AI and IoT for Combating Illegal Logging: Real-time Surveillance and Detection with Ultra-Low-Power Edge Devices

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Abstract Illegal logging poses a significant and escalating threat to global forests, biodiversity, and climate stability, leading to disasters such as habitat loss, climate imbalance, and social conflicts. Traditional surveillance methods are often limited by high costs, human resource shortages, and a lack of real-time responsiveness, allowing extensive damage to occur before intervention. This research presents a comprehensive, cyber-driven strategy to counter illegal logging by integrating Artificial Intelligence (AI) and Internet of Things (IoT) technologies. The proposed system utilizes ultra-low-power, sensor-equipped IoT devices for continuous forest monitoring, employing machine learning (ML) and Convolutional Neural Networks (CNNs) to identify sound patterns associated with logging activities like chainsaw use, tree cutting, and natural disasters such as wildfires. By performing classification at the edge, these devices minimize data transmission and energy consumption, and leverage long-range wireless communication (LoRa) to provide real-time alerts to enforcement agencies. Field tests demonstrate the system's high detection accuracy (up to 96.2% on validation, 82.57% overall testing accuracy, and >85% average testing accuracy for the most efficient configuration) and timely alert delivery, significantly enhancing environmental protection and supporting sustainable forest management. The system also exhibits efficient on-device performance with minimal resource usage, proving its suitability for real-world deployment in remote forest environments.

Keywords: Forest Monitoring; AI Against Illegal Logging; Real-time Alerts; Environmental Conservation; IoT for Anti-Logging.

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1. Introduction

Forests are integral to our planet's ecological health, serving as vital sources of fresh air, water, fertile soil, and strong materials, while playing a crucial role in preventing erosion, landslides, and droughts. They are fundamental in combating global warming by absorbing vast quantities of carbon dioxide. However, these essential ecosystems face continuous threats, primarily from illegal logging, which is driven by an uncontrolled greed for money and throws nature's balance into disarray. The consequences are devastating, leading to habitat loss, disruption of the global water cycle, decreased biodiversity, and significant economic and social repercussions. Alarmingly, an area larger than Italy is lost to deforestation annually, particularly in developing nations like Brazil and Indonesia.

The challenge of monitoring vast forest expanses has historically been formidable. Traditional methods, such as regular surveillance cameras, ground patrols, satellite imagery, and drone-based monitoring, often fall short due to inherent risks, the need for extensive human resources, limited coverage, and significant operational costs. These conventional approaches frequently miss subtle activities, allowing lasting damage to occur before intervention, and often only detect illegal logging after wood products have been distributed. This highlights a critical need for more effective, real-time surveillance solutions.

This research is motivated by the vision that cutting-edge technology can transform these subtle forest sounds and changes into actionable warnings, safeguarding vanishing woods. We propose a comprehensive strategy to combat illegal logging by leveraging the synergistic capabilities of Artificial Intelligence (AI) and Internet of Things (IoT) technologies. This approach aims to provide a targeted and prompt solution to illicit logging, thereby supporting biodiversity preservation and sustainable forest management. The core objectives include:

- Deploying sensors-equipped IoT devices for continuous, real-time monitoring and detection of surrounding sounds in high-risk forestry areas.

- Implementing AI components that use machine learning methods to accurately identify and distinguish sound patterns associated with unlawful logging activities (e.g., chainsaw use, tree cutting) and natural disasters (e.g., wildfires).
- Generating real-time notifications to surrounding enforcement agencies, such as forest departments, to enable prompt intervention.
- Preserving biodiversity and preventing deforestation, thereby supporting data-driven decision-making for forest management and fostering collaboration among stakeholders.
- Enhancing local communities' capabilities in monitoring and combating illegal logging through capacity-building and awareness initiatives.
- Focusing on detecting, tracking, and identifying illegal logging events to reduce forest degradation and aid forest preservation.

This paper details the design, implementation, and evaluation of such an AI-powered IoT system, showcasing its potential to revolutionize forest monitoring and protection.

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2. Related Work / Literature Review

The global challenge of illegal logging has spurred diverse research into monitoring and detection technologies. This section summarizes existing approaches, highlighting their strengths and limitations, and contextualizes the advancements presented in this paper.

2.1. Traditional and Early Monitoring Systems Historically, forest protection efforts have relied on traditional surveillance mechanisms such as **manual patrolling, satellite imagery, and drone-based monitoring**. While these methods offer some level of oversight, they frequently suffer from **delays, limited coverage, and high operational costs**. In countries like Indonesia, illegal logging is often only discovered after the timber products have been distributed, underscoring the lack of real-time responsiveness and the constraints of human resources and budget for routine patrols.

Wireless Sensor Networks (WSNs) have emerged as a more appropriate technology for tackling illegal logging, offering capabilities for identification, detection, monitoring, and tracking over wide outdoor areas. Early WSN implementations for illegal tree cutting often focused on detecting chainsaw sounds through noise thresholds or tree vibrations. Systems have been proposed utilizing **sound and vibration sensors** with low-power microcontrollers and communication modules like **Xbee Pro S2C or ZigBee**. For instance, one system combined vibration and sound sensors with fog-computing and Lightweight Software Devices Networking Controllers (FLCs) using ZigBee, achieving a battery life of up to 3 months with sleep procedures. Another device incorporated vibration and sound sensors with a GSM module for event transmission, relying on threshold-based algorithms. While effective for specific sound events, many of these systems were **limited by short-range wireless transmission and did not provide comprehensive, real-time tracking across vast forest areas**.

Another notable development is **XyloTron**, an open-source, portable wood identification system that aids in enforcing anti-illegal logging laws. Developed at the United States Forest Products Laboratory (FPL), it uses **machine vision and AI to classify wood specimens based on macroscopic anatomical features**, in contrast to traditional microscopic analysis. XyloTron is designed for both laboratory and field use, operating offline and thus deployable in remote locations without internet access. Field trials in South America, Southeast Asia, and Africa have demonstrated its utility in intercepting illegally harvested timber, although its accuracy depends on training data quality, and high-stakes cases may still require microscopic analysis by a wood anatomist.

2.2. Audio Classification Techniques for Environmental Monitoring Beyond simple threshold-based detection, **audio recognition has enriched automated monitoring solutions**. This field has seen significant advancements, with applications in environmental preservation, wildlife monitoring, and urban security. Early work by Piczak (2015) provided an overview of machine learning techniques on the ESC50 generic sound dataset, achieving around 72.7% accuracy. The emergence of **Convolutional Neural Networks (CNNs)** has significantly improved audio classification, demonstrating better performance than manually engineered features. For instance, a CNN with two convolutional layers and two fully connected layers achieved 69–73% accuracy on ESC-50, ESC-10, and

UrbanSound8K datasets. Further refinements, including three-layer CNN architectures and data augmentation techniques like Shift, Pitch Shift, Dynamic Range Compression, Background Noise, time stretching, and noise addition, have pushed accuracy to 79% and 81.9% on UrbanSound8K.

However, these high-performance neural networks are typically implemented on **energy-consuming, high-computation devices** such as personal computers, smartphones, or Raspberry Pi Systems on Chip (SoCs), making them **unsuitable for pervasive or distributed monitoring in remote, resource-constrained environments** like forests.

2.3. Edge Computing and LoRa for IoT Applications The concept of **edge computing** is crucial for extending IoT sensory systems, allowing low-power devices to "perceive" sound events directly at the source. This minimizes the amount of data transmitted, reducing both bandwidth and energy consumption. While studies on environmental sound classification increasingly focus on resource-efficient models for IoT, many contributions still rely on **SoC hardware (e.g., Raspberry Pi) rather than ultra-low-power microcontrollers** more suitable for pervasive, long-range IoT systems. For example, a system for large-scale urban sound classification tested configurations where feature extraction and classification were performed on an end device (Raspberry Pi), a remote server, or a hybrid approach, with the hybrid being most effective. However, some 1D CNN solutions, while reducing computation, still required 550,000 parameters, which is not feasible for ultra-low-power microcontrollers like ARM Cortex M4/M4F.

To address the resource constraints of IoT devices, advancements include **optimizing deep-learning techniques through knowledge distillation and 8-bit quantization**. The **CMSIS-NN framework** has been shown to speed up processing on ARM Cortex M processors, enabling the implementation of neural networks with model sizes as small as 34.3 kB, achieving about 68% accuracy on Urbansound8k.

For wireless communication in vast areas with low power consumption, **Low-Power Wide-Area Networks (LPWANs), particularly LoRa (Long Range) technology, have become a key solution**. LoRa, patented by Semtech, operates in Industrial, Scientific, and Medical (ISM) radio bands and provides wide coverage with low battery consumption and data rates suitable for small data sizes. Its **STAR of STAR topology** is robust for adding sensor nodes without altering network infrastructure. LoRa has been implemented in various WSN applications, including irrigation systems, smart parking, forest fire detection, geo-location tracking, and health monitoring. Compared to technologies like ZigBee, LoRa offers a significantly wider communication range (kilometers vs. 10-100 meters) and better energy consumption, making it ideal for illegal logging applications requiring a low-power, wide-area network.

Several audio detection frameworks specifically for illegal tree-cutting have been proposed:

- A system extracted **Haar-like features from spectrograms to detect chainsaw sounds**.
- Another study tested algorithms like **Gaussian Mixture Model, K-means Clustering, and Principal Component Analysis**, proposing a new algorithm with 92% accuracy for axe stroke detection.
- Monitoring stations with microphones forwarding audio to a server for neural network-based classification achieved 94.4% accuracy for chainsaw sounds, but relied on **server-side processing and short-range Wi-Fi/ZigBee**, which is expensive for large-scale deployment.
- A system using a three-tier architecture with **Time Difference Of Arrival (TDOA) and neural networks on a Raspberry Pi SoC** detected and located chainsaws with 96% accuracy, but still used short-range 802.15.4 protocol.
- A LoRa-based tree-cutting system, utilizing sound sensors and accelerometers with Arduino and Raspberry Pi, demonstrated several kilometers of single-hop communication and a battery duration of 140–195 hours.

Table 1 provides an overview of existing tree-cutting detection systems and their limitations, highlighting the necessity for ultra-low-power, long-range, and comprehensive threat detection at the edge:

Reference	Main Contribution	Main Limitations

	Low-power microcontroller with sound/vibration sensors and Xbee	Effective only with chainsaw sounds, no long-range wireless transmission
	Ultra-low-power device, sound/vibration sensors, Zigbee with fog computing	Effective only with chainsaw sounds, no long-range wireless transmission
	Low-power microcontroller with sound/vibration sensors and GSM communication	Threshold-based approach, no low-power wireless transmission
	Detection and location of chainsaws through air/soil sound TDOA	Effective only with chainsaw sounds, no wireless communication
	Arduino/Raspberry Pi sound detector with LoRa communication	Effective only with chainsaw sounds, medium–low-power hardware (i.e., Raspberry Pi)
	Chainsaw sound detection adopting spectrograms	Effective only with chainsaw sounds, no details are given on electronics and communication
	92% accuracy on axe stroke sound detection through Gaussian mixture model, K-means Clustering, and Principal Component Analysis	Effective only with axe stroke sounds, no details on electronics and communication
	94.4% accuracy on chainsaw sound detection through neural networks, WiFi and ZigBee communication	Server-side classification and short-range wireless protocols
	94% accuracy on chainsaw through Neural networks, chainsaw location through TDOA	Medium–low-power hardware (i.e., Raspberry Pi), no long-range communication (i.e., 802.15.4)

This paper builds upon these foundations by proposing a highly optimized, ultra-low-power edge computing solution that integrates advanced AI for a wider range of threat detection and robust, long-range LoRa communication, addressing key limitations of prior work.

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3. Methodology

The proposed methodology outlines a series of integrated steps, from data collection and preprocessing to real-world deployment, to establish an effective system for combating illegal logging using AI-enabled IoT devices. This research employs a development studies approach, encompassing theory building, system design, implementation, and rigorous experimental testing.

3.1. System Architecture The core of our approach is a **cyber-driven surveillance and alert system** that integrates IoT sensors, edge computing, and AI to continuously monitor protected forest zones. The system architecture follows the **open standard of LoRaWAN**, comprising sensor nodes (end-devices), gateways, and a network server, extended with a middleware layer and an application layer.

The system is conceptually divided into two main networks:

1. **Local Access Network:** This layer consists of **end-devices (sensor nodes)** and **gateways**. End-devices, acting as a measurement layer, supervise the real environment and connect to gateways using **LoRa Radio Frequency** in a **STAR topology**. This topology can be expanded into a **STAR of STAR architecture** for multi-hop communication, allowing flexible addition of new sensor nodes. The distance between sensor nodes and the gateway is

determined by the Received Signal Strength Indicator (RSSI).

2. **Remote Access Network:** This network comprises the **middleware layer** and the **application layer**. Gateways forward received uplink radio packets to the LoRa network server via an IP network. The LoRa network server, functioning as the middleware layer, processes and saves data (including RSSI, sensor data, latitude, longitude, and altitude) into a database. The application layer retrieves this information from the database, delivering **real-time alerts via web applications and a Telegram channel** to forest officials, local communities, and environmental groups. This allows for **GPS-based tracking of moving logs** on map applications.

3.2. IoT Node Design and Components The monitoring system implemented in the LoRa end node is composed of four key elements: an acquisition module, a pre-processing module, a CNN-based classifier, and a long-range low-power wireless communication module.

Our prototype for the AI-powered IoT device (sensor node) utilizes an **ESP32 microcontroller** (or a 32-bit ARM Cortex MF4 chipset running at 64 MHz, with 1 MB Flash and 256 kB SRAM). These low-power microcontrollers are made powerful through machine learning integration.

Key hardware components include:

- **Microcontrollers:** Arduino Uno and Raspberry Pi 3 B+ are used to handle sensors and are compatible with the LoRa GPS HAT Shield. The ESP32 serves as a sensor node and a central server node.
- **Sensors:** An **INMP441 microphone** (or omnidirectional microphone) records environmental audio. A **sound sensor** detects chainsaw sounds, and a **gyro accelerometer sensor** detects the slope of tree trunks or log movement, indicating tree felling.
- **Communication Module:** A **LoRa GPS HAT Shield** integrates GPS functionality and LoRa communication. The **Outdoor LoRa Gateway OLG01** acts as the gateway to interface local and remote access networks.
- **Power Supply:** A 10,050 mAh power bank or a 3.7V-1800 mAh Li-Po battery pack supplies energy to the sensor nodes.

Software requirements include Arduino IDE and Raspbian Jessie Stretch 2019.

3.3. Incoming Sound Acquisition The audio classification process begins with sound acquisition. The embedded microphone captures the audio signal, which is then digitized. The system acquires a **single audio channel** at a **sampling frequency of 16 kHz**, chosen to balance resource reduction (memory, computation, energy) with good input quality for environmental audio. Audio samples are quantized at either **32 bits (floating-point)** or a more compact **8 bits (integer)** per sample. To prevent compression artifacts, WAV PCM format with FLAC lossless compression is adopted.

For feature extraction, incoming sound is continuously processed using a **sliding window technique**. Audio signals are divided into fixed-length frames, with samples sliced into **overlapping temporal windows of 4000 ms**, each shifted by **50 ms** from the subsequent one. For example, a 5-second audio clip yields 21 distinct overlapping 4-second windows, providing a basic form of data augmentation to improve training accuracy.

3.4. Pre-processing (Feature Extraction) Environmental acoustic sounds are non-periodic, necessitating a **time-frequency representation** like a spectrogram to capture both temporal and spectral signatures. Three pre-processing techniques were evaluated:

1. **Linear Spectrogram:** Generated via **Short-Time Fourier Transform (STFT)**, where audio is split into 20 ms subframes with a 10 ms stride, and FFT is calculated using 256 frequency bands.
2. **Mel-Scaled Spectrogram:** Reduces input dimensionality for machine learning by applying a **Mel-scaled filterbank** to the linear spectrogram. This technique uses 32 filters, 20 ms subframes, 10 ms stride, and 256 FFT values, cutting correlation between adjacent frequency bins.
3. **Mel Frequency Cepstral Coefficients (MFCC):** Provides a compact and efficient representation of audio signals by applying a **Discrete Cosine Transform (DCT)** to a Mel spectrogram. This method further reduces

dimensionality to 13 cepstral coefficients (using 20 ms subframes, 20 ms stride, 256 FFT, and 32 filters), offering a good trade-off between performance and computational/memory cost. MFCC was selected as the optimal feature for audio classification due to its efficiency.

3.5. Classification Model (Neural Network Architecture) The sound classification task is performed using a **Convolutional Neural Network (CNN)**, an architecture well-suited for audio classification due to its performance and ability to process local structures in input data.

The neural network architecture includes the following layers:

- **Input Layer (3,960 features):** Reshapes features for model processing.
- **Reshape Layer (40 columns):** Corresponds to 40 filters from Mel-filter bank energy features.
- **1D Conv/Pool Layer (8 neurons, 3 kernel size, 1 layer):** First convolutional incidence.
- **Dropout (Rate 0.25):** Introduces regularization to prevent overfitting.
- **Conv/Pool Layer (16 neurons, 3 kernel size, 1 layer):** Additional convolutions for enhanced feature extraction.
- **Dropout (Rate 0.25):** Further regularization.
- **Flatten Layer:** Converts output into a one-dimensional array for subsequent layers.
- **Additional Layer:** Increases model complexity and abstraction.
- **Output Layer (4 classes):** Represents the four distinct audio classes: **Silence, Axe, Chainsaw, and Fire**. In an extended dataset, this layer supports seven classes: **Chainsaw, Chirping birds, Crackling fire, Crickets, Handsaw, Rain, and Wind**.

3.6. Training and Optimization The CNN model is trained using a **balanced dataset**. Training settings include **100 training cycles** and a **learning rate of 0.005**. To reduce memory and processing resource consumption, **network quantization to 8-bit integers** (instead of 32-bit floating-point) is performed. This optimization significantly improves runtime and energy savings with a negligible loss of accuracy. Furthermore, the neural network is compiled directly into C++ source code using the **CMSIS-NN library**, specifically designed to enhance the performance of learning kernels on ARM Cortex M processors.

3.7. Sound Dataset The dataset for tree-cutting detection is a subset of the **ESC50 dataset**, curated to include sounds relevant to forest environments and dangerous situations. It comprises **75 samples for each of four audio classes: Silence, Axe, Chainsaw, and Fire**. Each audio sample has a duration of 5 seconds. For a more extensive training, another dataset consists of **40 recorded clips (5-second duration)** for each of the seven sound classes: **Chainsaw, Chirping birds, Crackling fire, Crickets, Handsaw, Rain, and Wind**. The dataset is split into 79% for training and 21% for testing, with 10 clips per class randomly chosen for testing and 30 for training. All clips were downsampled from their original 44.1 kHz to 16 kHz to match the hardware's acquisition system.

3.8. Remote Sensing for Complementary Monitoring (GEE Approach) In parallel to the IoT-based audio detection, **remote sensing technology** utilizing **Google Earth Engine (GEE)** provides a macro-level monitoring solution for illegal logging. GEE, a cloud computing platform based on AI and machine learning, is used to analyze **Sentinel 1 SAR and Sentinel 2 Multispectral image data**.

The GEE-based methodology involves:

- **Data Collection:** Using Sentinel 1 SAR imagery (which can penetrate clouds, crucial for tropical regions) to analyze changes, and Sentinel 2 imagery to map forested areas. Data for 2021 was used.
- **Pre-processing:** Includes subsetting for the specific study area (Sulawesi Selatan Province), radiometric calibration, filter masking for Sentinel 2 images to minimize cloud cover (replacing cloudy pixels using the QA60 band), and speckle filtering (Lee speckle filter) for Sentinel 1 data to remove noise.
- **Image Classification:**
    - **Forest Cover Classification:** A supervised classification method using a **random forest algorithm** on the GEE platform identifies forest and non-forest areas.
    - **Illegal Logging Events Classification:** A segmentation process compares VV and VH polarization images from Sentinel 1

across three periods (January–April, May–August, September–December). Changes detected based on ratio calculations indicate illegal logging events, which are then overlaid with forest distribution maps.

- **Validation:** Classified data undergoes accuracy testing using external reference data from relevant agencies (e.g., Sulawesi Region Environmental and Forestry Law Enforcement Centre). The **Kappa accuracy coefficient** is used, with an acceptable threshold of 85%.

3.9. Prototype and Deployment The prototype of the proposed system (Figure 9 in) consists of multiple sensor nodes (Tx1, Tx2) connected wirelessly to an Outdoor LoRa Gateway OLG01. The **LoRa communication is configured at 923 MHz** (in Indonesia) or **868.1 MHz** (in Europe), with a **spreading factor (SF) of 12** (or 7), a payload of 8 bytes, a coding rate of 4/5, and a bandwidth of 125 kHz. An envisaged transmission delay for LoRa packets is proportional to the matching probability of a dangerous sound event to avoid collisions.

The operational scenario involves disseminating multiple IoT nodes within a monitored forest, under the wireless coverage of one or more gateways in a **star-of-stars topology**. The nodes and gateways can be strategically placed on trees or camouflaged poles for optimal sound detection. Upon detecting specific sounds related to illegal activities, the device sends an event notification with minimal bandwidth, leveraging LoRa's long-range capabilities.

3.10. Threat Detection Criteria and User Interaction Illegal cutting is detected when the sound sensor's value exceeds a predetermined threshold for chainsaw activity, and concurrently, the accelerometer data indicates a significant change in tree position. If both conditions are met, an illegal logging incident is confirmed. Aggregated data from the gateway is sent to the LoRa Network Server, computed in a cloud server, and displayed on a monitor or mobile device. Users, such as forest rangers, receive real-time messages via Telegram and can access a web application to view activity information, including the GPS position of moving logs, enabling them to track and apprehend perpetrators.

4. Results and Discussion

This section presents the findings from the experimental evaluation of the AI-powered IoT system for illegal logging detection, alongside results from the complementary remote sensing approach.

4.1. Audio-based AI/IoT System Performance

4.1.1. Pre-processing Performance The initial evaluation focused on the efficiency of different pre-processing techniques in extracting features from acquired audio samples (Table 2):

Method	Processing Time	Peak RAM
Linear Spectrogram	714 ms	208 kB
Mel Spectrogram	1414 ms	114 kB
MFCC	**928 ms**	**46 kB**

Mel Frequency Cepstral Coefficients (MFCC) demonstrated the best trade-off, requiring significantly lower peak RAM usage (46 kB) compared to Linear Spectrogram (208 kB) and Mel Spectrogram (114 kB), while maintaining a good processing time comparable to the fastest technique.

4.1.2. Neural Network Performance and Classification Accuracy The Convolutional Neural Network (CNN) model's performance was rigorously evaluated across different pre-processing methods and quantization bit depths (Table 3):

CNN Configuration	Inferencing Time	Peak RAM	ROM	Accuracy
Spectrogram-32	14126 ms	406.0 kB	289.8 kB	71.77 %
Spectrogram-8	3001 ms	104.6 kB	96.6 kB	54.31 %
Mel spectrogram-32	4132 ms	402.9 kB	144.3 kB	65.19 %

Mel spectrogram -8	878 ms	103.8 kB	60.2 kB	64.63 %
MFCC-32	**1089 ms**	**203.9 kB**	**93.9 kB**	**85.37 %**
MFCC-8	**232 ms**	**54.1 kB**	**47.6 kB**	**85.03 %**

The results clearly show that the **MFCC solution significantly outperforms all other methods in terms of accuracy and resource efficiency**. Specifically, **MFCC with 8-bit quantization** achieved an accuracy of **85.03%**, with a remarkable reduction in inferencing time (232 ms), peak RAM (54.1 kB), and ROM (47.6 kB) compared to 32-bit floating-point implementations. This configuration delivers an average testing accuracy greater than 85%, making it a state-of-the-art solution for resource-constrained devices.

The model achieved an exceptional **96.2% accuracy on the validation set** with a low loss of 0.10. Overall testing scenarios confirmed a robust **82.57% accuracy** for the model. The confusion matrix for MFCC with 32-bit quantization demonstrated high accuracy for key sound classes: **Chainsaw (84.5%), Crackling fire (83.3%), and Handsaw (92.9%)**, providing a reliable solution for logging detection. Even with 8-bit quantization, these classes maintained high accuracy, with only minor decreases for Chainsaw and Rain.

4.1.3. On-Device Performance The model demonstrated efficient inferencing on low-powered microcontrollers like the ESP32, showcasing its suitability for real-world deployment.

- **Inferencing time:** A mere **21 ms**.
- **Peak RAM usage:** Minimal at **10.6 Kb**.
- **Flash usage:** Low at **32.6 Kb**. These metrics highlight the model's efficacy in memory allocation and storage, crucial for constrained devices.

4.2. LoRa Communication and Tracking Performance

4.2.1. Range-Distance and Signal Strength (RSSI) Experimental tests evaluated LoRa communication performance in both Line-of-Sight (LoS) and Non-Line-of-Sight (N-LoS) conditions.

- **LoS Area (open field):** Communication range reached **0–900 m for Tx1 and 0–750 m for Tx2**. Another test showed a coverage radius exceeding **8 km**.
- **N-LoS Area (small urban forest):** The range was significantly reduced to **0–350 m**.
- **N-LoS Area (suburb forest):** The maximum range was around **300 m**.
- **Partial N-LoS (rural area with woods, buildings):** Coverage reduced to **2.5 km**.
- **Full N-LoS (hills, huge buildings):** Coverage was less than **1 km**.

The density and thickness of the environment, such as trees and high buildings, heavily affected signal strength, resulting in shorter ranges in N-LoS areas. Tests within an oak forest revealed an average path loss of approximately **−8.5 dBm/100m**, leading to an estimated coverage radius of less than 1 km. Optimal placement for sensor nodes and gateways was determined to be between **1.8 and 2.2 m from the ground** to maximize signal transmission distance.

4.2.2. Tracking Performance The system successfully tracked the new locations of moving logs within the gateway's range.

- **LoS Tracking:** Processing time for information delivery was **2–5 seconds**, considered real-time.
- **N-LoS Tracking (small forest):** Processing time ranged from **20–34 seconds**.
- **N-LoS Tracking (suburb forest):** Processing time ranged from **5–46 seconds**. The system could not detect new sensor node locations when moved beyond the effective range of the LoRa Gateway (e.g., beyond 901.13 m in LoS or 362.28 m in an N-LoS small forest). Information regarding illegal logging could be monitored and received by users at distances exceeding **7 km**.

4.2.3. Energy Consumption Energy consumption was evaluated for a single LoRa node with a 3.3V, 10,050 mAh battery.

- **LoRa performance without GPS:** Estimated battery life was **195.9 hours**.
- **System using GPS for tracking:** Battery life was reduced to **140.95 hours**, indicating that GPS usage significantly impacts energy consumption. For continuous sound monitoring and classification with MFCC

pre-processing and 8-bit integer variables, the device could operate for over **61 hours continuously** (average current intensity of 29.5 mA) without needing battery replacement or recharge, considering tree-cutting notifications as rare events. This performance paves the way for sustainable power supply through renewable solar sources in remote locations.

4.3. Google Earth Engine (GEE) Remote Sensing Results

4.3.1. Forest Cover Identification The use of GEE proved instrumental in mapping forest conditions in Sulawesi Selatan Province, Indonesia.

- In 2021, forest conditions were mapped over **2,843,938.87 hectares, representing 63% of the total area of Sulawesi Selatan Province**.
- Analysis of forest area functions revealed that **38.46% (approximately 1,093,841.79 ha) of the current forest area was designated as non-forest estates**, while **61.54% was within official forest areas** (35.42% protected, 20.24% production, 5.88% conservation). This highlights a significant potential for loss in forests located outside designated forest areas where government authority is limited.

4.3.2. Illegal Logging Events Identification GEE's ability to detect forest changes across time periods allowed for the identification of illegal logging incidents.

- **1971 spots of forest change events** were identified between the first (January–April) and second (May–August) periods.
- **1680 spots of forest change events** were identified between the second (May–August) and third (September–December) periods.
- The **total incidence area amounted to 7599.28 hectares**.

4.3.3. Validation of GEE Results An accuracy test comparing GEE's identification of illegal logging events with field monitoring data from the Sulawesi Regional Environmental and Forestry Law Enforcement Centre showed **high conformity, with a Kappa accuracy value of 0.89**. The overall accuracy was 95.80%. This validated the effectiveness of GEE in identifying high-potential illegal logging areas, which mostly occurred in undesignated forest zones. The study noted an increase in illegal logging during the COVID-19 pandemic due to insufficient monitoring, influenced by legal, law enforcement, facilities, and community factors.

4.4. Discussion The results clearly indicate that **sound classification on tightly resource-constrained devices, such as ARM M4F microcontrollers, is a non-trivial task that demands specific optimizations**. The choice of **MFCC pre-processing combined with 8-bit integer quantization proved to be the most efficient solution**, delivering high accuracy (85.03%) with significantly lower computational and memory footprints compared to spectrogram-based methods. This allows for the development of pervasive IoT monitoring systems with low power demands.

LoRa technology is a feasible communication solution for long-range monitoring, achieving over 8 km in Line-of-Sight scenarios and more than 2.5 km in light N-LoS conditions. However, **vegetation and other obstacles (buildings, hills) substantially degrade the signal**, reducing the communication range in dense woods to less than 1 km, with oak forests showing an attenuation rate of approximately 17 dBm/100m. This necessitates careful planning for gateway and node placement in actual forest deployments.

The strategy of transmitting alert information only when a dangerous event (chainsaw, handsaw, or fire) is detected is critical for energy efficiency, enabling the edge-computing device to perform continuous sound classification for over 61 hours on a single battery charge. The overall system response time, including processing (1160 ms for MFCC 8-bit) and transmission, is effective for illegal logging detection, as these scenarios do not typically have stringent real-time constraints.

Complementarily, the **GEE platform offers a powerful, large-scale monitoring solution** that overcomes limitations of traditional methods, providing accurate and timely identification of forest changes due to illegal logging across vast areas, even in challenging tropical regions. The high Kappa accuracy (0.89) validates its reliability for policy-makers and field patrols. The synergistic application of both AI-powered IoT devices for localized, real-time audio detection and GEE for broad-area satellite imagery analysis provides a robust, multi-layered approach to combating illegal logging.

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5. Conclusion and Future Work

5.1. Conclusion This research successfully demonstrates the effectiveness of integrating Artificial Intelligence (AI) and Internet of Things (IoT) technologies to combat illegal logging, a critical threat to global forests and biodiversity. We presented a comprehensive strategy that enables real-time monitoring and detection of illegal logging activities, such as chainsaw operation and tree felling, through the deployment of smart sensors equipped with AI algorithms.

Key achievements include the development of a lightweight Convolutional Neural Network (CNN) model, specifically optimized for resource-constrained edge devices, which achieved a spectacular **96.2% accuracy on the validation set**. The most efficient configuration, utilizing **Mel-filter bank energy features (MEF) and 8-bit quantization**, delivered an average testing accuracy of **85.03%** with minimal resource consumption: **232 ms inferencing time, 54.1 kB peak RAM, and 47.6 kB ROM**. This on-device performance on low-power microcontrollers like the ESP32 confirms its suitability for real-world deployment in challenging forest environments.

The integration of **LoRa communication technology** facilitates long-range data transmission to a centralized server, ensuring real-time data storage and accessibility via a Firebase database and mobile applications. Experimental tests validated LoRa's long-range capabilities, while also highlighting the impact of dense vegetation on signal attenuation. Furthermore, the complementary use of the **Google Earth Engine (GEE) platform with Sentinel 1 SAR and Sentinel 2 multispectral images** proved highly effective for large-scale forest condition monitoring and illegal logging detection, achieving a Kappa accuracy of **0.89**.

Collectively, this research underscores the robustness and generalization capacity of AI-powered IoT devices, coupled with remote sensing, as powerful tools for monitoring and preventing illicit logging, promoting sustainable forest management, and preserving the invaluable benefits forests provide to humanity and the planet.

5.2. Future Work Building on these promising results, several avenues for future enhancements and research are identified:

- **Drone-assisted validation and integration with satellite data** can further augment the surveillance system, providing multi-layered monitoring capabilities and enabling broader deployment across ecologically sensitive regions.
- Developing a **larger prototype** and integrating the system into the **entire logging process stage** (beyond just cutting detection) could offer a more comprehensive illegal timber supply chain monitoring solution.
- Further optimization of **energy consumption for LoRa/GPS HAT modules** is necessary, possibly by replacing current components with more power-efficient, Arduino-compatible LoRa series, and exploring the benefits of **extra antennas** while carefully managing their energy demands.
- Enhancing **GPS-free geolocation techniques** within the system could reduce reliance on power-intensive GPS modules, prolonging device battery life.
- Developing a more user-friendly **Graphical User Interface (GUI) for web applications** would improve accessibility and usability for forest rangers and other stakeholders.
- Conducting **extensive simulations and empirical validation of LoRa module transmission** under diverse weather conditions (e.g., rain, snow, wind, fog) and various vegetation scenarios (e.g., tropical jungle, conifer mountain forests) will provide a more accurate understanding of LoRa coverage in real-life conditions.
- Extending the framework to other scenarios involving **audio and image classification** for applications in smart cities and wildlife preservation could broaden its impact.

These future directions aim to refine the proposed system, making it even more robust, efficient, and versatile in the ongoing fight against illegal logging and for broader environmental conservation.

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