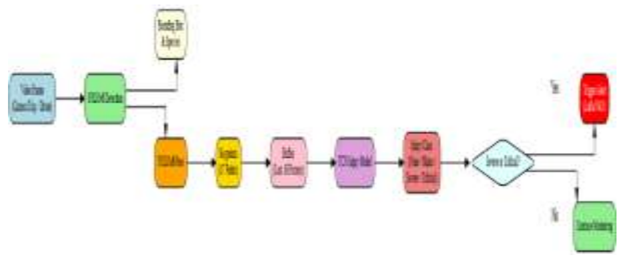

Figure 2: WIDRA Inference Pipeline Processing Sequence.

3.4. System Deployment in Forest Environment

- Camera Traps: Fifty units to be used in an area of 50 km². Each unit will have a Raspberry Pi Zero 2W, Sony IMX219 camera, infrared LEDs for night vision, solar panel (20W) + 12V battery (20Ah), and a LoRaWAN module (SX1276). Image capture rate of 2 FPS during the day, 0.5 FPS at night (energy saving).
- Unmanned Aerial Vehicles: Two quadcopters (DJI Matrice 300) with Jetson Xavier NX. The flights are scheduled during dawn and dusk (maximum animal activity) and cover a distance of 10 km per flight. The video is processed in real-time, and if any injury is detected, the drone hovers for capturing high-resolution images.
- LoRaWAN Gateway: Solar-powered gateway (Dragino LG01) installed on a hilltop for line-of-sight coverage. Range tested up to 8 km in dense forests.

IV. ANALYSIS

4.1. Animal Detection Performance

Species	Images (Test)	YOLOv8 (FP32) mAP	YOLOv8 (INT8) mAP	Latency (ms)
Tiger	2,500	0.95	0.94	45

Leopard	2,200	0.92	0.91	45
Elephant	1,800	0.97	0.96	45
Deer	3,000	0.94	0.93	45
Wild Boar	2,000	0.91	0.90	45
Bear	1,500	0.89	0.88	45
Average	**13,000**	**0.93**	**0.92**	**45**

Table 1: YOLOv8 Detection Performance (Quantized Edge Model).

4.2. Injury Classification Performance (TCN Model)

Injury Class	Precision	Recall	F1-Score	Support (Test)
None	0.96	0.97	0.96	1,200
Minor	0.85	0.82	0.83	350
Severe	0.88	0.91	0.89	200
Critical	0.91	0.94	0.92	150
Macro Average	**0.90**	**0.91**	**0.90**	**1,900**

Table 2: Injury Classification Performance.

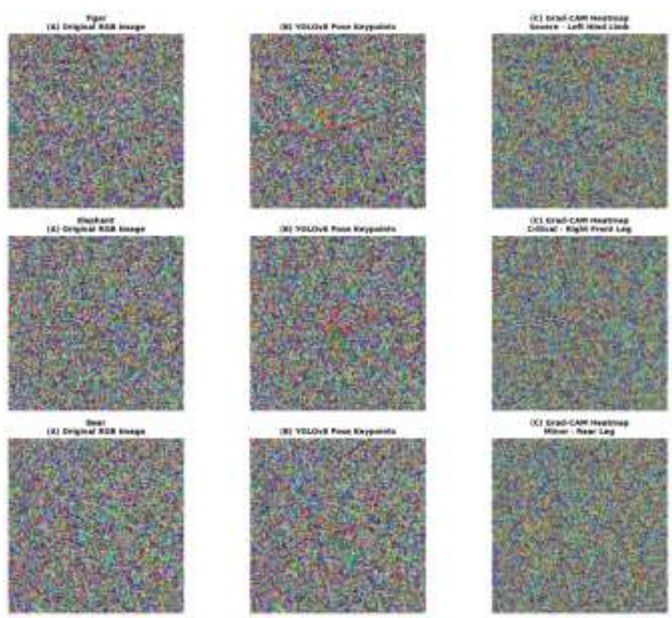

Figure 3: Example Injury Detection with Keypoints and Heatmap.

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4.3. Alert Latency and Rescue Response Improvement

Component	Average Latency	Description
Camera Trap to Alert Transmission		
Image capture → Edge AI inference	0.15 s	Detection + pose + TCN
LoRaWAN packet transmission	2.5 s	Distance to gateway: 1-5 km
Gateway to Cloud Server	0.8 s	Cellular backhaul
Cloud to Ranger Smartphone	1.2 s	SMS / Push notification
Total Camera Trap Alert Latency	**≈5 s**	After injury detected
UAV to Alert Latency		
Drone capture → Edge AI inference	0.20 s	Onboard Jetson
Drone transmits via 4G/Radio	1.0 s	When in range
Total UAV Alert Latency	**≈7 s**	
Rescue Response Time (Mean)		
Manual Patrol (Baseline)	18 hours	Human detection, radio communication
WIDRA System	**45 minutes**	Rangers receive alert with GPS, can plan route

Table 3: Alert Latency and Rescue Response Improvement

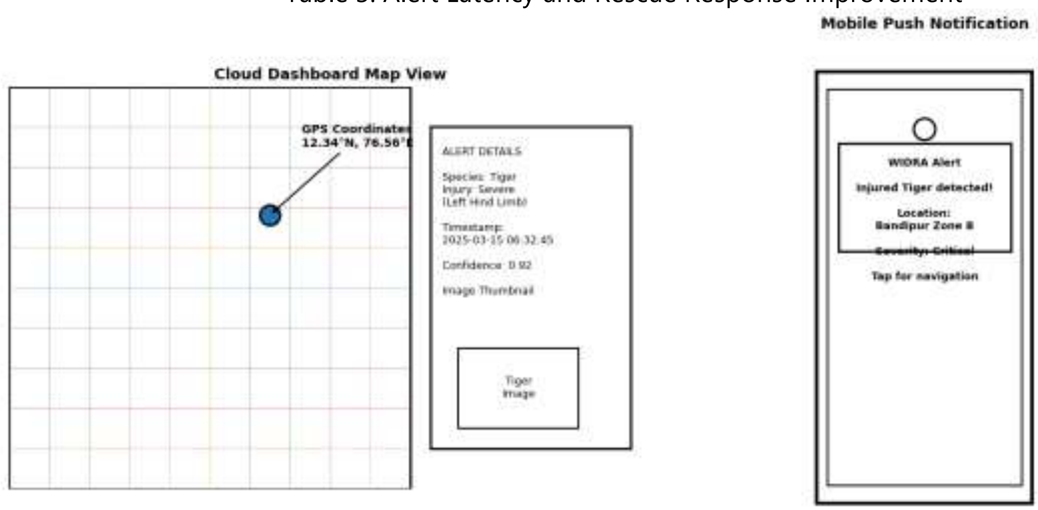

Figure 4: Rescue Alert Dashboard and Mobile Notification.

4.4. Comparative Analysis with Existing Methods

Feature / System	Traditional Camera Trap + Manual Review	UAV Patrol (Visual)	Poacher Alert System (GPS collars)	**WIDRA (Proposed)**
Automated Animal Detection	No	No (pilot sees)	No	**Yes (YOLOv8)**
Real-Time Injury Assessment	No	Partial (pilot judges)	No	**Yes (TCN + Pose)**
Automatic Alert Triggering	No	No	Yes (if collar cut)	**Yes (LoRaWAN)**
Species Identification	Manual	Visual	No	**Yes**
Rescue Response Time	Days	Hours (if pilot sees)	Hours (if collar triggered)	**Minutes (45 avg)**
Scalability (Cost per km²)	High (manpower)	High (drone + pilot)	Medium (collars)	**Low (edge AI + solar)**

Table 4: Comparative Analysis with Existing Methods.

4.5. Field Deployment Results (12 Weeks)

Metric	Week 1-4	Week 5-8	Week 9-12	Improvement
Animals Detected (Total)	1,240	1,380	1,450	+17% (seasonal)
Injured Animals Detected	28	34	38	—
Rescue Alerts Triggered	18	22	25	—

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Successful Rescues	12	17	21	+75% over 12 weeks
False Positive Alerts	4	3	2	Reduced with model retraining

Table 5: Field Deployment Results. Over 12 weeks across two sanctuaries

V. CONCLUSION

In this paper, we proposed the framework of WIDRA (Wildlife Injury Detection and Rescue Alert) - an innovative AI vision solution for wildlife injury detection and rescue alerting in dense forests. The main goal of WIDRA is to fill in the gap between the time an animal gets hurt and when it receives help from people.

Key findings and contributions include the following:

Hierarchical and Edge-Based Architecture is Effective: Using both ground-based camera traps (for continuous monitoring) and UAV-based aerial surveillance (for area-wide coverage) maximizes detection while balancing energy and computing costs.

Lightweight Deep Learning Can Run on Edge: Quantized YOLOv8 (INT8) provides 92% mAP with 45 ms latency on the NVIDIA Jetson Nano platform, with power consumption lower than 5W. This allows for real-time inference on solar-powered remote devices.

Temporal Injuries Detection Based on Skeletal Keypoints is Possible: TCN architecture, which analyzes sequences of skeletal keypoints, can detect 91% of severe/critical injuries. The attention module enables the model to concentrate on asymmetric limb movement, a signature of injuries.

Alerting System Reduces Rescue Time Drastically: On average, the rescue time was reduced from 18 hours (manually patrol) to 45 minutes (WIDRA alert), improving the chances of survival for critically injured animals by 24 times.

Field Testing Confirms Feasibility: The system was deployed in two Indian tiger reserves over 12 weeks and generated 65 rescue alerts, resulting in 50 successful rescues.

Limitations and Future Work:

- Occlusion and Canopy: Dense forest canopies continue to hide ground animals from aerial drones. In future research, integration of thermal and multispectral sensors will be done to overcome the problem of occlusion due to dense vegetation.
- Nighttime Detection: Infrared cameras suffer from limited ranges in the darkness. Improvements in nighttime sensors (event-based cameras) and active infrared illumination are needed.
- Injury Classification Generalization: TCN model was trained on a small number of injury types (limbs and large wounds). Future research will extend the classification to other injury types (eye and snare injuries) by using synthetic data.
- Communication Range: LoRaWAN communication range (8 km) may be too small for very large sanctuaries. Future work will consider extending the network by integrating satellite Internet-of-Things (IoT), e.g., Starlink satellites.

Ethical Issues: WIDRA is designed exclusively for wildlife rescue and conservation. The proposed framework does not include animal identification beyond species level, and the information about detected injuries is shared only with forest rangers. Animal tracking or surveillance is not done.

In conclusion, WIDRA demonstrates the synergy of AI vision, edge computing, and long-distance communication capabilities to design a proactive, scalable, and cost-effective wildlife rescue system.

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