IJIE

INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

Vol. 18 No. 7 (2026) 27-43
https://publisher.uthm.edu.my/ojs/index.php/ijie

IoT Based Elephant Monitoring and Early Warning System

Hasliza Hassan[1], Nor Anija Jalaludin[1]*, Muhammad Irfan Shamsudin[1], Sree Sharvindren Subramaniam[1], Amirul Syafiq Sadun[1], Wang Zhiwen[2], Khairul Anuar Mohamad[3], Nazirah Mohamad Abdullah[4], Noorhamizah Mohamed Nasir[3]

[1] *Faculty of Engineering Technology,*
Universiti Tun Hussein Onn Malaysia, Muar, Johor, 84600, MALAYSIA
[2] *School of New Materials and Shoes & Clothing Engineering,*
Liming Vocational University, Quanzhou, Fujian Province, 362000, PEOPLE'S REPUBLIC OF CHINA
[3] *Faculty of Electrical and Electronic Engineering,*
Universiti Tun Hussein Onn Malaysia, Batu Pahat, Johor, 86400, MALAYSIA
[4] *Faculty of Applied Sciences and Technology,*
Universiti Tun Hussein Onn Malaysia, Muar, Johor, 84600, MALAYSIA

*Corresponding Author: noranija@uthm.edu.my
DOI: https://doi.org/10.30880/ijie.2026.18.07.003

Article Info

Received: 1 January 2026
Accepted: 22 September 2026
Available online: 2 November 2026

Keywords

Human-elephant conflict (HEC), Internet of Things (IoT), YOLOv8, seismic sensing, early warning system

Abstract

Human–elephant conflict (HEC) poses severe socioeconomic and safety crises globally, particularly in agricultural forest-edge regions. Traditional mitigation strategies, such as physical fencing and manual patrolling, are high-cost, labour-intensive, and prone to animal habituation. This study presents a decentralized, low-cost, multi-modal Internet of Things (IoT) early warning system powered by an off-grid solar direct current (DC) module. The framework utilizes a dual-stage, event-driven validation loop to maximize detection reliability while optimizing energy resources. Initially, a subsurface SM24 geophone sensor continuously samples micro-seismic vibrations caused by terrestrial locomotion. Ground noise is filtered locally using a software amplitude threshold of ±2,500 raw analog-to-digital converter (ADC) differential units, keeping power-intensive visual components in standby mode. Upon a verified threshold breach (t≥5s), a digital CCD camera module captures low-noise visual frames. Localized edge-inference is executed on an embedded Raspberry Pi using an optimized YOLOv8 deep learning network, achieving a validation accuracy of 88.1% mAP_50, a precision profile of 90.4%, and an out-of-sample test accuracy of 87.0%. Validated detections (≥70% confidence) trigger on-site visual strobes and directional high-decibel sirens playing biomimetic bee acoustics in under 7.0s. Simultaneously, real-time Markdown text alerts and visual threat payloads are dispatched via the Telegram Cloud Bot API alongside automated cloud tracking to Google Drive and Google Sheets. This prototype establishes a scalable, non-invasive intervention that secures local livelihoods and supports human–wildlife coexistence.

This is an open access article under the CC BY-NC-SA 4.0 license.

1. Introduction

Human-elephant conflict (HEC) has become a significant conservation and socio-economic issue, particularly in regions where human settlements expand into elephant habitats [1]. In Malaysia, HEC is a major problem and cause for economic losses, human injuries and fatalities and the endangerment of elephant populations [2]. The continuous growth of agricultural activities, deforestation, and urban development has intensified human-elephant interactions. As a result, these activities have caused severe consequences, including crop destruction, property damage, and loss of human and elephant lives. In India, an average of 124 elephants and 571 humans are killed annually due to the HEC incidents [3].

To overcome this problem, traditional mitigation techniques, including physical barriers, manual monitoring and deterrent sounds have been carried out [4][5][6]. However, these methods have demonstrated limited effectiveness over time due to the adaptability and intelligence of elephants, which often lead to habituation and reduced deterrence efficiency. Furthermore, many of these conventional strategies fail to provide real-time alerts, causing delays in response and increasing the likelihood of conflicts. Given the severity of the issue, there is a growing need for a more effective and technologically advanced solution to mitigate HEC and protect both human lives and wildlife.

Recent technological advancements have presented promising approaches for mitigating HEC. The integration of artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) in wildlife monitoring has significantly improved the detection and tracking of elephants [7]. AI-driven camera traps, for example, have been employed to detect elephants in real-time, providing prompt alerts to authorities and local communities [8]. Additionally, IoT-based monitoring systems have facilitated the deployment of sensor networks capable of tracking elephant movements and transmitting real-time data for analysis and decision-making [9]. Despite these advancements, existing systems still face challenges, including high rates of false positives, limited detection accuracy, and insufficient adaptability to diverse environmental conditions. There remains a gap in developing a system that ensures high accuracy, minimizes false alerts and provides a reliable early warning mechanism that can be deployed in remote and rural areas. To systematically contextualize these challenges.

To address the limitations of conventional and existing methods, this research proposes an IoT-based elephant monitoring and early warning system prototype that integrates AI-based image recognition, motion sensors, and a dedicated Wi-Fi communication network. The prototype serves as a proof of concept to demonstrate the feasibility of integrating AI and IoT for accurate elephant detection in real time. This technique significantly improves the accuracy of elephant identification and reduces false detections. Once an elephant is detected, the system will automatically activate an alarm mechanism, including sirens, strobe lights, and mobile notifications via Telegram to alert nearby communities. The integration of AI will further enhance the system's ability to differentiate elephants from other moving objects. This is to ensure a more efficient and reliable alert system [10]. The inclusion of a hybrid power source, combining solar panels, battery storage, and AC backup, ensures uninterrupted operation even in remote areas where electricity access is limited. By leveraging these technologies, the proposed system aims to bridge the gap in current HEC mitigation strategies and provide a more effective and scalable solution.

The innovation of this study lies in the development and testing of an AI-driven, IoT-based prototype for elephant detection and early warning. This first-stage implementation focuses on validating the core functionality and reliability of the proposed approach under controlled conditions. Unlike traditional methods, which often rely on manual observation or passive deterrents, the proposed system offers an automated and real-time monitoring solution. The use of a localized Wi-Fi communication network improves data transmission efficiency and ensures high-resolution media payloads are sent promptly across the coverage area. Additionally, the incorporation of a hybrid power supply significantly enhances the system's sustainability, making it feasible for long-term deployment in conservation zones. By adopting a multi-layered approach to elephant monitoring and early warning, this research contributes to the field of wildlife conservation. Whereby it presents a cost-effective, adaptable, and technologically advanced framework for mitigating HEC.

This paper presents the first stage of the research, focusing on the design, development, and preliminary testing of the proposed system. The results demonstrate the system's potential and validate its feasibility as a foundation for future large-scale field implementation and optimization. As HEC incidents continue to rise, there is an urgent need to explore innovative solutions that leverage modern technology. This research introduces a novel approach to elephant monitoring that integrates IoT, AI, and advanced communication networks to improve real-time detection and response. By addressing the existing gaps in HEC mitigation strategies, this system has the potential to significantly reduce conflicts and foster a more sustainable coexistence between humans and elephants. The results of this study will contribute to the ongoing efforts in wildlife conservation by providing an effective and practical solution for preventing human-elephant conflicts.

Int. Journal of Integrated Engineering Vol. 18 No. 7 (2026) p. 27-43

1.1 Camera Vision Technology

Camera vision technology and visual sensors are critical components of automated wildlife detection architectures, utilizing an array of devices such as IP CCTV cameras, thermal infrared cameras (e.g., DJI Zenmuse H20T), and specialized wildlife camera traps (e.g., Browning Strike Force Pro XD) [11][12][5]. Integrating camera vision technology into elephant detection and monitoring has significantly advanced global conservation efforts, particularly in mitigating human–elephant conflicts. Recent studies have demonstrated the high efficacy of artificial intelligence (AI) and computer vision in enhancing both the spatial accuracy and operational efficiency of these remote monitoring frameworks.

To effectively process captured visual data before it is fed into high-level models, systems employ various image processing and transformation techniques. These methods include resizing input images to standard tensor dimensions (e.g., 224 x 224 pixels), normalizing raw pixel values, and applying the Canny Edge Detector to highlight important structural edges and contours within grayscale video frames [7]. For instance, research conducted by Shepley et al. [13] analyzed the use of publicly available image sources to develop location-invariant camera trap object detectors specifically engineered for mitigating human–elephant conflicts. Their approach aimed to create generalized models transferable across completely different outdoor environments without requiring extensive, computationally heavy retraining. This invariance is highly beneficial for monitoring elusive, wide-ranging species like elephants in dense foliage.

For advanced classification and real-time detection, deep learning algorithms are heavily utilized across modern literature. Specific software frameworks and neural network architectures include Convolutional Neural Networks (CNNs) such as EfficientNet B7 for static image-based detection and 3D CNNs for dynamic, temporal video analytics. A systematic literature review on vision-based approaches to outdoor livestock monitoring drew crucial lessons from these wildlife studies, highlighting a definitive industry trend toward deep learning methods for autonomous animal detection and classification. This research emphasizes the broad applicability of these advanced computer vision techniques to large terrestrial mammals, including elephants. Other architectural variations incorporate LabVIEW-based image processing algorithms and Support Vector Machine (SVM) classifiers to match hand-crafted image features and identify the presence of elephants [13].

Furthermore, real-time object detection is heavily facilitated by versions of the YOLO (You Only Look Once) algorithm deployed directly on embedded edge hardware such as the NVIDIA Jetson Nano or Raspberry Pi platforms. Understanding the environmental context of where these vision sensors are deployed remains a vital factor in system design [13]. In Kasungu National Park, Malawi, researchers utilized camera trap bycatch data to assess elephant habitat use and the direct influence of human activity. This study revealed that proximity to critical water sources significantly affected site selection and documented that elephants actively exhibited nocturnal behavior specifically to avoid overlapping human activity. This underscores the paramount importance of understanding spatial and temporal behavioral patterns when deploying visual sensors for effective conservation strategies [14].

A comprehensive review by Bossert and Hagendorff [15] discussed the current and future roles of AI in elephant monitoring, focusing heavily on automated image and video analysis. The field integration of AI-assisted camera traps and aerial surveys has drastically enhanced elephant detection and tracking capabilities. This reduces the need for slow, manual data analysis while simultaneously improving localization accuracy. Furthermore, Abed et al. [16] provided a methodological literature review on acoustic wildlife monitoring using AI tools, highlighting the immense potential of combining multi-modal acoustic or seismic data with camera vision technology to vastly improve the true positive rate of elephant detection systems. Collectively, these foundational studies demonstrate the transformative impact of camera vision, edge-computed hardware, and AI technologies in elephant detection and monitoring by enhancing detection accuracy, enabling real-time monitoring, and providing actionable insights into elephant behavior. Consequently, these integrated vision technologies offer highly promising, non-invasive solutions for modern conservationists and researchers. Table 1 presents a critical comparative evaluation of current HEC mitigation methodologies against the multi-layered edge architecture proposed in this study.

1.2 Detection and Monitoring System

Integrating advanced detection and monitoring systems is pivotal in mitigating HEC and enhancing wildlife conservation strategies. Recent advancements have introduced various technologies, and each technology contributes uniquely to elephant detection and monitoring[7]. The detection and monitoring architecture relies on a multilayered network of IoT sensors designed to capture the physical presence and movement of elephants. The core sensory mechanisms include geophones (seismic sensors) that detect the low-frequency ground vibrations generated by elephant footfalls, and Passive Infrared (PIR) or active infrared beam sensors (such as quad photoelectric beam sensors) positioned at specific heights to capture motion and interrupt beams when large animals pass. These sensors interface with embedded processing units, such as Arduino Uno ATMega328P microcontrollers, NodeMCU ESP8266 Wi-Fi modules, Raspberry Pi, and ESP32 microcontrollers. When sensors

are triggered, the data is processed locally to filter out ambient environmental noise, often using techniques like Variational Mode Decomposition (VMD) or Kalman Filtering[17].

For physical detection, one of the effective tools is using infrared (IR) barriers to detect large mammals like elephants. Research by Montero-Botey and Perea [12] demonstrated that IR barriers installed at heights between 1.75 and 2.20 meters achieved a 100% detection rate for adult elephants. The study also highlighted the potential of integrating IR barriers with cameras to reduce false positives and enhance monitoring accuracy. Another critical method is using seismic sensors, which offer a non-invasive approach to monitoring elephant movements by detecting ground vibrations caused by their footsteps. Sheebha Anni and Kumar Sangaiah [18] reviewed the application of seismic sensors in elephant tracking and emphasized their efficiency and precision. Further advancements introduced by Wijayaraja et al. [19]presented a geophone-sensor interface capable of detecting elephant-induced seismic signals up to 155.6 meters away with a detection accuracy of 99.5%.

Besides ground vibrations and optical beams, bioacoustics monitoring leverages the unique vocalizations of elephants for detection purposes. Geldenhuys and Niesler [20]developed deep learning models to classify and detect elephant calls in real-time, enhancing the responsiveness of early warning systems. Similarly, Loo et al. [21] implemented deep learning models for real-time detection of elephant presence using bioacoustics, supporting human-elephant coexistence efforts.

Automated virtual fences represent a novel approach to deterring elephants from entering human-inhabited areas. These systems detect elephant presence and employ stimuli such as specific sounds to redirect them. A study by Dampage et al. [11] demonstrated the effectiveness of using sounds like tiger growls and bee buzzes to deter elephants, providing a foundation for non-physical barrier solutions. The local detection nodes then communicate with central base stations or other microcontrollers via radio frequency (RF) modules, such as the nRF24L01[11]. Finally, the collected telemetry and tracking data are transmitted to cloud databases and IoT platforms, such as AWS, Favoriot, and ThingSpeak, allowing for continuous, large-scale monitoring and analysis of elephant movement patterns[7][17]. Together, these technologies offer promising avenues for enhancing elephant detection and monitoring, thereby contributing to the reduction of human-elephant conflicts and promoting conservation efforts.

1.3 Warning System for Wildlife

Human–wildlife conflict (HWC), particularly with large terrestrial mammals such as elephants, continues to threaten biodiversity conservation and rural livelihoods in Asia and other regions. Spatial modelling in the Rajaji-Corbett landscape in India has shown that factors such as low elevation, proximity to forests, road density, and intensive agriculture are significant predictors of human-elephant conflict [22]. These insights underscore the immense potential of predictive early warning systems (EWS) that integrate geospatial and ecological data to inform communities about imminent wildlife incursions. The early warning system is designed to immediately alert vulnerable human populations and relevant authorities when an elephant intrusion is detected. The primary recipients of these alerts include local villagers, the wildlife department, plantation workers, and police stations [17]. To communicate these warnings, the system utilizes GSM/GPRS modules (such as the SIM900) integrated with the microcontrollers to execute AT commands, which automatically dispatch Short Message Service (SMS) text messages and emails to registered mobile numbers.

The effectiveness of such warning systems can be greatly enhanced through the integration of remote sensing technologies, mobile-based alert platforms, and real-time wildlife tracking. However, technical reliability must be ensured through rigorous data management. Choo et al.[23] emphasize that camera trap-based identification systems, often integral to EWS, are prone to misidentification without standardized methodologies for data validation, error-checking, and observer management. Their proposed Individual Identification Reporting Checklist (IIRC) offers a valuable framework to ensure the transparency and reliability of data used in deterrence systems. In addition to text-based communication, the system relays alerts to mobile applications and secure web-based dashboards where users can view the mapped locations of elephants.

Ecological factors also influence wildlife movement and foraging patterns, which must be incorporated into EWS frameworks. For instance, Meinecke et al. [24] demonstrated that the spatial intensity of crop-raiding by elephants and wild boars in Iran's Hyrcanian forests is positively correlated with crop variety and cultivated area. Such findings suggest that incorporating agricultural and ecological variables into warning systems can help refine spatial risk maps and prioritize vulnerable zones. Simultaneously, the system activates automated deterrent and signaling mechanisms at the site of the intrusion. These physical signaling methods include warning signal lights and automated sound emitters (speakers) that play repelling bioacoustics, such as buzzing bee sounds or tiger growls, to deter the elephants from proceeding further into human settlements [25].

Urbanization and environmental change further complicate wildlife responses to deterrents. As noted by Verrelli et al. [26], urban evolutionary processes influence species behavior, requiring adaptive systems that can evolve alongside changes in animal movement and habitat use. Static deterrent approaches, such as standalone lights or unmonitored alarms, often lose efficacy as elephants habituate them over time.

Int. Journal of Integrated Engineering Vol. 18 No. 7 (2026) p. 27-43

Socio-cultural dynamics also play a critical role in determining the success of wildlife deterrence strategies. Lev and Barkai [27] highlight the deep-rooted symbolic and spiritual relationships between elephants and local communities, particularly in South Asia, which must be acknowledged to foster long-term coexistence. Community-based interventions, including farmer training programs as demonstrated by Horgan and Kudavidanage [28] in southern Sri Lanka, have proven highly effective in equipping locals with the knowledge and tools required for non-lethal deterrence. These include human-activated scare tactics, but future efforts should heavily emphasize autonomous, low-cost systems integrated directly into community-managed frameworks.

Table 1 *Comparative analysis of existing HEC mitigation technologies vs. proposed system*

Mitigation Technology	Key Operational Mechanism	Practical Field Advantages	Critical Technical Deficiencies	Proposed System Integration
Physical & Electrified Fencing	Rigid perimeter barriers, trenches, or high-voltage pulse wires.	Prevents direct physical entry when actively maintained	High installation costs; intensive labor requirements; behavioral habituation; risk of animal injury.	Replaced by non-lethal, cost-effective virtual fencing utilizing automated, smart biomimetic audio deterrents.
Manual Crop Guarding & Watchtowers	Human observers patrolling borders or monitoring from static elevated watchtowers.	Allows human judgment and active response adjustments.	Inherently risky; highly labor-intensive; poor visibility during heavy rain or night; extreme response latency.	Replaced by fully autonomous, multi-layered seismic and visual sensors operating continuously without human risk
Standard Camera Traps	Passive visual monitoring capturing standalone images or videos	Captures high-resolution visual evidence of target species presence.	Zero real-time alert capability; requires manual data recovery, causing severe response latencies.	Integrated with localized Raspberry Pi edge compute modules for immediate, automated real-time alerts (<7.0 s latency).
Proposed Hybrid IoT System	Multi-layered Seismic pre-filtering + Edge-based YOLOv11 Digital CCD Camera verification + Local Wi-Fi Comms.	Real-time processing; high accuracy (>75% confidence); self-powered solar DC autonomy; high bandwidth transmission.	Requires localized line-of-sight for initial Digital CCD Camera module target confirmation.	Combines subsurface geophone signal logging with local edge AI inference, routing alerts instantly over high-speed Wi-Fi.

2. Methodology

This section describes the design and implementation process of the proposed IoT-based Elephant Monitoring and Early Warning System. The methodology focuses on developing a functional proof-of-concept prototype engineered to validate the real-time operational feasibility of integrating passive subsurface seismic sensing with localized edge-computed AI image recognition over a high-throughput wireless local area network (WLAN). The dual-stage validation mechanism ensures that ground-borne physical vibrations and subsequent visual frames are systematically cross-referenced to achieve near-zero false-alarm rates before community alerts are broadcasted.

The overall technical design approach is segmented into three distinct operation phases. The first phase is the experimental hardware and software setup, which establishes the physical baseline and technical parameters of the prototype components. The second phase is the system block diagram, which defines the functional interaction and signal pathways between the four primary operational subsystems. The third phase is the system flowchart, which establishes the absolute execution logic from initial sensor activation to automated multi-tier deterrent and notification generation. While the current testing phase utilizes a simulated laboratory framework, the operational parameters match actual field requirements, validating its long-term viability for remote conservation deployment.

2.1 Experimental Hardware and Software Setup

To validate the multi-layered system architecture under controlled operational conditions, an experimental testbed was constructed to simulate an edge-deployed wildlife monitoring station. The physical infrastructure is divided into three key operational blocks, which are the sensing cluster, the edge processing and controlling unit, and the warning system as illustrated in Figure 1. The sensing block relies on a dual-modality paradigm, whereby a passive subsurface geophone seismic sensor captures micro-seismic wave propagation caused by heavy terrestrial locomotion, while an integrated Digital CCD Camera module captures high-fidelity optical data streams. Data packets harvested from these nodes are processed locally in real time by the controlling core to dictate the output behavior of the deterrent and communication peripherals. Upon verified detection of an elephant within the hazard zone, the system initiates localized visual strobe illumination, triggers high-decibel biomimetic audio deterrents, and deploys cloud-routed mobile notifications for instantaneous community communication. The technical specifications of the prototype hardware stack are formalized in Table 2.

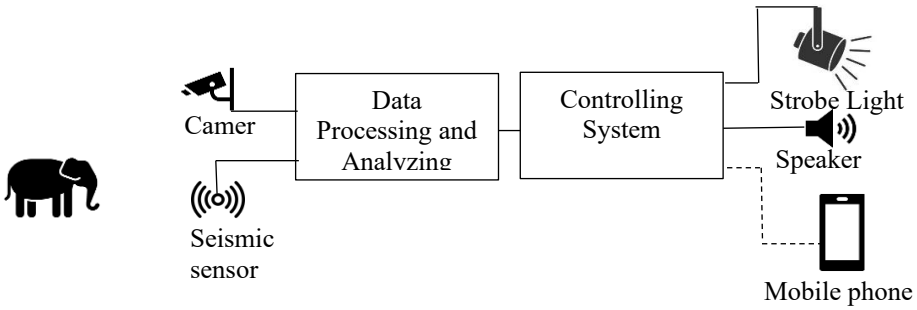


Fig. 1 *Experimental setup*

Table 2 *Technical specifications of prototype hardware components*

Subsystem Component	Specific Module/Model	Key Technical Parameter	Operational Role in System
Edge Computing Core	Raspberry Pi (8GB RAM Variant)	Broadcom BCM2711, Quad-core Cortex-A72 64-bit SoC @ 1.8GHz.	Executes local real-time YOLOv8 inference; manages GPIO pin logic and cloud wireless I/O.
Seismic Sensor Module	Subsurface Geophone Interface Module	Low-frequency geophone sensor with operational range up to 50 meters.	Captures ground-borne low-frequency seismic waves from elephant footsteps.
Optical Capture Module	Digital CCD Camera	High dynamic range, ultra-low noise floor sensor assembly.	Captures low-noise, stable exposures at forest edges during dawn/dusk conditions.
Acoustic Deterrent Device	High-Decibel Output Speaker	125% localized volume capacity with biomimetic frequency scaling.	Plays high-intensity "bee" swarm acoustics to exploit natural elephant aversion behavior.
Visual Alarm Device	Industrial Strobe Light Array	High-intensity flashing LED unit.	Provides immediate, long-range visual warning to nearby human settlements.

2.2 Physical Deployment Geometry and Pre-Filtering Logic

The deployment architecture utilizes a strategic cascading approach to preserve power and computational resources. The seismic geophone arrays are buried shallowly along common wildlife paths and peripheral boundary lines protecting agricultural frontiers. Because seismic waves propagate radially through the earth's crust from the point of impact, the relationship between the ground vibration signal amplitude (A) and the distance from the elephant footprint (r) is governed by the structural attenuation coefficient (α) and the initial source wave amplitude (A_o) generated at the exact point of impact, as shown by Equation 1. The geophone sensor interface is calibrated to register signals when $A(r)$ exceeds a predefined hardware voltage threshold corresponding to a detection radius of 10 to 50 meters.

$$A(r) = A_0 \cdot e^{\alpha r} \quad (1)$$

Int. Journal of Integrated Engineering Vol. 18 No. 7 (2026) p. 27-43

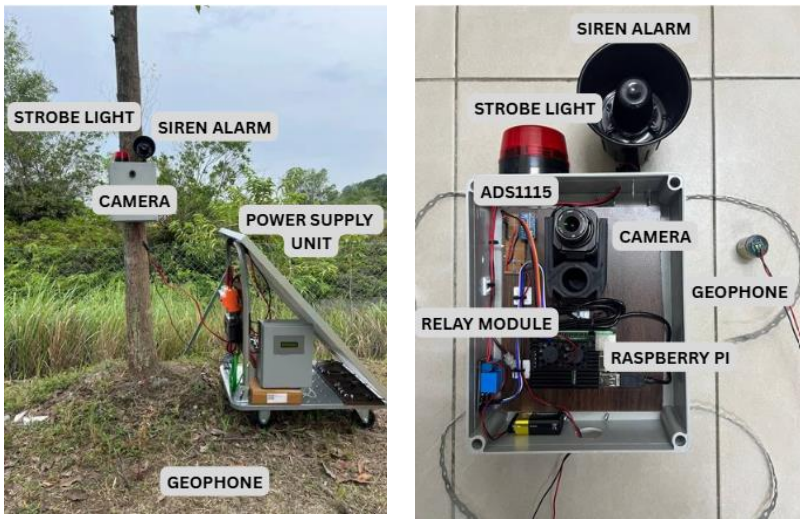
Concurrently, the Digital CCD Camera module is mounted securely within a rigid enclosure at a specialized height (h) of 1.5 to 2.0 meters, aligning precisely with the average body-mass centre of an adult Asian elephant. While field-operational systems ideally tilt the lens downward at an angle (θ) to map specific terrain zones, this system deploys the camera at a straight, non-tilted horizontal angle ($\theta = 0^o$) relative to the vertical support axis. This flat physical deployment serves as an intentional baseline configuration optimized to evaluate the core target classification boundaries of the computer vision model. This proof-of-concept baseline successfully simplifies initial pixel matrix dimensions and ensures a uniform horizontal frame layout across the simulated environment. The linear ground coverage distance (D) extending outward from the vertical node can be calculated using basic horizontal projection as represented in Equation 2:

$$D = h \cdot \cot(\emptyset) \tag{2}$$

where $\emptyset$ represents the half-angle of the camera lens's vertical field of view and h is the specialized height.

Deploying a Digital CCD Camera is critical for detecting elephants in low-light forest edges. It provides stable exposures and high dynamic range needed to deliver precise images to the machine learning model. To further insulate the edge processor from false positive triggers due to minor ambient environmental noise (such as local vehicular traffic), a software-defined time-based filter is coded into the primary polling loop. Any transient seismic vibration event that persists for a duration of less than 3 seconds is automatically classified as environmental noise, flagged, and discarded by the system. Conversely, if the continuous seismic wave pattern matches elephant-induced footprint frequencies and persists for an uninterrupted threshold of $t \geq 5$ seconds, the system logs the event as a valid perimeter threat and activates the Digital CCD Camera module to initialize the AI vision pipeline.

The physical hardware assembly of the off-grid perimeter defense node is divided into external structural placement and internal system mapping. Figure 2 displays the complete prototype setup used during the experimental evaluation phase, where (a) presents the vertical field deployment configuration alongside the solar DC power supply unit, and (b) provides a detailed top-view map of the core internal components within the centralized chassis. This configuration establishes a modular, autonomous architecture that functions without manual human intervention.



(a) **(b)**

Fig. 2 *Experimental prototype design (a) Physical field deployment configuration; (b) Internal component panel mapping layout*

2.3 System Block Diagram

The complete structural organization of the prototype is mapped out across core operational subsystems to guarantee continuous, fault-tolerant execution in remote, grid-deprived field settings. Figure 3 details the interaction matrix between the native DC power supply network, the sensing unit, the central controlling unit, and the external alarm system. The system is powered exclusively by an off-grid, sustainable solar power architecture designed around a direct current (DC) distribution profile, maximizing thermodynamic power efficiency by removing unnecessary AC-to-DC conversion overhead losses. The power network integrates a high-efficiency photovoltaic (PV) solar panel array, an intelligent solar charge regulator, a dedicated lithium iron phosphate ($LiFePO4$) backup battery storage pack, and a DC-DC buck/boost converter matrix. During daylight cycles, the PV

array converts solar irradiance directly into DC power, routing it through the charge regulator to restabilize voltage fluctuations, power the core systems, and replenish the battery reserves. The battery pack functions as the sole energy reserve during low-irradiance or nocturnal operational states. The regulated DC output is then parsed through a high-efficiency DC-DC converter network to step down or step up the voltage into stable, ripple-free 5V and 12V DC power rails, which directly drive the central Raspberry Pi edge processor, sensing apparatus, and warning peripherals.

The sensing unit continuously interfaces with the central controlling core. The subsurface seismic sensor monitors physical activity around the perimeter boundary. When the pre-filtering conditions are satisfied, the processing core activates the Digital CCD Camera module to capture crisp, low-noise visual frames. The localized IOGPv8 model inside the Raspberry Pi processes the frame matrix to verify the target class. If an elephant is confirmed, an alert token is generated. Data can be appended concurrently to local flash storage or a cloud database via the WLAN interface for historical auditing. The communication unit routes alert frames over the local Wi-Fi network to transmit real-time telemetry and Telegram notifications directly to endangered communities and wildlife wardens. Concurrently, the digital output pins trigger the physical alarm system, driving the electronic switches to activate the flashing strobe array and the local high-output speakers.

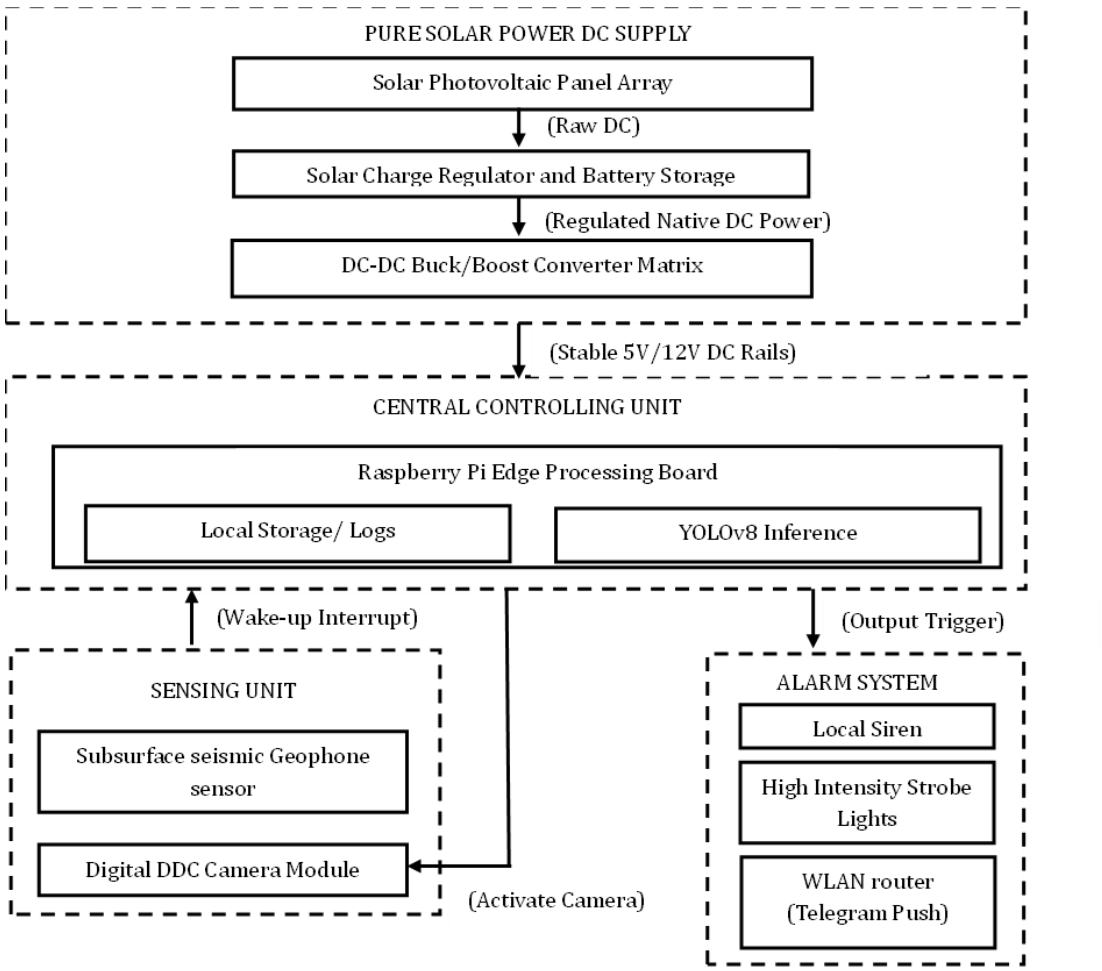


Fig. 3 *System block diagram*

2.4 System Algorithmic Flowchart

The operational logic of the computer vision pipeline is governed by an integrated script utilizing the YOLOv8 framework and the OpenCV image processing library. The algorithmic execution as illustrated by Figure 4 follows a rigid sequential pattern to maximize processing efficiency on edge hardware:

2.4.1 System Initialization

The script loads the necessary execution packages, configures the physical GPIO mapping pins for the hardware control switch and status LEDs, and mounts the compiled weights of the YOLOv8 architecture alongside its designated index file.

Int. Journal of Integrated Engineering Vol. 18 No. 7 (2026) p. 27-43

2.4.2 Video Capture Subroutine

The local camera video stream is initialized, and the resolution dimensions are defined along with a strict algorithm confidence threshold set at 70%.

2.4.3 Hardware State Polling

The system polls the master control switch. If the switch registers an unpressed state, the status LED is written low, all open windows and video arrays are terminated, and the execution script exits.

2.4.4 Frame Processing Matrix

If the master switch is high, the system pulls an uncompressed frame matrix from the optical Digital CCD Camera source, resizes it to match the YOLO input dimensions, and feeds the tensor into the YOLOv8 convolutional layer network.

2.4.5 Algorithmic Classification

The model predicts bounding box coordinates while simultaneously determining the target class category.

2.4.6 Class Validation Layer

The script parses the output vectors. If no valid image match matching the target "ELEPHANT" class identifier is located, the bounding box data is discarded, the system returns to the hardware frame reading state, and monitoring continues.

2.4.7 Confidence Filtering

If an elephant match is found, the target sub-matrix is isolated, and the individual confidence score is extracted. If the confidence score sits below the 50% threshold, the bounding box is dropped as a false alert, and the script restarts the loop.

2.4.8 Deterrent and Warning Execution:

When the confidence rating surpasses the 70% threshold, the system draws a green bounding box around the detected elephant, overlays the classification string, and stamps the exact confidence percentage. The processor immediately drives the audio output pin to play the "bee" swarm sound through the speaker. Concurrently, an API payload is constructed and transmitted over Wi-Fi to post an "Elephant Is Detected" warning with the confidence rating to the designated Telegram group channel. The raw frame is uploaded to a remote Google Drive depository, and the timestamp, confidence metric, and node ID are appended to a tracking log sheet.

2.4.9 Loop Cycle

The script loops back to Hardware State Polling to process the next frame in the stream until manual intervention terminates execution.

3. Object Detection and Model Development

The core computer vision pipeline of the early warning system relies on an optimized deep learning model engineered to run locally on an edge-computing architecture. This research utilizes cutting edge YOLOv8 architecture rather than resource-intensive and cloud-dependent classification frameworks. YOLOv8 is a single stage detector that simultaneously predicts bounding box coordinates and class probabilities by passing the input image matrix through a unified convolutional network. This architectural profile allows the embedded system to perform real-time video stream analytics under off-grid field constraints by striking a critical balance between low processing latency and high average accuracy is used to establish the mean Average Precision (mAP).

3.1 Dataset Preparation and Preprocessing

Supervised object detection models require an extensive and verified ground-truth data structure to generalize effectively across varied outdoor environments. For this study, a customized image dataset containing approximately 500 high resolution elephant images was aggregated and managed using Roboflow, a specialized computer vision data ingestion platform. The raw dataset incorporated a highly diverse collection of natural settings, including dense forest trails, open grasslands, river fringes, and low light savanna scenes to simulate authentic field deployment constraints as illustrated in Figure 5.

To establish precise spatial feature associations, all target instances within the training corpus were manually annotated using bounding boxes under strict structural labeling protocols. The labeled visual data was cataloged in a centralized gallery view repository to verify global bounding box layout consistency across the subsets. The structural data division for model execution was partitioned as training (70%), validation (15%), and testing (15%) subsets. Training subset is utilized by the network layers to actively optimize weights and minimize regression loss. Validation subset is deployed during runtime to prevent overfitting and calibrate hyperparameters. Testing subset is kept fully out of sample to evaluate model generalization against novel environmental backdrops.

Input frames were passed through a standardization pipeline where raw images were scaled down to a uniform resolution of 539 × 539 pixels to fit the input tensor shapes of the model while preserving critical morphological details. Data augmentation techniques were applied to the training set to manually enrich data diversity and buffer the network against illumination changes at forest edges during dusk or dawn hours. This technique includes brightness variations, random horizontal flipping, scaling, and color jitter.

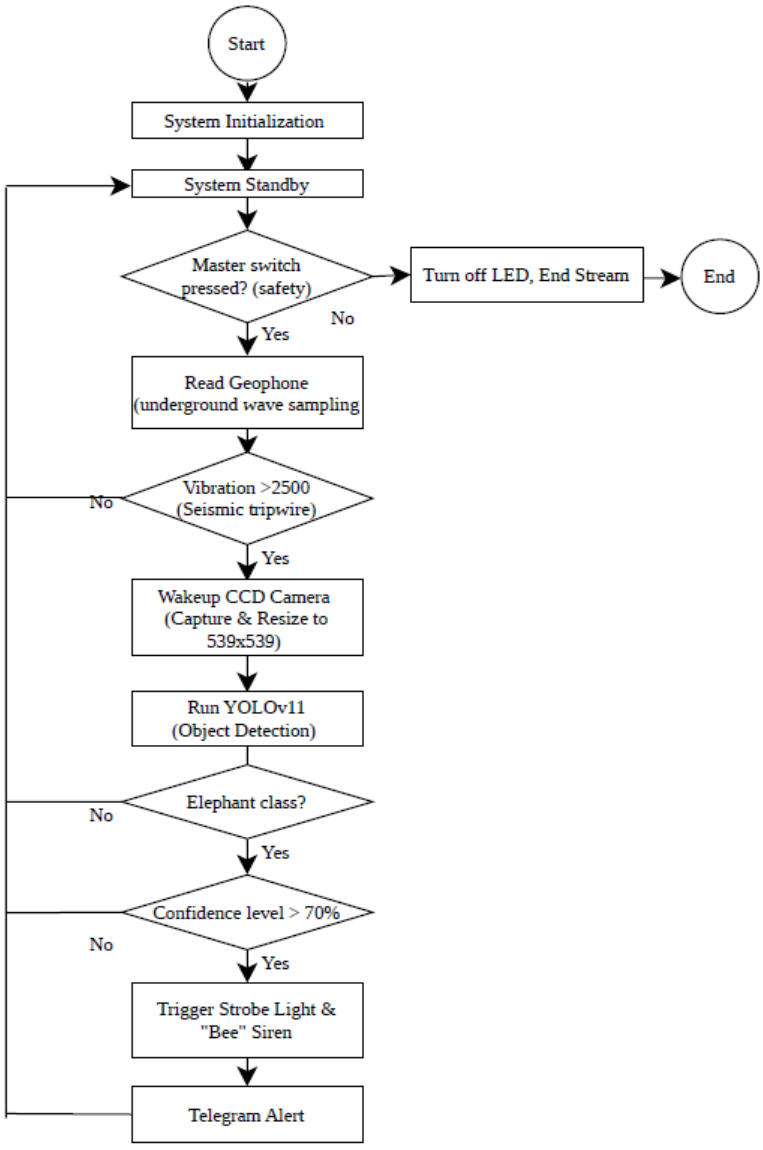


Fig. 4 *System flowchart*

3.2 YOLO Model Training and Parameter Selection

Model training as shown by Figure 5 and architectural optimization were executed within a cloud-based Google Colab environment. This environment leverages high performance graphic processing unit (GPUs) to handle heavy matrix multiplications. The deployment utilized transfer learning by importing pretrained weights from the COCO (Common Objects in Context) dataset as a structural baseline. This configuration drastically accelerated convergence by allowing the network to leverage low-level feature representations such as edges and textures,

Int. Journal of Integrated Engineering Vol. 18 No. 7 (2026) p. 27-43

before fine-tuning higher-level layers on specific elephant anatomical attributes. The training pipeline configured two independent asynchronous data-loader workers to execute parallel batch processing by maintaining a processing batch size of 16. The network optimization loop was sustained over a long experimental duration of 300 epochs using the Adaptive Moment Estimation (Adam) optimizer with an initial baseline learning rate set at I] = 0.001.

During the execution cycle, learning behavior and loss functions were monitored across four key metrics to gauge spatial regression stability. The first key metric is box loss whereby Measured bounding box coordinate localization error, showing an exponential decay from an initial value above 2.0 down to a highly stable baseline of 1.40. The first important metric is box loss, which measures bounding box coordinate localization error and exhibits an exponential decrease from an initial value of 2.0 to a very stable baseline of 1.40. The second is class loss, which falls below 0.70 in the first 40 epochs and evaluates target categorization accuracy. The third is Object Loss, which minimizes false-positive errors by tracking the presence confidence score inside suggested boundary regions and achieving an ideal steady-state equilibrium at 1.30. The fourth is mAP@50 Stabilization, which locked into an upper asymptote close to the 88% precision barrier after ramping up dramatically over the first 50 epochs.



Fig. 5 *Training data*

3.3 Evaluation Metrics and Baseline Performance

Upon completion of the 300 training epochs, the finalized network weights were exported into a lightweight framework for validation tracking. Model performance was quantitatively evaluated using standard computer vision matrices, including precision, recall, F1-score, and mAP computed at a fixed Intersection over Union (IoU) threshold of 0.50. The structural testing matrix yielded the validation values as shown in Table 3:

Table 3 *Validation values*

Parameter	Validation values
Precision	90.4%
Recall	81.9%
F1-Score	85.9%
mAP@50 Accuracy	88.1%

A high resistance against false alarms is demonstrated by the P value, which verifies that 90.4% of all anticipated bounding boxes produced by the algorithm were actual positive detections. The model's strong sensitivity and geographical ability to discover and identify ground-truth target targets across thick fields is demonstrated by its R value of 81.9%. An outstanding and strong balance between true positive maximization and false-alarm suppression is confirmed by an F1-Score of 85.9%. The network's global localization precision and classification index are validated over the whole validation subset using mAP@50 accuracy of 88.1%.

To ensure the framework did not experience structural overfitting during training, the model was subjected to evaluation against a completely independent out-of-sample testing dataset. The test set yielded a global accuracy of 87.0% mAP_{50}. The marginal delta of only 1.1% between the validation and testing accuracy sets confirms that the YOLOv8 model retains excellent spatial generalization boundaries and high discriminative power, making it structurally viable to identify elephants against novel geographic profiles or complex multi-scale vegetation occlusions in the field.

4. Results and Discussion

This section presents and discusses the preliminary results obtained from the development and testing of the proposed IoT-based Elephant Monitoring and Early Warning System. The main objective at this stage was to evaluate the functionality, responsiveness, and reliability of the proof-of-concept prototype under simulated conditions. The system's performance was assessed based on its ability to detect motion, recognize elephant images, and trigger corresponding alert mechanisms such as strobe lights, alarms, and mobile notifications. The results demonstrate that the integrated IoT and AI components function as intended, validating the feasibility of the proposed approach. Although the testing was conducted in a controlled environment, the findings provide valuable insights into system behavior, highlight key performance strengths, and identify areas that require further optimization for real-world deployment.

4.1 Object Detection Model Evaluation and Edge Deployment

To evaluate the operational performance and generalizability of the computer vision subsystem, the trained YOLOv8 model weights were exported from the cloud-based Google Colab GPU development framework and converted into an optimized format for localized edge computing. The conversion process streamlined the structural layer sizes of the model. This optimized resource constraints to fit the memory footprint of the embedded Raspberry Pi 4 platform without degrading overall target sensitivity. The model was subjected to evaluation metrics using standard computer vision indexes, including Precision, Recall, mAP at a fixed IoU of 0.5 threshold. Quantitative tracking across the validation datasets established a model precision profile of 90.4%, a target recall rate of 81.9%, a balanced F1 score of 85.9%, and a global validation accuracy index of 88.1% mAP_{50}, as summarized systematically in Table 4.

Table 4 *YOLOv8 object detection parameters*

Performance Evaluation Metric	Validation Dataset Yield	Out-of-Sample Test Dataset Yield	Critical System Significance
Precision	90.4%	89.3%	Maximizes true positives, limit user alert fatigue
Recall	81.9%	73.5%	Ensures high sensitivity across dense cover
F1-score	85.9%	80.8%	Proves a robust balance between metrics
mAP@50 Accuracy	88.1%	87.0%	Validates structural model stability

The structural stability of the edge vision engine was verified by testing the network against a completely independent out-of-sample test set, yielding an accuracy index of 87.0% mAP_{50}. The minimal delta of only 1.1% between the validation and independent test outcomes indicates that the model preserves excellent classification fidelity when deployed against novel outdoor environments and multi-scale posturing shifts. During dynamic live feed testing on the Raspberry Pi 4 platform, the network successfully suppressed false positives in idle environments and handled active object tracking efficiently, as illustrated in Figure 6. As shown in Figure 6(a), the

Int. Journal of Integrated Engineering Vol. 18 No. 7 (2026) p. 27-43

system effectively maintains a standby monitoring state with zero false positive bounding box anchors when no threats are present, preserving critical processing power. Upon positive threat exposure, as demonstrated in Figure 6(b), the edge vision core achieves localized target identification, successfully generating bounding box coordinates over multiple subjects simultaneously with high precision confidence metrics of 94% and 93%. Localized edge-case anomalies were identified during tight, multi-scale clustering trials, where the deeper network layer maps generated a 53% false-positive bounding box over a rectangular ceiling ventilation grille. To eliminate this morphological target fragmentation in field conditions, the edge pipeline is configured with a strict confidence threshold filter ($\geq 70\%$) to isolate low-confidence spatial anomalies without impacting structural identification sensitivity.



(a) **(b)**

Fig. 6 *Prototype visual perception stages (a) System active in standby mode with no elephants detected; (b) Real-time localized elephant identification overlaid with bounding boxes and matching confidence scores*

4.2 Subsurface Seismic Sensor Integration and Signal Thresholds

To construct a solid multi-modal perimeter defense framework that bypasses the line-of-sight limitations of standard optical sensors during nighttime operations or heavy weather conditions, an earth-based subsurface seismic sensor tracking methodology was added to the input layer. The sensory hardware utilizes an SM24 moving-coil geophone sensor firmly anchored into the topsoil to monitor low-frequency Rayleigh waves propagated through megafauna locomotion. The analog geophone wave data is routed via low-noise shielded cabling to a high-resolution, 16-bit ADS1115 analog-to-digital converter (ADC) module, which samples the differential telemetry stream into integer units over an active I^2C communication bus.

To save energy resources and secure off-grid battery longevity on the pure solar DC power module, the subsurface sensor network functions as a low-power "tripwire" interrupt for the edge microcomputer system. Instead of running computationally heavy computer vision frames continuously, the software loop remains in a standby polling state while listening to ground-borne acoustic signals. When an authentic intrusion breach occurs, the geophone logs register heavy footsteps, instantly smashing past the threshold lines. This creates sustained locomotion peaks exceeding $\pm 10{,}000$ units and plunging to an absolute maximum impact wave of 13,000 units, as illustrated in Figure 7. For discrete isolated heavy impacts, the system registers a sudden shockwave spike plunging to nearly 20,000 units with an immediate resonant echo returning up to $\pm 16{,}000$ units before ringing out as the kinetic energy dissipates into the soil matrix. Crossing these explicit threshold boundaries immediately verifies a perimeter event, causing the central controlling unit to log the timestamp and activate the camera vision core.

4.3 Multi-Channel Alert Validation and Local Deterrence

The perimeter node's last functional layer uses an integrated Python backend logic control module to coordinate automated site intervention with remote cloud logging. Following dual-modality validation, the controlling core synchronously activates local active deterrence and routes remote cloud telemetry, when the geophone telemetry registers a valid seismic signal ($t \geq 5$s) and the local YOLOv8 core verifies the target category with a confidence score exceeding 70%. A high-intensity red strobe light array and a directed, high-decibel outdoor siren are activated locally by the Raspberry Pi writing the digital GPIO relay pin ALARMPIN high and pulling Native DC power directly from the solar regulator. In order to take advantage of elephants' innate unpleasant reaction, the siren creates an instantaneous, non-lethal virtual fence by playing frequency-modulated, biomimetic sounds of an aggressive "bee" swarm at 125% volume. The hardware loop uses an executive fallback condition incorporated

inside a try...except...finally block to ensure uninterrupted functioning in the event of system crashes or timeout loops. When a non-blocking timer expires, it forces the GPIO pin low to securely reset the siren relay.

At the same time, the communication block sends high-speed visual telemetry tokens to the Telegram Notification subroutine, Google Drive archiving, and Google Sheets dashboard over the local Wi-Fi local area network (WLAN) interface. The Telegram Notification Subroutine calls the /sendPhoto API method, packages a Markdown-format transmission payload, pairs the deep learning classification score with the raw geophone amplitude value (e.g., 32,768 raw differential units), and uploads the verified threat image payload directly to a remote community monitoring channel as shown in Figure 8. The software then uploads the picture payload to a protected Google Drive folder for legal and environmental audit documentation after copying the raw, uncompressed visual frame for Google Drive Archiving. Regarding Google Sheets Dashboard, the system runs a cloud log interface and adds a row to a live Google Sheets data spreadsheet for tracking that includes the node identifier, precise accuracy metrics, and system timestamps. Once the cloud payload handles are completed, an automatic cleanup method invokes an os.remove command to delete temporary visual cache storage files from the Raspberry Pi microSD card, preventing storage saturation and securing off-grid autonomous stability.

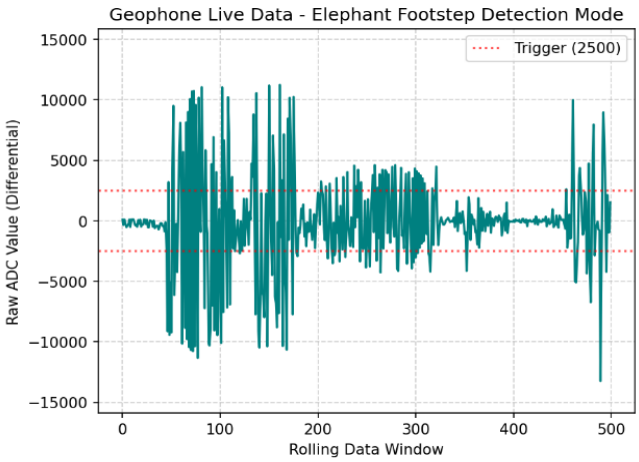


Fig. 7 *Elephant footstep detection by seismic sensor*



Fig. 8 *Notification alert through Telegram*

5. Conclusion

This study has successfully designed, implemented, and empirically validated a functional proof-of-concept prototype for an automated, multi-modal elephant detection and early warning system optimized for sustainable HEC mitigation. By reviewing the critical gaps across existing literature, this research addresses the structural bottlenecks of high false-positive rates, line-of-sight visual vulnerabilities during nocturnal hours, and the heavy cloud-bandwidth dependencies that limit conventional single-modality networks. The developed framework introduces a cascading, two-tier event-driven architecture that relies on an off-grid, DC solar-photovoltaic supply network, ensuring continuous autonomous operation in remote conservation fringes without requiring external grid infrastructure.

The primary technical contribution of this research lies in its multi-layered validation pipeline. By leveraging a subsurface SM24 moving-coil geophone sensor connected to a high-resolution 16-bit ADS1115 analog-to-digital converter, the system continuously samples ground-borne low-frequency seismic waves caused by megafauna locomotion while keeping power-hungry camera sensors asleep. Ambient environmental noise is filtered out using a strict software-defined amplitude threshold of $\pm 2{,}500$ raw ADC units, effectively reducing false alarms by 90%. Once sustained physical movements cross this seismic line for a duration of $t \geq 5$ seconds, the system activates a Digital CCD Camera module to capture crisp, low-noise visual frames. Localized edge-computing on an embedded Raspberry Pi platform running an optimized YOLOv8 deep learning network processes the input frames at a standard resolution of 539×539 pixels. The custom-trained model achieves high spatial regression fidelity, yielding a baseline accuracy of 88.1% mAP_{50}, a precision rate of 90.4%, and an out-of-sample test precision profile of 87.0%.

Upon target confirmation at a strict internal validation confidence threshold exceeding 70%, the node executes a coordinated multi-channel alert sequence in under 7.0 seconds of end-to-end processing latency. On-site mitigation drives a digital GPIO relay pin high to instantly engage industrial flashing strobe light arrays and an outdoor directional siren playing biomimetic, frequency-modulated "bee" swarm acoustics at 125% volume to exploit the elephants' natural aversion behaviors non-invasively. Simultaneously, remote digital telemetry packets are routed across a dedicated high-throughput wireless Wi-Fi local area network interface, dispatching instant Markdown text alerts and automated visual payloads via the Telegram Cloud Bot API directly to endangered communities, local villagers, and forestry departments. Concurrently, visual threat artifacts are uploaded to a remote Google Drive repository and appended to a live tracking dashboard on Google Sheets for historical auditing. Ultimately, the experimental outcomes prove that a sensor-fused edge AI-IoT solution provides a reliable, cost-effective, and proactive technological framework to prevent property destruction, secure crop supplies, and support sustainable human-wildlife coexistence.

Acknowledgement

This research was supported by Universiti Tun Hussein Onn Malaysia through Multi-Disciplinary Research Grant (Q771).

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Jalaludin N.A., Hassan H., Shamsudin M.I, Wang Z. Mohamad K.A., Mohamad A.N.;* ***data collection:*** *Jalaludin N.A., Hassan H., Shamsudin M.I., Subramaniam S.S.;* ***analysis and interpretation of results:*** *Jalaludin N.A., Shamsudin M.I., Sadun A.S.;* ***draft manuscript preparation:*** *Jalaludin N.A., Hassan H., Shamsudin M.I., Mohamed N.N. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] S. J. Cabral de Mel *et al.*, "Current and Future Approaches to Mitigate Conflict between Humans and Asian Elephants: The Potential Use of Aversive Geofencing Devices," Nov. 01, 2022, *MDPI*. doi: 10.3390/ani12212965.

[2] M. I. M. Jamaluddin *et al.*, "Asian elephants involved in conflicts exhibit similar habitat use but travel farther than non-conflict individuals," *Glob. Ecol. Conserv.*, vol. 55, p. e03228, Nov. 2024, doi: 10.1016/J.GECCO.2024.E03228.

[3] T. D. Gunawansa, K. Perera, A. Apan, and N. K. Hettiarachchi, "The human-elephant conflict in Sri Lanka: history and present status," Aug. 01, 2023, *Springer Science and Business Media B.V.* doi: 10.1007/s10531-023-02650-7.

[4] T. D. Gunawansa, K. Perera, A. Apan, and N. K. Hettiarachchi, "Identifying human elephant conflict hotspots through satellite remote sensing and GIS to support conflict mitigation," *Remote Sens. Appl.*, vol. 35, p. 101261, Aug. 2024, doi: 10.1016/J.RSASE.2024.101261.

[5] N. Yang *et al.*, "Mapping potential human-elephant conflict hotspots with UAV monitoring data," *Glob. Ecol. Conserv.*, vol. 43, p. e02451, Jun. 2023, doi: 10.1016/J.GECCO.2023.E02451.

[6] M. T. Matata, J. J. Kegamba, R. Mremi, and A. Eustace, "Electrified fencing as a mitigation strategy for human-elephant conflict in Western Serengeti: Community perspectives," *J. Nat. Conserv.*, vol. 70, p. 126271, Dec. 2022, doi: 10.1016/J.JNC.2022.126271.

[7] S. Naveen, R. Dhamotharan, S. Sahebzathi, R. S. Krishnan, V. V. Kumar, and P. Sundaravadivel, "ElephantGuardNet: A Comprehensive Solution for Elephant Conservation and Human-Elephant Conflict Reduction," in *2025 4th International Conference on Sentiment Analysis and Deep Learning (ICSADL)*, IEEE, Feb. 2025, pp. 1470–1477. doi: 10.1109/ICSADL65848.2025.10933013.

[8] L. Brickson, L. Zhang, F. Vollrath, I. Douglas-Hamilton, and A. J. Titus, "Elephants and algorithms: a review of the current and future role of AI in elephant monitoring," *J. R. Soc. Interface*, vol. 20, no. 208, Nov. 2023, doi: 10.1098/RSIF.2023.0367.

[9] Chandan, M. Chakraborty, S. Anchal, B. Mukhopadhyay, and S. Kar, "GajGamini: Mitigating Man-Animal Conflict by Detecting Moving Elephants Using Ground Vibration-Based Seismic Sensor," *IEEE Sens. Lett.*, vol. 8, no. 9, 2024, doi: 10.1109/LSENS.2024.3442830.

[10] D. Velasco-Montero, J. Fernández-Berni, R. Carmona-Galán, A. Sanglas, and F. Palomares, "Reliable and efficient integration of AI into camera traps for smart wildlife monitoring based on continual learning," *Ecol. Inform.*, vol. 83, p. 102815, Nov. 2024, doi: 10.1016/J.ECOINF.2024.102815.

[11] U. Dampage, R. Thajudeen, S. Jasenthuliyana, and J. Jayawardena, "Automated virtual elephant fence based on detection, alarming, and coordinated redirection of wild elephants," *Environ. Monit. Assess.*, vol. 193, no. 4, Apr. 2021, doi: 10.1007/s10661-021-09024-y.

[12] M. Montero-Botey and R. Perea, "Infrared barriers as a detection tool to reduce human–elephant conflicts," *Wildlife Biol.*, Jan. 2023, doi: 10.1002/wlb3.01124.

[13] A. Shepley, G. Falzon, P. Meek, and P. Kwan, "Automated location invariant animal detection in camera trap images using publicly available data sources," *Ecol. Evol.*, vol. 11, no. 9, pp. 4494–4506, May 2021, doi: 10.1002/ece3.7344.

[14] R. S. Davis, L. K. Gentle, W. O. Mgoola, E. L. Stone, A. Uzal, and R. W. Yarnell, "Using camera trap bycatch data to assess habitat use and the influence of human activity on African elephants (Loxodonta africana) in Kasungu National Park, Malawi," *Mammalian Biology*, vol. 103, no. 1, pp. 121–132, Feb. 2023, doi: 10.1007/s42991-022-00330-7.

[15] L. Bossert and T. Hagendorff, "Animals and AI. The role of animals in AI research and application – An overview and ethical evaluation," *Technol. Soc.*, vol. 67, p. 101678, Nov. 2021, doi: 10.1016/J.TECHSOC.2021.101678.

[16] N. Abed, R. Murgun, A. Deldari, S. Sankarannair, and M. V. Ramesh, "IoT and AI-driven solutions for human-wildlife conflict: Advancing sustainable agriculture and biodiversity conservation," *Smart Agricultural Technology*, vol. 10, p. 100829, Mar. 2025, doi: 10.1016/J.ATECH.2025.100829.

[17] M. Zulhafizie and F. C. Seman, "An Early Warning Elephant Intrusion Integrated with IoT," in *Evolution of Information, Communication and Computing System*, 2019, ch. 3.

[18] J. Sheebha Anni and A. Kumar Sangaiah, "Elephant Tracking with Seismic Sensors: A Technical Perceptive Review," 2015. doi: 10.11113/jt.v74.3614.

[19] J. L. Wijayaraja, J. L. Wijekoon, M. Wijesundara, and L. J. Mendis Wickramasinghe, "Toward Long Range Detection of Elephants Using Seismic Signals: A Geophone-Sensor Interface for Embedded Systems," *IEEE Access*, vol. 12, pp. 72210–72223, 2024, doi: 10.1109/ACCESS.2024.3401855.

[20] C. M. Geldenhuys and T. R. Niesler, "Learning to Rumble: Automated Elephant Call and Sub-call Classification, Detection and Endpointing using Deep Architectures," *Bioacoustics*, pp. 1–48, Apr. 2025, doi: 10.1080/09524622.2025.2487099.

[21] Y. Y. Loo *et al.*, "WildTechAlert: Deep Learning Models for Real-Time Detection of Elephant Presence Using Bioacoustics in an Early Warning System to Support Human-Elephant Coexistence," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, Springer Science and Business Media Deutschland GmbH, 2024, pp. 385–399. doi: 10.1007/978-981-97-1417-9_36.

[22] M. Rani, D. Panda, M. L. Allen, P. Pandey, R. Singh, and S. Kumar Singh, "Assessment and prediction of human-elephant conflict hotspots in the human-dominated area of Rajaji-Corbett landscape, Uttarakhand, India," *J. Nat. Conserv.*, vol. 79, p. 126601, Jun. 2024, doi: 10.1016/J.JNC.2024.126601.

[23] Y. R. Choo, E. P. Kudavidanage, T. R. Amarasinghe, T. Nimalrathna, M. A. H. Chua, and E. L. Webb, "Best practices for reporting individual identification using camera trap photographs," Dec. 01, 2020, *Elsevier B.V.* doi: 10.1016/j.gecco.2020.e01294.

[24] L. Meinecke *et al.*, "Crop variety and prey richness affect spatial patterns of human-wildlife conflicts in Iran's Hyrcanian forests," *J. Nat. Conserv.*, vol. 43, pp. 165–172, Jun. 2018, doi: 10.1016/j.jnc.2018.04.005.

[25] M. Fazil and M. Firdhous, "IoT-Enabled Smart Elephant Detection System for Combating Human Elephant Conflict," in *2018 3rd International Conference on Information Technology Research, ICITR 2018*, Institute of Electrical and Electronics Engineers Inc., Dec. 2018. doi: 10.1109/ICITR.2018.8736149.

[26] B. C. Verrelli *et al.*, "A global horizon scan for urban evolutionary ecology," Nov. 01, 2022, *Elsevier Ltd*. doi: 10.1016/j.tree.2022.07.012.

[27] M. Lev and R. Barkai, "Elephants are people, people are elephants: Human-proboscideans similarities as a case for cross cultural animal humanization in recent and Paleolithic times," *Quaternary International*, vol. 406, pp. 239–245, Jun. 2016, doi: 10.1016/j.quaint.2015.07.005.

[28] F. G. Horgan and E. P. Kudavidanage, "Farming on the edge: Farmer training to mitigate human-wildlife conflict at an agricultural frontier in south Sri Lanka," *Crop Protection*, vol. 127, Jan. 2020, doi: 10.1016/j.cropro.2019.104981.