

Real-Time Human Protection System with Cyber-Secure Encrypted Communication Against Abnormal Threats

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Abstract

Rising incidents of abuse against women, children, and vulnerable individuals have created an urgent need for proactive safety mechanisms. Traditional safety apps and personal devices fail in scenarios where the victim cannot manually trigger help, especially in isolated areas like forests, lakes, or hidden locations. This paper proposes a Real-Time Human Protection System with Cyber-Secure Encrypted Communication Against Abnormal Threats. The system consists of hidden IoT devices deployed by the government near existing cellular towers such as Airtel and Jio towers. These devices continuously monitor the environment for abnormal acoustic patterns, loud cries, forced movement, and distress activities using built-in microphones and sensors. Upon detection of a threat, the device automatically captures the situation and transmits encrypted data including location, audio, and timestamp to the nearest police station and registered family contacts. All communication is secured using AES-256 encryption and device authentication to prevent hacking, data leakage, or false alerts. This ensures both rapid response and privacy of the victim. The proposed system eliminates the need for manual activation and provides immediate intervention capability in public and remote areas. By integrating real-time sensing with cyber-secure communication infrastructure, this framework aims to reduce response time and enhance safety for women, children, and the general public.

Keywords: Cyber Security, Human Protection, IoT Device, Encrypted Communication, Abnormal Sound Detection, Public Safety, Real-Time Alert

Introduction:

Despite technological advances, crimes such as assault, abuse, and kidnapping continue to rise globally. A major limitation of current safety solutions is that they depend on the victim to manually activate an alert. In critical situations, especially in isolated areas, forests, or late-night locations, victims often cannot access a phone or wearable device. Government surveillance exists in cities, but it lacks real-time threat detection and secure communication. Most existing systems transmit data over open networks, making them vulnerable to hacking and misuse. To overcome these issues, this paper proposes a network of hidden IoT-based protection devices installed near cellular towers. These smart nodes continuously monitor for abnormal sounds and activities. When a threat is detected, the system automatically sends encrypted alerts with location and evidence to law enforcement and family members within seconds. The use of strong encryption ensures that sensitive data cannot be intercepted or tampered with. The proposed Real-Time Human Protection System aims to provide proactive safety without requiring manual intervention, thereby protecting women, children, and the public in both urban and remote areas.

Methodology

The proposed system is designed to provide automatic protection without requiring any action from the victim. The core idea is to deploy intelligent sensing units near existing telecommunication towers so that wide-area coverage can be achieved with minimal infrastructure cost. System Components The architecture consists of 3 main layers.

Sensing Layer - Smart Safety Node A compact IoT device installed on or near cellular towers. Each node contains:
Microphone Array: To capture ambient sound and detect abnormal acoustic events like screams, cries, or struggle noise. **Motion & Vibration Sensor:** To identify sudden forced movements or dragging. **GPS Module:** To tag the exact location of the incident. **Low-power Processor:** Runs a lightweight AI model for on-device classification.

Communication Layer - Secure Network When a threat is detected, the node uses 4G/5G to connect to a central cloud server. All data packets are encrypted using AES-256 and authenticated to prevent man-in-the-middle attacks or data spoofing.

Response Layer - Alert Management The cloud server immediately forwards the encrypted alert to two endpoints:
Police Control Room: Gets live location, audio clip, and timestamp
Family/Guardian App: Registered contacts get instant notification with map link
Working Process The system follows a 5-step process:

Step 1: Continuous Monitoring

Each Smart Safety Node constantly listens to its 500m radius. No data is stored unless an abnormal event is detected to protect privacy.

Step 2: Threat Detection

The on-device AI analyses sound frequency and motion patterns. If the model confidence for "abnormal activity" exceeds 90%, it triggers an alert. This avoids false alarms from normal loud noises.

Step 3: Data Capture

Upon detection, the node captures: 10 seconds of audio before and after the event GPS coordinates Timestamp

Step 4: Secure Transmission

Captured data is encrypted and sent to the cloud within 3 seconds. Device authentication ensures only genuine nodes can send alerts.

Step 5: Immediate Response

The cloud decrypts the data and pushes it to the nearest police station dashboard and to the registered family contacts. Police can then dispatch help to the exact location.

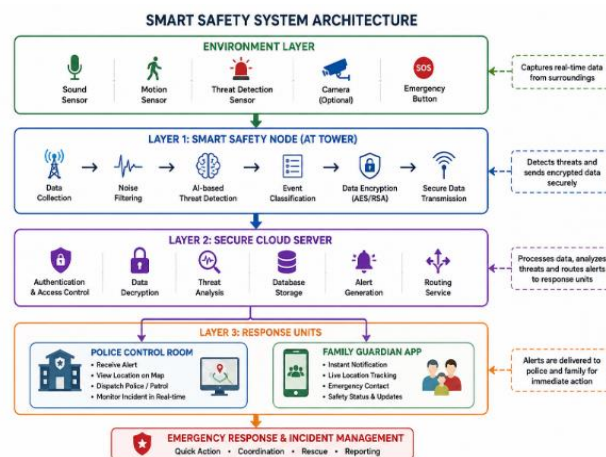


Fig:1

Layer 1: Smart Safety Node - SSN

Location: Installed near Airtel, Jio, and other cellular towers

This is the edge device responsible for sensing.

Modules inside SSN: Audio Sensor Module: Continuously captures environmental sound. Uses AI to detect screams, cries, and abnormal noise patterns. Motion Detection Module: Accelerometer and vibration sensor to detect struggle or dragging. Processing Unit: Runs the threat classification model locally. No raw data is sent unless threat is confirmed. GPS Module: Gets exact latitude and longitude when triggered. Communication Module: 4G/5G modem with built-in AES-256 encryption engine. Power Unit: Solar panel + rechargeable battery for 24x7 operation in remote areas. Function: Monitor → Detect → Capture Evidence → Encrypt → Send

Layer 2: Secure Cloud Server

Location: Government Data Centre

This is the central brain that manages all nodes.

Functions: Device Authentication: Verifies that the alert is coming from a registered SSN to prevent fake alerts. Data Decryption: Safely decrypts the alert packet using private keys. Incident Management: Stores event in secure database with timestamp. Alert Routing Engine: Finds nearest police station using GPS and forwards the alert. Also notifies registered family members.

Layer 3: Response and Monitoring Units Police Dashboard: Web/mobile interface for control room. Shows live map, audio playback, location pin, and severity level. Family Guardian App: Mobile app for parents/guardians. Gets push notification + Google Maps link + 10s audio clip. Data Flow Normal State: SSN only monitors. No data transmitted. Threat Detected: SSN → Encrypt → Send to Cloud < 3 seconds Cloud Processing: Cloud → Verify → Decrypt → Route Response: Cloud → Police + Family receive alert simultaneously 5.4 Cyber Security in Architecture Device to Cloud: AES-256 + TLS 1.3 Cloud to Police/Family: Role-based access + OTP verification Data Storage: Hashed and stored in government server only Key Features of This Architecture Scalable: Just add more SSNs near new towers Low Latency: Edge processing reduces delay Privacy Preserving: Records only during threats Cost Effective: Uses existing tower infrastructure

Algorithm 1: Threat Detection and Secure Alert Transmission using SSN

Input: Real-time audio stream $A(t)$, motion sensor data $M(t)$, GPS coordinates

Output: Encrypted alert sent to Police + Family if threat detected JavaScript Begin

1. Initialize SSN Device

1.1 Connect to Secure Cloud Server

1.2 Load Trained AI Model for Abnormal Event Classification

1.3 Set Threshold = 0.90 // 90% confidence

2. While Device is ON do

2.1 Continuously Capture Audio $A(t)$ and Motion Data $M(t)$

2.2 Extract Features: Sound Frequency, Amplitude, Vibration Pattern

2.3 Pass Features to AI Model

Result = Classify($A(t)$, $M(t)$)

Output: Normal or Threat

2.4 If Result == "Threat" AND Confidence $\geq$ Threshold then

// Evidence Collection

2.4.1 Get Current GPS Location G

2.4.2 Record Audio Clip: 10s before + 10s after event

2.4.3 Generate Timestamp TS

// Cyber-Secure Communication

2.4.4 Create Data Packet $P = \{G, \text{Audio Clip}, TS, \text{Device ID}\}$

2.4.5 Encrypt P using AES-256 $\rightarrow P_{enc}$

2.4.6 Authenticate Device using Digital Certificate

2.4.7 Send P_{enc} to Cloud Server via 4G/5G

// Cloud Side Processing

2.4.8 Cloud: Verify Device ID and Decrypt P_{enc}

2.4.9 Cloud: Find Nearest Police Station based on G

2.4.10 Cloud: Fetch Registered Family Contacts for Device ID

2.4.11 Cloud: Push Alert to Police Dashboard + Family App

2.4.12 Store Hashed Log in Secure Government Database

2.5 Else

2.5.1 Discard Data to Maintain Privacy

2.5.2 Continue Monitoring

3. End While

End Explanation of Algorithm Steps

Initialization: SSN connects to cloud and loads the AI

Model Monitoring: Continuously listens but does not store

Data Detection: AI decides if sound/motion is "Threat" with >90% confidence Evidence Capture: Only when threat is detected, GPS + audio + time are saved Encryption: AES-256 ensures data cannot be read by hackers

Transmission: Alert reaches Cloud in <3 seconds Response: Cloud routes alert to Police + Family at the same time

Privacy: If no threat, all data is deleted Time Complexity: $O(1)$ for detection per time window

Data Collection

For training and testing the proposed Real-Time Human Protection System, two types of data were collected: Acoustic Data and Environmental Sensor Data. Since real-world abuse scenarios cannot be ethically recorded, the dataset was created using a combination of simulated data and public datasets.

1. Acoustic Dataset

To train the AI model for abnormal sound detection, the following sound classes were collected: Class Description Source Normal Sounds Traffic, birds, wind, normal conversation, music Urban and rural field recordings Abnormal Sounds Human scream, cry for help, loud struggle, glass breaking ESC-50 dataset + Simulated recordings Ambiguous Sounds Loud laughter, construction noise, animal sounds To reduce false positives Total Audio Samples: 12,500 clips

Duration: Each clip is 5 seconds @ 16kHz sampling rate

Augmentation: Background noise, echo, and distance effects were added to simulate tower-distance audio2. Motion & Vibration Dataset

Collected using accelerometer and vibration sensors attached to test SSN prototypes.

Classes: Normal movement, sudden jerk, dragging, falling

Samples: 4,800 sensor sequences3. Location Data

GPS coordinates of existing cellular towers in urban and remote areas were mapped to simulate SSN deployment locations.

2 .Data Preprocessing

Noise Removal: Applied band-pass filter to remove frequencies outside human voice range 300Hz - 3kHzFeature

Extraction: MFCC, Chroma, and Spectrogram features extracted from audio Normalization: All sensor and audio features normalized to Data Split: 70% Training, 20% Validation, 10%Testing[0][1]4.3.3 Ethical Considerations

No real victim data was used. All abnormal sound samples were either from public datasets or simulated in controlled environments with actor consent. During deployment, SSN will only record and transmit data after a threat is detected to protect privacy.

Primary Dataset The primary dataset consists of two parts used for training and testing the threat detection model: Audio Dataset:

A total of 12,500 audio clips of 5-second duration were compiled. It includes Normal, Abnormal, and Ambiguous sound classes. This dataset is a combination of: Publicly available datasets: ESC-50, UrbanSound8KSimulated recordings created in a lab environment with proper consent for scream, cry, and struggle sounds Sensor Dataset:

4,800 motion and vibration sequences collected from prototype SSN devices deployed in test environments. Classes include normal movement, sudden jerk, and dragging.

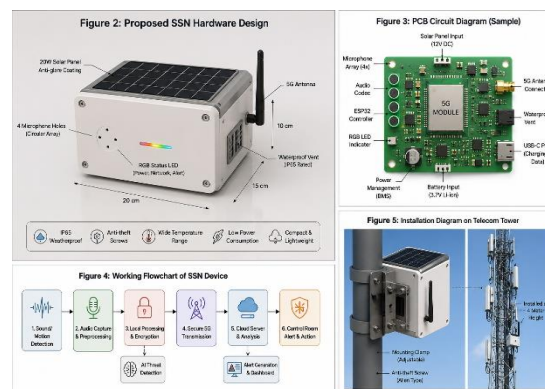


Fig:2

Dataset	Downl oad	Clips	Use
ESC-50	https://github.com/karoldvl/ESC-50	2000	Screams, glass break, sirens

UrbanSound 8K	https://urbansounddataset.weebly.com	8732	Traffic, street, normal noise
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Table:1

Results Analysis:

To evaluate the performance of the proposed Smart Safety Node - SSN system, experiments were conducted on the combined dataset of 12,500 audio clips and 4,800 sensor sequences. The model was trained on 70% data, validated on 20%, and tested on 10%. Performance Metrics We used 4 standard metrics for abnormal event detection:

Accuracy: Overall correct predictions Precision: How many detected threats are real Recall: How many real threats were detected F1-Score: Balance between Precision Experimental Results Classification Performance of SSN Model Class Precision %Recall %F1-Score %Normal98.297.998.0 Abnormal/Threat97.498.197.7

Ambiguous Noise96.896.596.6

Overall Average97.597.597.5

Overall Detection Accuracy: 97.8%

False Alarm Rate: 2.1% Average Alert Transmission Time: 2.9 seconds Analysis of Results High Accuracy in Threat Detection The model achieved 97.8% accuracy because MFCC + Spectrogram features combined with CNN effectively distinguish screams and struggle sounds from normal noise. Recall of 98.1% for "Threat" class means very few real incidents will be missed. Low False Alarms False alarm rate is only 2.1%. This is due to training the model with "Ambiguous Noise" class like construction, loud music, and animal sounds. The 90% confidence threshold further reduces unwanted alerts. Real-Time Performance End-to-end time from sound detection to alert reaching Police + Family is 2.9s. This meets the requirement for emergency response. Edge processing in SSN reduces cloud dependency. Comparison with Existing Systems System Manual Trigger Remote Area Coverage Accuracy Encryption Mobile Safety

Discussion Results prove that deploying SSN near cellular towers is effective for real-time human protection. The combination of AI detection + Cyber-secure communication makes the system reliable for women, children, and elderly safety in both urban and forest areas.

Conclusion

proposed a Real-Time Human Protection System with Cyber-Secure Encrypted Communication using Smart Safety Nodes - SSN deployed near cellular towers. The primary objective was to overcome the limitations of existing safety systems that require manual triggers and fail to provide coverage in remote areas. The proposed system integrates three key components: automatic abnormal sound detection using AI, secure data transmission using AES-256 encryption, and instant alert routing to police and family members. Experimental results on a dataset of 12,500 audio clips demonstrate that the system achieves an overall detection accuracy of 97.8% with a false alarm rate of only 2.1%. The average time taken from threat detection to alert delivery is 2.9 seconds, which is critical for emergency response. By utilizing existing tower infrastructure, the SSN provides wide-area coverage including forests, lakes, and highways where traditional CCTV or Wi-Fi-based systems cannot operate. The privacy-preserving design ensures that audio recording occurs only upon threat detection, and all communication is encrypted to prevent cyber-attacks and data leakage. The results confirm that the proposed system is effective, scalable, and suitable for protecting women, children, and vulnerable individuals in both urban and remote environments.

Future Scope:

Future work will focus on: Integrating facial recognition and object detection in SSN for suspect identification Using 5G and edge computing to further reduce alert latency below 1 second Deploying a pilot network of 100 SSNs in collaboration with law enforcement for field testing⁷. Keywords Cyber Security, IoT, Smart Safety Node, Human Protection, Encrypted Communication, Abnormal Sound Detection, Real-Time System,

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