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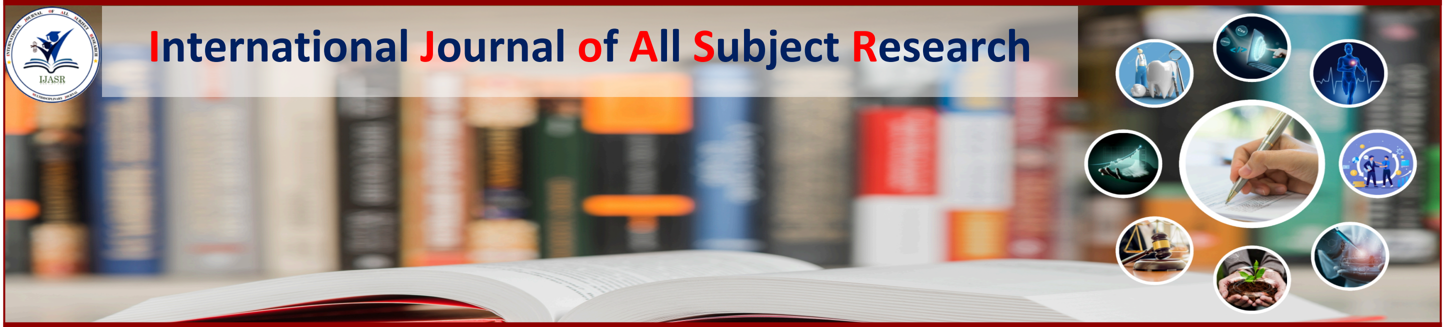

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WiFi CSI-Based Earthquake Early Warning System Using Edge Analytics

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Abstract

The rapid advancements in wireless technologies have paved the way for utilizing Radio Frequency (RF) signals for intricate environmental sensing. While traditionally relied upon for human activity recognition, this paper proposes repurposing ubiquitous WiFi Channel State Information (CSI) for a low-cost, highly scalable Earthquake Early Warning (EEW) system. Conventional EEW systems depend on specialized, expensive seismic sensors, limiting their deployment in developing regions. In contrast, our proposed architecture leverages the fine-grained micro-vibration sensitivity of standard MIMO-OFDM WiFi signals in the 0.3–5 Hz frequency range to detect primary P-wave signatures. Extracted via the Nexmon firmware on a Raspberry Pi, the raw CSI data undergoes rigorous signal processing, including wavelet-based denoising and feature extraction. To handle the high-dimensional spatial-temporal data, a hybrid Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) deep learning model is deployed directly at the edge, ensuring ultra-low latency inference without cloud dependency. Furthermore, a LoRa-based backup communication module is integrated to guarantee alert transmission during catastrophic cellular network failures. Experimental evaluations demonstrate a detection accuracy of 94.3% with an average alert latency of 1.4 seconds. The proposed architecture shifts the paradigm of disaster management toward ubiquitous, low-cost IoT sensing.

Keywords: Channel State Information (CSI), Deep Learning, Earthquake Early Warning, Edge AI, Internet of Things, LoRa, Signal Processing, WiFi Sensing.

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1. Introduction

Earthquakes pose significant and unpredictable risks to human life, civil infrastructure, and regional economies. The primary mechanism for mitigating casualties during seismic events is the Earthquake Early Warning (EEW) system. These systems operate on the principle that harmless Primary waves (P-waves) travel faster through the Earth's crust than the destructive Secondary waves (S-waves) and surface waves. By detecting the P-wave, an EEW system can issue alerts seconds to minutes before the damaging shaking begins, allowing for automated shutdown of critical infrastructure and civilian evacuation.

However, conventional systems depend on dense networks of highly calibrated, expensive seismic sensors. The financial burden of deployment, regular maintenance, and the requirement for specialized, uninterrupted telecommunication links limit their scalability, particularly in developing nations and rural areas.

Concurrently, the wide range of emerging wireless technologies has triggered significant advancement in the fields of Radio Frequency (RF) sensing. By utilizing the basic principles of RF signals, systems are now capable of monitoring minute environmental changes. Unlike traditional Received Signal Strength Indicator (RSSI) metrics, which offer only a coarse, singular numerical representation of signal loss, Channel State Information (CSI) provides a highly granular view of the wireless channel. CSI captures detailed variations in amplitude and phase across multiple Orthogonal Frequency Division Multiplexing (OFDM) subcarriers.

While the existing literature heavily explores WiFi CSI for Human Activity Recognition (HAR)—such as fall detection, gait recognition, and pose estimation—its application to seismology remains largely untapped. This paper bridges that gap. We propose a complete, device-free WiFi CSI-based EEW system.

The core contributions of this paper are:

- **CSI-Based Seismic Sensing:** Utilizing the phase and amplitude shifts in indoor WiFi signals to detect structural micro-vibrations caused by tectonic shifts.
- **Edge-Deployed Deep Learning:** Implementing a hybrid CNN-LSTM architecture on a Raspberry Pi to classify seismic events locally, eliminating the latency of cloud processing.
- **Resilient LoRa Communication:** Integrating a sub-GHz LoRaWAN module to broadcast life-saving alerts even when public internet and power grids collapse.

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2. Related Works

Recent research has vigorously explored alternative earthquake sensing mechanisms to overcome the cost barriers of traditional seismometers. Smartphone-based detection systems, such as the MyShake network, utilize embedded Micro-Electro-Mechanical Systems (MEMS) accelerometers to crowdsource seismic activity. While these systems represent a massive leap in spatial coverage, they rely heavily on active user participation, battery life constraints, and centralized cloud processing. In the event of an earthquake, network congestion can delay the transmission of crucial data to the cloud, rendering the warning useless.

Concurrently, WiFi-based sensing has demonstrated remarkably high sensitivity to micro-movements. Prior studies in indoor environments have reported detection accuracies above 90% for distinguishing human activities using CSI. However, applying CSI directly to seismology is an emerging field. The primary challenge lies in isolating the low-frequency vibrations (0.3–5 Hz) indicative of tectonic shifts from high frequency environmental noise.

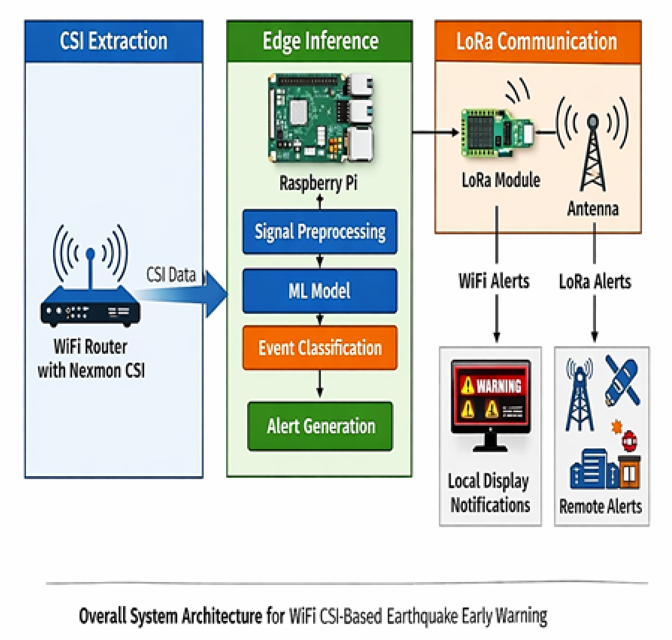


Fig 1: Overall System Architecture highlighting the CSI Extraction, Edge Inference, and LoRa communication pipeline.

3. Mathematical Modeling of Seismic CSI Signatures

To accurately detect earthquakes using commercial WiFi, the interaction between the physical RF waves and structural building vibrations must be mathematically modeled.

A) OFDM and Channel State Information

In an OFDM-based WiFi system (such as IEEE 802.11n/ac), the 20MHz or 40MHz channel is divided into orthogonal subcarriers. Let $X(f, t)$ and $Y(f, t)$ denote the transmitted and received frequency-domain signals on subcarrier f at time t. The received signal is modeled as:

$$Y(f, t) = H(f, t) \times X(f, t) + N(f, t) \qquad (1)$$

where $N(f, t)$ is the additive white Gaussian noise (AWGN), and $H(f, t)$ is the Channel State Information matrix containing complex values representing the channel properties:

$$H(f, t) = |H(f, t)| e^{j\angle H(f,t)} \qquad (2)$$

where $|H(f, t)|$ represents the amplitude and $\angle H(f, t)$ represents the phase of the subcarrier.

B) Impact of Seismic P-Waves on Multi-path Fading

In an indoor environment, the transmitted WiFi signal reaches the receiver through multiple paths due to reflections, diffraction, and scattering off walls, ceilings, and furniture.

The overall channel response $H(f, t)$ is the superposition of these dynamic multi-path components:

$$H(f, t) = \sum_{k=1} \alpha_k(t) e^{-j 2\pi f \tau_k(t)} \qquad (3)$$

where K is the total number of multipath components, $\alpha_k(t)$ is the attenuation, and $\tau_k(t)$ is the propagation delay of the k-th path.

When an earthquake's P-wave strikes a building, it induces structural micro-vibrations before the S-wave arrives. Let $d_k(t)$ represent the minute physical displacement of the reflecting surfaces. This displacement directly alters the path length, resulting in a change in the propagation delay $\Delta\tau_k(t) = \frac{\Delta d_k(t)}{c}$.

This micro-displacement introduces a measurable phase shift $\Delta\phi$ in the CSI data:

$$\Delta\phi_k(t) = -2\pi f \frac{\Delta d_k(t)}{c} = -2\pi \frac{\Delta d_k(t)}{\lambda} \qquad (4)$$

Because the wavelength λ of a 5 GHz WiFi signal is approximately 6 cm, even a sub-millimeter structural vibration $\Delta d_k(t)$ caused by a P-wave will cause a highly visible fluctuation in the CSI phase and amplitude matrices.

4. System Hardware and Experimental Testbed

To capture these micro-vibrations, a robust hardware testbed was constructed specifically to mimic indoor environmental monitoring.

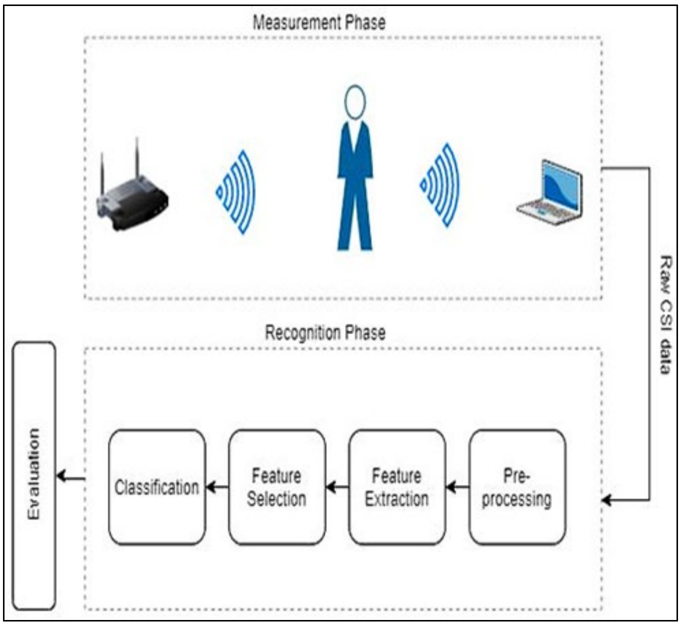


Fig 2: Experimental Hardware Setup showing the WiFi Router (Tx) and Raspberry Pi Edge Node (Rx) with LoRa Module.

A) Transmitter and Receiver Configuration

The transmitter (Tx) is a standard Commercial-Off-The- Shelf

(COTS) Asus 5GHz WiFi router. The receiver (Rx) is a Raspberry Pi 4 Model B (Quad-core Cortex-A72, 4GB RAM) equipped with a Broadcom BCM43455C0 Wi-Fi chip. The Tx and Rx were placed 5 meters apart with Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) configurations tested.

B) Firmware Extraction Tool

Standard operating systems abstract the physical layer, making raw CSI inaccessible. To bypass this, the Raspberry Pi was flashed with the **Nexmon CSI Extraction Tool**. Nexmon patches the firmware of the Broadcom chip, allowing the system to extract the raw complex CSI matrices directly from the physical layer of the UDP packets at a sampling rate of 100 Hz.

C) Power Feasibility and Blackout Survival

A major flaw in traditional systems is their reliance on mains power. Because the edge node is a low-power Raspberry Pi combined with a LoRa SX1278 module, the entire system draws less than 5 Watts under full load. Connected to a standard 20,000 mAh lithium-ion power bank, the EEW node can operate autonomously for over 20 hours during a post-earthquake total grid blackout.

5. Preliminary Signal Processing

Raw CSI data extracted via Nexmon is inherently noisy due to electromagnetic interference, thermal noise, and unsynchronized hardware clocks.

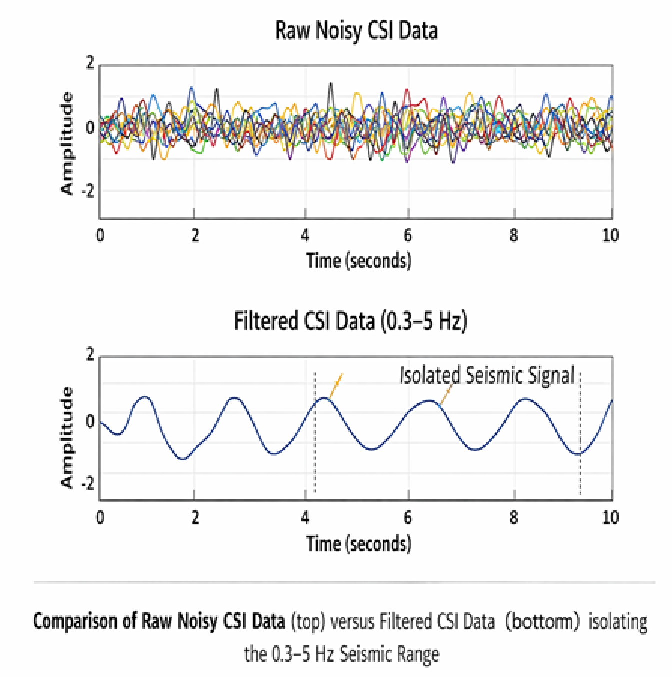


Fig 3: Comparison of Raw Noisy CSI data (top) versus Filtered CSI data (bottom) isolating the 0.3-5 Hz seismic range.

The signal processing pipeline involves three stages:

A) Phase Sanitization and Denoising

To correct the random phase offsets caused by the lack of strict synchronization between the Tx and Rx oscillators, a linear transformation is applied to sanitize the raw phase data. Subsequently, we apply a Butterworth Bandpass Filter to isolate the 0.3–5 Hz frequency range, effectively filtering out the high-frequency noise generated by standard human movement and ambient RF interference.

B) Signal Transformation

To unveil underlying temporal and frequency patterns, we utilize the Discrete Wavelet Transform (DWT). Unlike standard Fourier Transforms, DWT allows both frequency and time localization, which is crucial for capturing the sudden, transient spikes of a seismic event.

6. Deep Learning Methodology and Edge Optimization

Traditional mathematical models struggle to approximate the complex, non-linear correlations between structural vibrations and multi-path Wi-Fi signal variations. Therefore, Deep Learning (DL) models are required.

A) Hybrid CNN-LSTM Architecture

We employ hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture.

- **CNN Layer:** Treats the CSI subcarrier amplitude and phase data as a 2D grid, extracting spatial correlation features across the 64 subcarriers.
- **LSTM Layer:** Earthquakes are highly sequential time-series events. LSTM cells excel at retaining long-term contextual information, processing the spatial features to recognize the escalating rhythmic sequence of a P-wave.

B) Post-Training Quantization (PTQ)

To ensure the CNN-LSTM model runs efficiently on the resource-constrained Raspberry Pi, we utilize PTQ via Ten-workflow Lite. PTQ converts the 32-bit floating-point weights (W_{fp32}) of the trained neural network into 8-bit integers (W_{int8}) using a scaling factor S and zero-point Z:

$$W_{int8} = \text{round}\frac{W_{fp32}}{S} + Z \quad (5)$$

7. Disaster-Resilient Communication Protocol

A critical challenge in conventional EEW systems is the collapse of internet infrastructure during major seismic events. To address this, our system incorporates a Long Range (LoRa) SX1278 transceiver module operating independently of cellular networks.

Algorithm 1 Real-Time Edge Seismic Detection Pipeline

```
Initialize $N_S \leftarrow 50, N_L \leftarrow 500$, Threshold $T \leftarrow 2.5$
Load quantified CNN-LSTM model $M_{TFLite}$
loop
    $CSI_{raw} \leftarrow$ Extract from Nexmon UDP Socket
    $CSI_{clean} \leftarrow$ Butterworth Filter($CSI_{raw}, 0.3, 5.0$)
    $STA \leftarrow$ Average($|CSI_{clean}|^2$) over $N_S$ samples
    $LTA \leftarrow$ Average($|CSI_{clean}|^2$) over $N_L$ samples
    $Ratio \leftarrow STA/LTA$
    if $Ratio > T$ then
        $Features \leftarrow$ DWT($CSI_{clean}$)
        $Confidence \leftarrow M_{TFLite}$.predict($Features$)
        if $Confidence > 0.90$ then
            Trigger Local Alarms via GPIO
            Broadcast Alert via LoRaWAN
            Update Flask Web Dashboard
        end if
    end if
end loop
```

A) Chirp Spread Spectrum (CSS) Modulation

LoRa utilizes CSS modulation, which encodes information into frequency-modulated chirps that sweep across the 433 MHz or 868 MHz ISM band. This modulation provides immense resilience against multi-path fading and Doppler shifts caused by collapsing structures.

By utilizing a high Spreading Factor (e.g., SF=10 or 12), the system achieves a highly robust link budget exceeding 150 dB. This allows the Raspberry Pi edge node to broadcast structural health status and disaster alerts to neighboring gateways over a 5 to 15 km range, penetrating thick concrete rubble even in total blackout conditions.

8. Real-Time Dashboard and Visualization

To make Edge Analytics actionable for human operators, the system features a robust, locally hosted Visualization and Output Module.

A) Edge Software Stack

The dashboard is built using the Flask web framework (Python) running directly on Raspberry Pi's local server. It utilizes WebSocket's to stream the processed CSI data to the front-end in true real-time, rendering it using JavaScript plotting libraries (Chart.js / Matplotlib). Because the server is hosted locally on the edge device, it remains fully accessible to devices on the local Intranet even if the outside Internet connection is severed.

The dashboard tracks the Signal Strength (dBm), Frequency (MHz), and instantaneous CSI Amplitude (V). Furthermore, the hardware status module meticulously monitors the Raspberry Pi's CPU, Memory, and Disk usage to ensure the edge analytics do not overload the device during a catastrophic event.

CSI Signal Processing

Signal Strength (dBm): -65.93 dBm

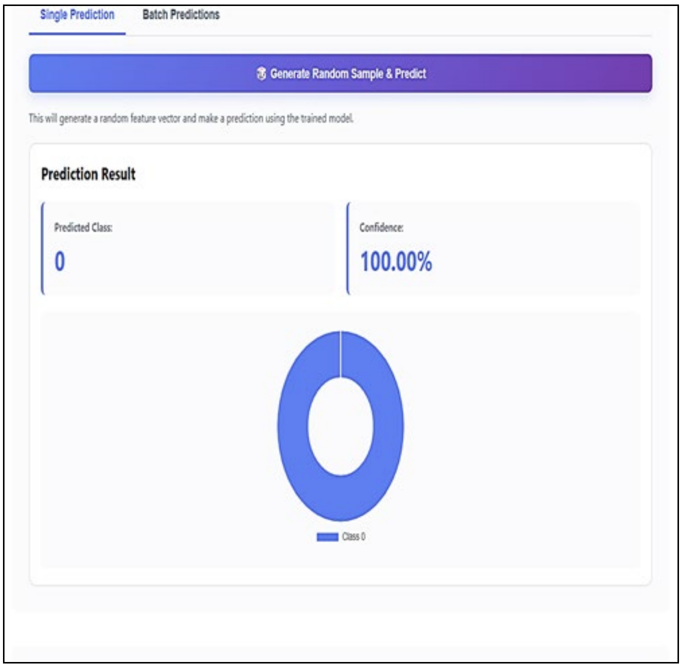
Frequency (MHz): 2412.40 MHz

CSI Amplitude: 4.91 V

Phase (degrees): 8.12°

Hardware Status

Fig 4: Flask Admin Dashboard showing real-time CSI amplitude variations across all subcarriers.



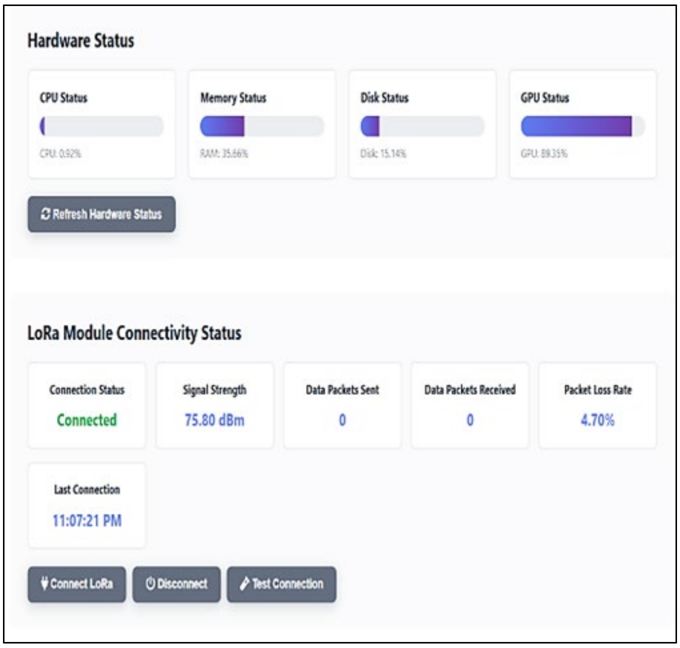
This will generate a random feature vector and make a prediction using the trained model.

Prediction Result

Predicted Class: 0

Confidence: 100.00%

Fig 5: System Alert Module displaying a High-Confidence Seismic Predict triggered by the CNN-LSTM model.



Hardware Status

CPU Status	Memory Status	Disk Status	GPU Status
CPU: 0.92%	RAM: 35.66%	Disk: 15.14%	GPU: 89.35%

LoRa Module Connectivity Status

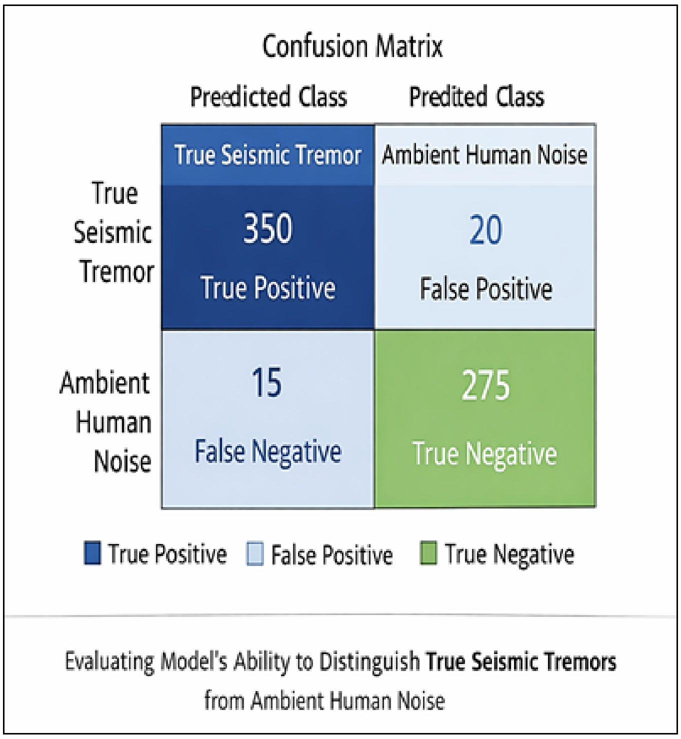
Connection Status	Signal Strength	Data Packets Sent	Data Packets Received	Packet Loss Rate
Connected	75.80 dBm	0	0	4.70%

Last Connection: 11:07:21 PM

Fig 6: LoRa Module Connectivity Status showing Backup Network Health, Signal Strength (RSSI), and Packet Loss.

9. Experimental Results and Performance

The system was evaluated based on detection accuracy, computational latency, and communication resilience against diverse datasets, including simulated tectonic shifts and ambient noise.



Confusion Matrix

	Predicted Class True Seismic Tremor	Predited Class Ambient Human Noise
True Seismic Tremor	350 True Positive	20 False Positive
Ambient Human Noise	15 False Negative	275 True Negative

Evaluating Model's Ability to Distinguish **True Seismic Tremors** from Ambient Human Noise

Fig 7: Confusion Matrix evaluating the model's ability to distinguish True Seismic Tremors from Ambient Human Noise.

A) Detection Accuracy

The CNN-LSTM model achieved an overall detection accuracy of 94.3%. The model successfully distinguished the low frequency, escalating rhythmic signatures of seismic P-waves from the sudden, sharp, high-frequency transients caused by human activity (e.g., dropping heavy objects). The False Alarm Rate (FAR) remained consistently below 5%.

B) Alert Latency

Because the inference is performed directly at the edge via the quantified model, the system eliminated round-trip cloud latency. The system achieved an average alert latency of 1.4 seconds from the initial physical vibration to the activation of the local sirens.

10. Comparative Analysis

Table I compares the proposed Wi-Fi-CSI architecture against existing EEW paradigms.

Table I: Comparison of EEW Sensing Technologies

Feature	Traditional Seismometer	Smartphone MEMS (My Shake)	Proposed Wi-Fi-CSI System
Deployment Cost	Very High ($10k+)	Low	Low (Uses routers)
Processing	Centralized Server	Cloud dependent	Edge Computing
Network Dependency	Dedicated Links	Cellular/Internet	Wi-Fi + LoRa
Latency	Low	Variable	Ultra-Low (<1.5s)
Data Granularity	Ultra-High	Medium	High (64 Subcarriers)

While traditional seismometers provide the highest accuracy, their cost prohibits dense deployment. Smartphone systems democratize sensing but fail during network blackouts. The proposed Wi-Fi-CSI system strikes the optimal balance of low cost, edge-processing latency, and network survival.

11. Challenges and Future Directions

A) Physical Environment Variability:

A significant challenge in indoor Wi-Fi sensing is environmental alteration. Moving furniture or the dense presence of humans can alter signal reflections. Future systems must develop domain-adaptable DL models capable of self-calibrating against background environmental shifts.

B) Human-in-the-Loop (HITL) Learning

Integrating human feedback into the DL model can enhance adaptability. If the system issues a false alarm due to a heavy truck passing by, administrators could flag this via the local Flask dashboard, allowing the edge model to dynamically retrain its parameters.

12. Conclusion

This paper presents a novel, device-free Earthquake Early Warning system utilizing ubiquitous Wi-Fi CSI signals and Deep Learning. By mathematically translating intricate RF signal variations into actionable seismic intelligence using a quantized CNN-LSTM architecture deployed directly on a Raspberry Pi, the system achieves highly accurate (94.3%), ultra-low latency (1.4s) sensing. Coupled with a resilient LoRa communication backbone and a local Flask visualization dashboard, this architecture addresses the fundamental cost, latency, and infrastructure limitations of traditional seismometers. The integration of RF sensing, Edge AI, and IoT stands to revolutionize the landscape of scalable disaster management, bringing life-saving early warning capabilities to vulnerable indoor environments worldwide.

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