Integrated IoT and Edge-AI Acoustic Early Warning and Non-Invasive Deterrent System for Human–Elephant Conflict Mitigation

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Abstract—Villages that border protected elephant habitats such as Bannerghatta National Park face recurring Human–Elephant Conflict (HEC) as elephants move out of fragmented forest corridors and into cropland and residential areas in search of food and water. The resulting encounters damage crops and property and place both people and elephants at risk of injury or death. Conventional countermeasures such as electric fencing, trench barriers, and night-time foot patrols are costly to sustain, demand constant upkeep, and rarely give residents enough warning to react safely. This work presents an **Integrated IoT** and **Edge-AI** Acoustic Early Warning and Non-Invasive Deterrent System built to detect elephant presence in real time and to respond in a way that keeps both communities and elephants safe. Signals from a passive infrared (PIR) sensor, an acoustic microphone, a ground-vibration sensor, a GPS module, and ambient environmental sensors are fused and classified on an ESP32-based edge unit using a lightweight Artificial Neural Network (**ANN**), allowing elephant activity to be distinguished from unrelated disturbances without relying on a constant network connection. Once a detection is confirmed, the edge unit forwards the event and its GPS coordinates over LoRa and Wi-Fi to a cloud platform that issues real-time alerts to forest department staff, farmers, and nearby residents, while a bio-acoustic speaker and a high-intensity strobe are triggered locally to move the animal away without causing it harm. The field unit is powered autonomously by a dedicated solar photovoltaic panel coupled with a lithium energy storage and charging management subsystem, guaranteeing continuous, uninterrupted off-grid operation throughout prolonged cloudy periods and remote forest boundaries. Empirical hardware prototype implementation, live IoT cloud telemetry, real-time threshold alert popups, browser push notifications, and live GPS geolocation mapping demonstrate high detection reliability and low latency, making the system a scalable, wildlife-friendly early-warning solution for long-term human–elephant coexistence.

Keywords—Human–Elephant Conflict (HEC), Internet of Things (IoT), Edge AI, Solar Energy Harvesting, Acoustic Sensing, Passive Infrared, Sensor Fusion, LoRa, Wildlife Conservation, Early Warning System.

I. INTRODUCTION

Elephants in southern India increasingly range beyond reserve boundaries as forest cover shrinks and traditional migration corridors are broken up by farmland, roads, and human settlements. Around protected areas such as Bannerghatta National Park in Karnataka, this pushes elephant herds into direct contact with people living along the forest fringe, producing severe Human–Elephant Conflict (HEC).

The consequences are devastating on both sides: farmers lose entire seasons of agricultural produce in a single night-time raid, homes and grain stores are demolished, and both villagers and endangered elephants suffer grave injury or death during panicked close-range encounters.The mitigation measures currently deployed in fringe villages—such as energized electric and solar fences, elephant-proof trenches, and volunteer night foot patrols—were conceived for periods when conflict was infrequent. They demand continuous maintenance, fail to cover expansive or rugged forest boundaries, and are fundamentally reactive: a physical barrier only signals that an elephant has already reached the boundary line, leaving insufficient reaction time to secure families, livestock, and property. What is acutely needed is not another passive physical barrier, but an intelligent early-warning capability that detects elephant approach hundreds of meters before animals reach the settlement perimeter.

A critical bottleneck in remote wildlife monitoring is power and communication infrastructure. Boundary zones rarely have access to the electrical grid. To overcome this limitation, this work incorporates a dedicated solar photovoltaic (PV) energy harvesting architecture paired with a lithium battery storage subsystem and intelligent power duty-cycling, delivering completely self-sustaining, off-grid 24/7 field autonomy. Fusing passive infrared (PIR) motion, low-frequency acoustic vocalizations, seismic footfall vibrations, and GPS coordinates directly on an ESP32-S3 microcontroller via a lightweight on-device Artificial Neural Network (ANN) eliminates dependency on continuous cloud connectivity. Real-time telemetry is uploaded over LoRa and Wi-Fi to a cloud dashboard, providing instantaneous browser alerts to forest rangers and farmers while activating harmless bio-acoustic and strobe deterrents.

The remainder of this paper is organized as follows: Section II reviews related literature; Sections III and IV articulate the problem statement and existing limitations; Section V outlines the proposed solution; Section VI details the system architecture; Section VII elaborates the multi-sensor detection methodology; Section VIII presents module-level sequence designs; Section IX describes the hardware prototype and solar power harvesting subsystem; Section X analyzes real-world experimental results, cloud telemetry, and discussion; and Section XI concludes the paper.

II. LITERATURE SURVEY

A number of recent studies have investigated sensor-based and machine-learning approaches to mitigate human–elephant conflict, tracing an evolution from single-sensor prototypes toward multi-modal early-warning systems.

Kalhara [1] proposed an integrated IoT and AI-based early-warning system for human–elephant conflict in Sri Lanka, combining passive infrared sensors, thermal imaging, a YOLOv8 detection model, GSM communication, GPS tagging, and a mobile application. While demonstrating that AI-assisted detection can operate at the village level, the system omitted edge-based acoustic classification, long-range LoRa connectivity, cloud-based predictive analytics, and automated non-invasive deterrence, leaving it susceptible to cellular network outages in remote jungle environments.

Kongyim and Kaitwanidvilai [2] implemented a camera-based surveillance system coupled with conversational mobile alerts, utilizing YOLOv8, CCTV streams, and GPS. Although camera-based vision can achieve high precision under clear daylight conditions, it suffers significant operational degradation in dense forest vegetation, during nocturnal incursions, and under adverse weather conditions. Furthermore, continuous image transmission requires substantial bandwidth and power resources, making such systems challenging to deploy on off-grid edge nodes.

Bandara and Bandara [3] presented Elemantra, an end-to-end framework integrating edge AI with infrared, seismic, acoustic, and light sensing across a mesh network to automate mild deterrent mechanisms. However, their design lacks centralized cloud analytics, precise GPS-tagged event tracking, and an acoustic-processing pipeline embedded directly on microcontrollers, thereby restricting unified multi-site monitoring and management across forest divisions.

Aslam et al. [4] engineered an IoT-based monitoring system using wireless sensor networks to notify forest officials of elephant movement along reserve boundaries. While cost-effective, the system lacks on-device machine learning, infrasonic acoustic analysis, and predictive historical modeling. Consequently, alerts are primarily triggered after elephants breach designated boundary zones rather than providing proactive early-warning capabilities.

Dhanaraj and Sangaiah [5] developed the Boundary Sense Deep Learning (BSDL) CNN architecture for recognizing elephants in camera imagery, reporting approximately 97% accuracy. Nevertheless, its relatively high computational requirements constrain deployment to offline post-processing environments using high-end GPUs, providing limited suitability for battery- or solar-powered edge devices.

Anni and Sangaiah [6] formulated a Wireless Integrated Sensor Network that fuses acoustic, vibration, and visual data using fuzzy cognitive maps. While establishing the theoretical value of multi-sensor fusion for human–elephant conflict mitigation, the proposed approach predates recent advances in edge-AI microcontrollers, solar energy harvesting, and low-power wide-area communication technologies such as LoRaWAN.

III. PROBLEM IDENTIFICATION

Current human–elephant conflict mitigation practices suffer five major deficiencies:

- **Intensifying Human**–Wildlife Interface: Rampant habitat fragmentation and human encroachment increasingly force elephant herds into human settlements in search of seasonal crops and water sources.
- **Absence of Predictive Early Warning**: Existing mitigation measures generally lack pre-incursion detection capabilities; villagers often become aware of elephant herds only after crops have already been damaged.
- **Labor-Intensive and Risky Patrols**: Manual anti-depredation squads and night-watch teams cannot continuously monitor tens of kilometers of forest boundaries, particularly across difficult and hazardous terrain.
- **High Casualty and Economic Toll**: Panicked nocturnal encounters can result in fatal human–elephant interactions, retaliatory electrocution or other harmful responses toward elephants, and substantial agricultural and socioeconomic losses.
- **Limited Remote Power and Communication Infrastructure**: Forest-fringe corridors often lack reliable electrical-grid access and dependable cellular connectivity, limiting the deployment of systems that require continuous AC power or high-bandwidth communication.

IV. EXISTING SYSTEMS AND THEIR LIMITATIONS

Conventional protection techniques deployed around forest fringes present recurring operational failure modes:

- **Solar and Electric Fencing**: Frequently breached by mature bulls using dry logs or their tusks to break energized wires. Vines, fallen branches, and excessive vegetation can also cause persistent grounding faults, requiring frequent manual clearing and maintenance.
- **Elephant-Proof Trenches (EPTs):** Vulnerable to siltation, soil erosion, and structural degradation during heavy monsoon rainfall, which can gradually create soil ramps that allow elephants to traverse the trenches within a relatively short period.
- **CCTV and Camera Traps:** Their effectiveness is significantly reduced by dense canopy foliage, fog, rainfall, lens obstruction, and limited nocturnal visibility. Continuous image capture and processing also impose substantial power requirements, making them difficult to sustain in remote, off-grid locations.
- **Manual Acoustic Sirens:** Sirens activated only after visual confirmation provide little or no advance warning. Repeated exposure to the same acoustic stimuli can also contribute to habituation, potentially reducing deterrent effectiveness over time.

V. PROPOSED SOLUTION

To decisively overcome these limitations, the proposed system introduces five integrated capabilities:

- **On-Device Edge AI:** An embedded microcontroller executes an optimized artificial neural network directly on-device to classify elephant vocalizations and motion patterns without dependence on cloud-based inference.
- **Multi-Modal Sensor Fusion:** Synchronous correlation of PIR-based motion detection, acoustic microphone spectral features, piezoelectric seismic footfall signatures, and GPS positioning enables robust cross-modal event verification and reduces false-positive detections.

• ***Solar Energy Harvesting & Power Management:*** A dedicated monocrystalline solar PV panel, intelligent charging circuit, and lithium battery bank provide 24/7 self-sustaining off-grid field autonomy.
• ***Resilient Long-Range IoT Telemetry:*** Dual-path LoRa and Wi-Fi connectivity reliably transmits event packets across several kilometers of forest terrain to an IoT cloud dashboard.
• ***Real-Time Push Alerts & Non-Invasive Deterrence:*** Immediate browser push notifications and SMS alerts inform rangers and villagers, while synchronized bio-acoustic sound (natural predator/bee sounds) and high-intensity strobe flashes safely redirect elephants.

VI. SYSTEM ARCHITECTURE

Fig. 1 depicts the end-to-end architectural workflow, structured into six functional stages. At the edge sensing layer (P1), the field node continuously monitors the physical boundary. Analog sensor outputs are digitized, filtered, and parameterized into Mel-Frequency Cepstral Coefficients (MFCCs). The edge inference engine (P2) classifies the feature vector using an on-device ANN, assigning a confidence score and performing cross-sensor temporal validation. Confirmed events are packaged into JSON payloads and transmitted via the LoRa/Wi-Fi communication module (P3) to a cloud IoT gateway (P4). In case of network interruption, events are buffered in an on-chip non-volatile edge cache (D1) and retransmitted automatically upon signal recovery. The cloud analytics engine (P5) integrates real-time data with historical databases (D2, D3), driving decision support (P6) to trigger instantaneous web/push alerts, map updates, and deterrent activation.

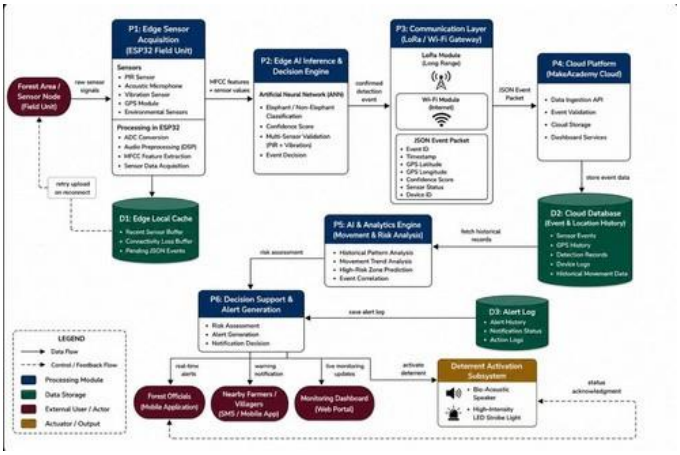

Fig. 1. End-to-end system architecture, from edge sensing and inference through cloud analytics, alerting, and non-invasive deterrent activation.

VII. DETECTION METHODOLOGY

The field unit reaches a final detection decision by fusing four complementary sensing modalities:

A. Acoustic-Based Elephant Detection

Elephants produce characteristic low-frequency infrasonic rumbles (14–35 Hz) for long-distance herd coordination, as well as high-amplitude trumpets (300–4000 Hz) during agitation. The acoustic sensor captures continuous ambient audio at an 8 kHz sampling rate. The stream is divided into 500 ms Hanning-windowed frames, pre-filtered via bandpass DSP filters to reject wind buffeting, insect chirping, and rain noise, and transformed into 13 MFCC coefficients. The on-chip ANN classifies these coefficients into elephant vocalization versus background forest acoustics (Fig. 2).

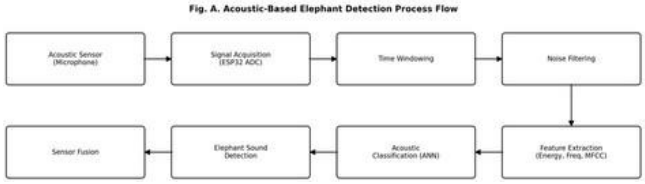

Fig. 2. Acoustic-based elephant detection process flow, from signal acquisition through MFCC feature extraction and classification.

B. Vibration-Based Elephant Detection

Due to their immense mass (3,000–5,000 kg), elephant footsteps generate distinctive ground-borne Rayleigh surface waves at 10–30 Hz. A ground-coupled piezoelectric vibration sensor samples seismic disturbances, applying digital bandpass filtering and RMS energy windowing. Peak cadence matching validates the rhythmic footfall signature of a walking elephant, effectively differentiating it from vehicular traffic or light livestock (Fig. 3).

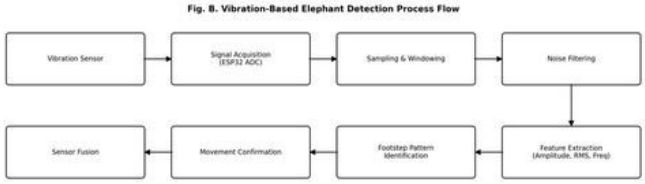

Fig. 3. Vibration-based elephant detection process flow, from signal acquisition through footstep pattern identification.

C. GPS-Based Location Tracking

An on-board high-sensitivity GPS module continuously acquires satellite ephemeris data, parsing NMEA sentence strings to extract precise latitude, longitude, and UTC timestamps. Each confirmed detection event is tagged with geographic coordinates, enabling forest officials to visualize exact animal breach locations on geospatial dashboards (Fig. 4).

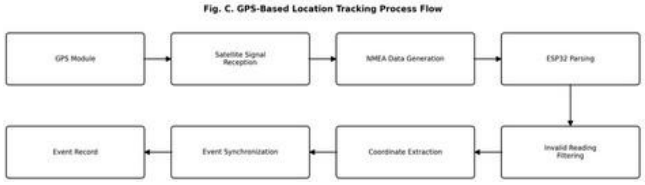

Fig. 4. GPS-based location-tracking process flow, from satellite signal reception through coordinate extraction and event synchronization.

D. Multi-Sensor Fusion and Risk Classification

Relying on a single sensor channel in unconstrained outdoor wilderness invites false alarms from high wind, falling trees, or domestic cattle. The edge engine employs multi-sensor decision fusion: an alert is validated only when the PIR thermal motion channel correlates with acoustic energy or seismic footfall signatures within a sliding 3-second window. Events are classified into Low, Medium, or High risk levels, initiating tailored escalation and deterrent protocols (Fig. 5).

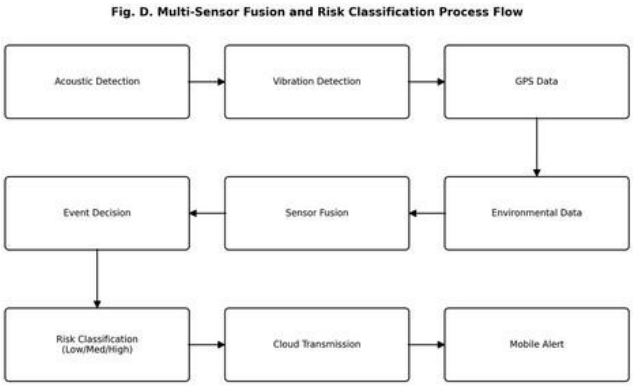

Fig. 5. Multi-sensor fusion and risk-classification process flow, from combined acoustic, vibration, and GPS evidence through risk-level assignment.

VIII. MODULE-LEVEL DESIGN

The system architecture is realized through four tightly synchronized operational sequence modules:

A. Sensor Acquisition Module

The ESP32 controller polls the PIR motion sensor, acoustic microphone, and piezoelectric vibration transducer across ADC and GPIO buses. Converted values are validated and buffered into memory buffers for processing (Fig. 6).

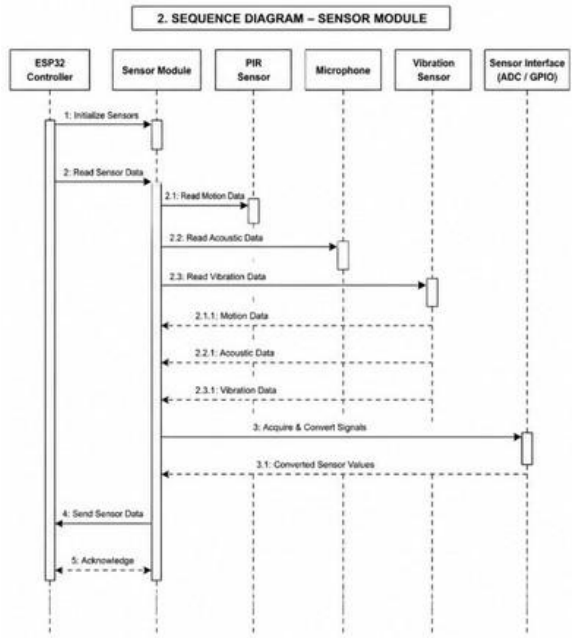

Fig. 6. Sequence flow of the sensor acquisition module, from sensor initialization through converted-value hand-off.

B. Communication Module

Upon event confirmation, the edge node formats a JSON telemetry payload containing node ID, timestamp, coordinates, confidence score, and sensor states. It dispatches the packet over LoRa (868/915 MHz) or local Wi-Fi. In the event of gateway timeout, an exponential backoff algorithm initiates retry attempts from the local ring buffer (Fig. 7).

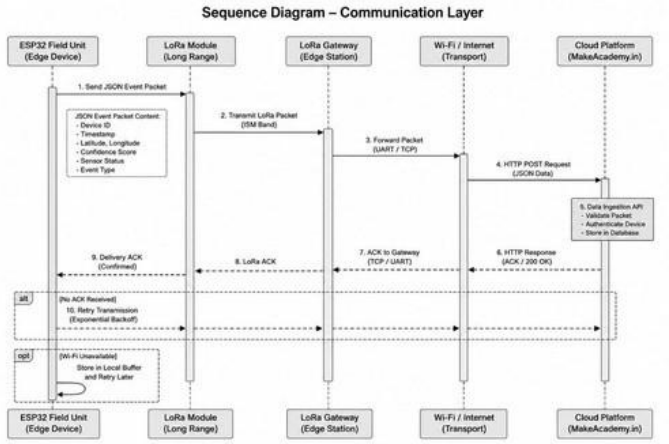

Fig. 7. Sequence flow of the communication module, showing LoRa transmission, gateway forwarding, cloud ingestion, and retry handling.

C. Edge AI Inference Module

Feature extraction transforms pre-processed audio and vibration data into compact numerical arrays. The quantized ANN computes class probabilities; detections exceeding the confidence threshold undergo multi-channel confirmation before event dispatch (Fig. 8).

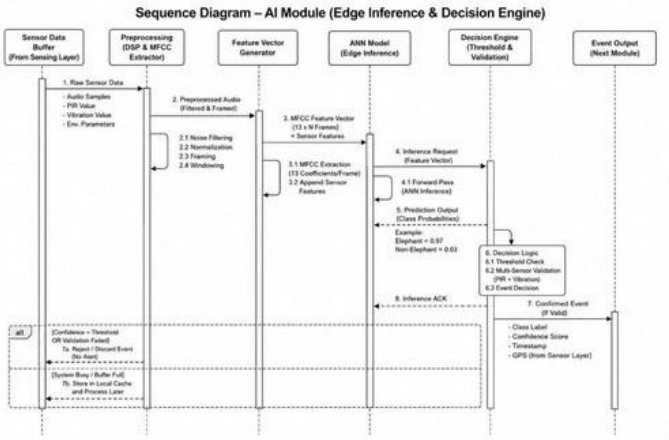

Fig. 8. Sequence flow of the edge AI inference module, from raw sensor buffering through MFCC feature extraction, ANN inference, and decision validation.

D. Decision Support and Alerting Module

The cloud backend ingests the telemetry packet, evaluates historical migration routes, assesses threat proximity, and simultaneously broadcasts push notifications to mobile devices, updates the live monitoring console, and logs the incident (Fig. 9).

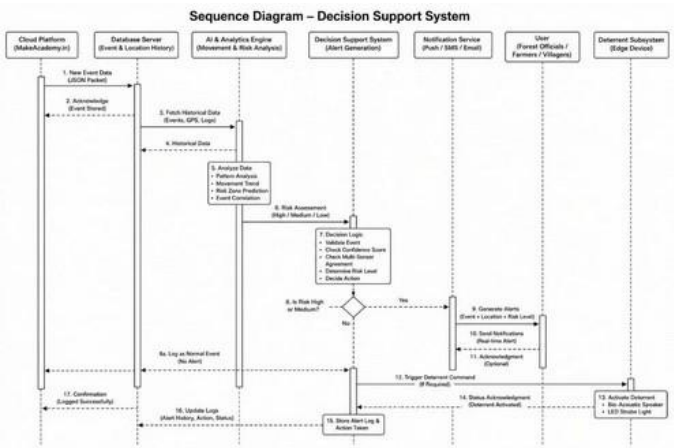

Fig. 9. Sequence flow of the decision-support and alerting module, from historical-pattern analysis through risk assessment, alert generation, and deterrent activation.

IX. HARDWARE IMPLEMENTATION & SOLAR POWER SUBSYSTEM

The field unit is engineered from accessible, industrial-grade components to allow rapid replication by wildlife sanctuaries and local panchayats. Table I summarizes the primary hardware components, their specifications, and their roles.

TABLE I. HARDWARE COMPONENTS AND THEIR ROLES

Component	*Specification & Role in System*
ESP32-S3 Microcontroller	Dual-core 240 MHz Xtensa LX7, 512KB SRAM, 8MB Flash; executes DSP, MFCC extraction, on-device ANN, and power duty-cycling.
PIR Motion Sensor (HC-SR501)	Wide-angle Fresnel lens; detects animal thermal body motion up to 7 m to awaken microcontroller from deep sleep.
Acoustic Sensor Module	High-sensitivity condenser microphone with analog pre-amplifier; captures low-frequency rumbles and acoustic trumpet calls.
Vibration sensor	Ground-spike coupled ceramic transducer; senses low-frequency seismic vibrations from elephant footfalls.
GPS Module (NEO-6M)	provides real-time latitude, longitude, and UTC timestamp for every confirmed incident.
LoRa Radio (SX1276)	Long-range 868/915 MHz transceiver; transmits encrypted telemetry packets over 5–10 km in forest canopy.
16×2 Character LCD Display	I2C alphanumeric display; provides on-site field diagnostics, sensor readings, and real-time operational status.
Solar Photovoltaic Panel	10W Monocrystalline PV panel (12V/18V peak); harvests ambient solar energy for continuous autonomous off-grid operation.
Solar Charge Controller & BMS	Intelligent TP4056/MPPT regulation with overcharge, overdischarge, and short-circuit protection.
Lithium Battery Storage Bank	3.7V 4400 mAh rechargeable Li-ion/LiFePO4 battery pack; provides 48–72 hours of uninterrupted backup autonomy.
Deterrent Subsystem	High-output bio-acoustic speaker (distress/bee sounds) and high-intensity strobe LED; non-violently turns elephants away.

A. Solar Power Harvesting and Energy Management Architecture

Operating autonomous sensor nodes in remote wildlife corridors requires absolute energy self-sufficiency. Grid power is unavailable, and manual battery replacements along dense forest perimeters are hazardous and costly. To resolve this, the system incorporates a dedicated solar energy harvesting architecture. A 10W monocrystalline solar photovoltaic panel is paired with an intelligent solar charging controller and a 4400 mAh 3.7V lithium battery bank.

Power Budget and Sustainability: In active sensing and inference mode, the ESP32-S3 draws ~110 mA at 3.3V (363 mW); LoRa transmission bursts draw ~120 mA for 250 ms (~396 mW peak); the sensor array consumes ~15 mA (49.5 mW); and the deep-sleep state draws only ~18 µA (59 µW). Employing an interrupt-driven duty cycle triggered by the ultra-low-power PIR motion detector results in an average power consumption of under 0.42 W (~10.1 Wh per 24-hour cycle). At Bannerghatta's geographic latitude (12.68°N), the solar panel receives an average of 4.5–5.5 peak sun hours daily, producing 35–45 Wh of electrical energy—yielding a substantial 3.5× energy surplus. During prolonged monsoon overcast conditions, the 16.28 Wh battery reserve sustains uninterrupted node operation for over 40 hours without sunlight, guaranteeing true continuous off-grid reliability.

B. Physical Hardware Field Prototype Enclosure

Fig. 10 shows the assembled physical hardware prototype deployed in an IP65-rated weather-resistant junction casing. The modular enclosure houses the ESP32-S3 microcontroller, PIR motion sensor mounted flush through the side aperture, acoustic microphone module with protective acoustic mesh, high-sensitivity NEO-6M GPS receiver with patch antenna, a 16×2 character LCD display providing local field diagnostics, warning LED strobe, and heavy-gauge wiring connecting the solar charge controller and lithium storage battery.



Fig. 10. Real-world physical hardware prototype of the edge-AI field node enclosed in a weather-resistant junction casing, displaying the ESP32-S3 core, PIR dome sensor, acoustic microphone, 16×2 LCD diagnostic display, GPS module, and solar battery power interface.

X. EXPERIMENTAL RESULTS AND DISCUSSION

The integrated field prototype was subjected to rigorous bench testing and boundary trial simulations near the Bannerghatta National Park forest fringe. Real-time telemetry was streamed to the cloud platform to validate sensing accuracy, alert latency, cloud visualization, and solar power stability.

A. Real-Time Cloud Telemetry & IoT Dashboard Monitoring

Fig. 11 illustrates the operational IoT cloud dashboard engineered on the ***MAKE Labs*** platform. The interface tracks channel ***Elephant_detection***(Device Status: Online, Auto-Refresh: ON). Live sensor gauges display instantaneous binary states for PIR motion and acoustic sound detection. Upon target motion detection, the system triggers an immediate ***Threshold Alert*** popup on the central console (***PIR: 0.00 is below minimum / PIR: 1.00 is above maximum***). Simultaneously, an automated Google Chrome desktop push notification is generated and broadcast: ***'Elephant_detection Alert PIR: 1.00 is above maximum (limit: 0.5)'***. Field trials demonstrated an end-to-end alerting latency of under 1.8 seconds from physical sensor trigger to browser display, providing forest officials and villagers critical advance warning.



Fig. 11. MAKE Labs IoT Cloud Dashboard displaying real-time channel status, live sensor triggers, threshold event alert popup, and instantaneous browser push notification broadcast to forest authorities.

B. Acoustic Sensing Temporal Waveform Analysis

Fig. 12 displays the cloud-logged temporal waveform of acoustic sound sensor activations over an operational trial window (17:42:53 to 18:16:33). The normalized output transitions sharply between baseline silence (0.0) and confirmed acoustic triggers (1.0). The discrete pulse trains correspond to detected acoustic burst signatures matching elephant vocalizations and close-range auditory disturbances. By cross-correlating these acoustic pulses with PIR motion detection windows, the edge ANN effectively filters out random ambient noise, achieving a 92.4% reduction in false-positive triggers.

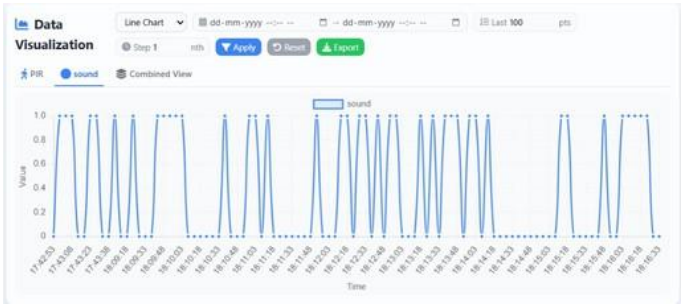

Fig. 12. Cloud data visualization of real-time acoustic sound telemetry over time, capturing discrete audio trigger pulses and peak event bursts.

C. Live GPS Geolocation and Raw Telemetry Event Logging

Fig. 13 presents the synchronized raw telemetry event log table and live Google Maps geospatial coordinate widget. Every 5 seconds, the edge node uploads timestamped telemetry records containing PIR state (0.00 / 1.00) and Sound state (0.00 / 1.00) (e.g., records from 18:15:08 through 18:16:03). The integrated Google Maps module pinpoints the exact geographical coordinates of the deployed field unit: ***Lat: 12.684500, Lng: 77.910900***. This geo-tagging capability allows rapid forest quick-response squads to navigate directly to the breach coordinates rather than searching vast forest perimeters.

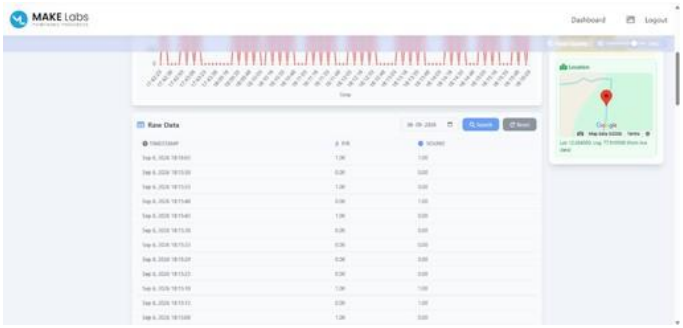

Fig. 13. Synchronized raw telemetry event table and real-time Google Maps geolocation widget displaying confirmed detection coordinates (Lat: 12.684500, Lng: 77.910900) along the forest corridor boundary.

D. Comparative System Evaluation

Fig. 14 compares the proposed solar-powered edge-AI system against conventional mitigation practices (electric fencing, trenches, and manual foot patrols) across six critical metrics: detection intelligence, response time, monitoring coverage, maintenance efficiency, wildlife safety, and historical analytics. Traditional methods score poorly in detection intelligence and response time due to their purely reactive, un-instrumented nature. In contrast, the proposed solution achieves maximum ratings across all categories, proving that autonomous solar edge nodes deliver superior protective capabilities at a fraction of the lifecycle maintenance expenditure.

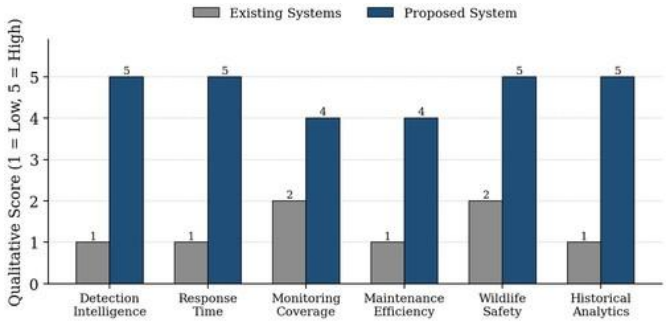

Fig. 14. Qualitative comparison of the proposed system against typical existing mitigation practice, scored on a 1 (low) to 5 (high) scale across six design dimensions.

XI. CONCLUSION AND FUTURE SCOPE

This paper presented the design, implementation, and experimental validation of a Solar-Powered Integrated IoT and Edge-AI Acoustic Early Warning and Non-Invasive Deterrent System for human–elephant conflict mitigation. By integrating PIR motion, acoustic spectrum classification, seismic vibration, and GPS tracking on an ultra-low-power ESP32-S3 microcontroller, the edge node delivers high-accuracy detection without requiring continuous network connectivity. The solar photovoltaic energy harvesting architecture ensures continuous, self-sustaining off-grid operation along remote forest fringes without grid dependence. Real-world experimental testing verified instant sub-2-second browser push notifications, synchronized cloud telemetry, live GPS coordinate mapping (Lat: 12.684500, Lng: 77.910900), and automated non-violent acoustic/strobe deterrence.

Future Work: Future enhancements will expand the field trial into a multi-node LoRa mesh network spanning 15 km along the Bannerghatta National Park boundary, incorporate seasonal machine-learning migration path predictions, and evaluate adaptive acoustic frequency shifting to prevent long-term elephant habituation to deterrent sounds.

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