Development of an AI-Enabled Raspberry Pi Robot for Monitoring and Combating Illegal Logging Activity

Ayobami O. Adedokun[1]

[1] Department of Computer Engineering, Federal University of Technology PMB 704, Akure, Ondo State
*Corresponding author email: aayoadedokun@gmail.com

Abstract. Preserving natural ecosystems and biodiversity is crucial for fostering a fair and equitable society, promoting economic functionality, and securing a sustainable future. However, illegal logging activities recently in Nigeria have been posing a significant threat to the forests, the natural environment, leading to adverse consequences such as deforestation and loss of biodiversity with great effect on climate change. The surge in illegal logging can be attributed to various factors, including economic hardship, high youth unemployment rates, and corruption among officials. Addressing these challenges requires innovative solutions. This research proposed the development of an Artificial intelligent robot that intelligently sensed and recognize the sounds of chainsaws or tree-cutting activities along a predetermined route. Upon detecting such sound, the robot will promptly alert the forest guards or law enforcement agents and provide them with the GPS coordinates of the source of the noise, facilitating quick identification of the affected area. The AI model for the design is trained through edge impulse and loaded on raspberry pi with microphone as input for sound detector, GPS sensor and GSM module for the alert system and the monitoring is done in real time. Through integration of AI and Robotics, this research aims to combat illegal logging activity, safeguard forest ecosystems and mitigate climate change impacts in Nigeria.

Keywords: Artificial Intelligence, Logging, Robot, Forest, Climate Change

1 Introduction

According to Food and Agriculture Organization of the United Nations report in 2015 estimated forest reserves in Nigeria to be 10 million hectares, representing over 10% of the nation's total land area, which spans approximately 96.2 million hectares or 923,768 square kilometers [1]. As of 2006, the population within these areas was reported to be around 170,790 individuals. According to the Federal Department of Forestry (2010), Nigerian forests are experiencing an annual depletion rate of 3.5%. Previously, approximately 20% of Nigeria's land area was covered by natural forests; however, this has dwindled to around 10%. The country has lost an alarming 60% of its natural forest cover due to agricultural encroachment, extensive logging, and rapid urbanization between the 1960s and the year 2000 [2]. Even though illegal logging presents a worldwide challenge, affecting every nation with extensive forest resources and a diverse range of logging operations [3]. Addressing this issue proves challenging due to the multitude of illicit activities involved, including corruption at the macro level, irregularities in licensing procedures, logging in restricted or prohibited zones, unauthorized

I. Adimula et al. (eds.), *Proceedings of the 8th URSI-NG Annual Conference (URSI-NG 2024)*, Advances in Physics Research 12,
https://doi.org/10.2991/978-94-6463-644-4_13

logging within legally designated concessions, falsification of reports, and illegal transportation [4]. Nigeria, with its vast forest resources, is not excluded to this issue. The unchecked exploitation of forests for timber and other resources has led to environmental degradation and socio-economic challenges in the country. In response to this pressing concern, technologically innovative approaches are needed to effectively monitor and combat illegal logging activities. By harnessing the potential of artificial intelligence coupled with robotics, we can explore avenues to effectively address the myriad challenges associated with illegal logging activities in Nigeria's forests. This study focuses on the creation of a specialized AI-enabled Raspberry Pi robot designed to combat illegal logging throughout Nigeria. By incorporating advanced AI algorithms, along with high-sensitivity microphones, sensors, GPS, GSM modules, and autonomous navigation capabilities, this robot is positioned to significantly advance forest monitoring initiatives.

2. Related Works

There is increase in global concern about deforestation, particularly illegal logging [5]. And this had led to the development of various technological solutions aimed at monitoring and preventing this activity [6]. Traditional methods for forest surveillance, such as manual patrolling and satellite imaging, though effective to some extent, face limitations in terms of cost, coverage, and real-time monitoring capabilities. In response to these limitations, advancements in Artificial Intelligence (AI), the Internet of Things (IoT), and robotics have opened new possibilities for real-time forest surveillance and environmental monitoring [7].

In 2022, tropical regions lost 10% more primary rainforest compared to 2021, according to the University of Maryland and WRI’s Global Forest Watch. This deforestation threatens the livelihoods of 1.6 billion people, including nearly 70 million Indigenous Peoples, and exacerbates local climate effects, impacting health and agriculture. Nearly 30% of global forest loss is attributed to illegal logging, primarily in the tropics. Traditional surveillance methods, like human patrols and drones, are costly and ineffective in covering large, dense forest areas, creating a need for autonomous, real-time monitoring solutions with minimal human intervention [8].

Integrating AI into environmental monitoring systems has proven to be a game-changer in addressing large-scale environmental issues. Machine learning algorithms are increasingly being applied to tasks such as wildlife monitoring, forest surveillance, and ecosystem management [9]. For instance, AI-based models have been employed to analyze satellite imagery for detecting changes in forest cover, while acoustic sensors powered by AI have been used to identify chainsaw sounds in forests [10]. AI algorithms can enhance the detection of illegal logging activities by processing large volumes of environmental data from multiple sensors, enabling the system to detect patterns and anomalies with high precision and accuracy.

The Internet of Things (IoT) has also offered a framework for creating interconnected networks of devices that can collect and transmit data in real-time. IoT-based systems for environmental monitoring have been widely adopted due to their ability to cover large areas and provide continuous data collection. In combating illegal logging, IoT sensors can be deployed across forests to detect vibrations from tree cutting or engine noise from machinery used in logging. Studies by [11] highlighted the effectiveness of IoT-enabled networks in detecting and reporting illegal logging activities. These systems can be paired with AI algorithms for real-time detection and classification of events, providing an efficient solution for forest management authorities.

The proposed AI-enabled Raspberry Pi robot for monitoring and combating illegal logging activity builds upon the foundational research in AI, IoT, and robotics for environmental monitoring. The robot will utilize a combination of audio sensors to detect chainsaw sounds and AI algorithms for real-time data processing and anomaly detection. The integration of IoT capabilities will enable the robot to transmit data the law enforcement authority for further analysis and action. This system aims to address the limitations of current surveillance methods by providing a cost-effective, autonomous, and scalable solution for forest management and the prevention of illegal logging activities.

3. Materials and Method

The Fig. 1 depicts the proposed system block diagram, which is designed to balance affordability and simplicity without compromising on accuracy, essential for an effective illegal logging monitoring system. The system's hardware consists of seven primary components: Raspberry Pi 4, power supply unit, high-sensitivity microphone, GSM module, GPS, robot chassis, DC motor, and ultrasonic sensor.

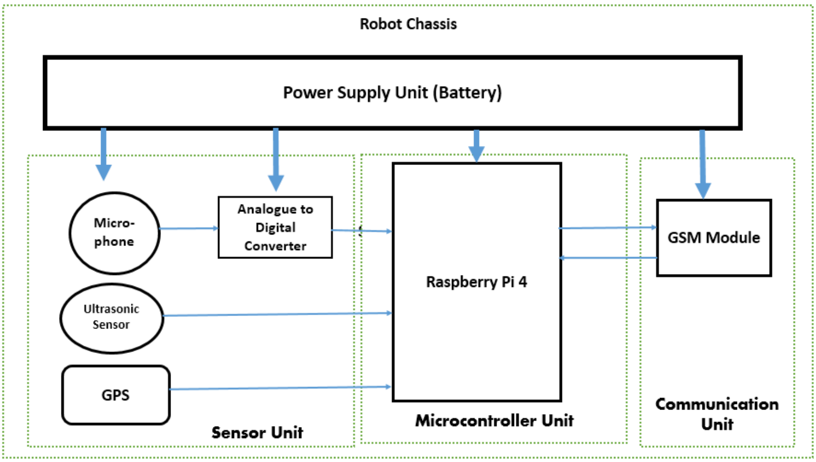

Fig. 1. Block Diagram

3.1 The Hardware Components

As shown in Figure 2, the system's hardware design using Frizting and incorporates essential components including Raspberry Pi 4, DC motor, GPS module, GSM module, microphone, and other electronic elements. The microphone serves the purpose of detecting the sound produced by chainsaw and tree-cutting activities. Utilizing edge impulse, the Raspberry Pi is trained to recognize chainsaw sounds specifically, disregarding other ambient noises as irrelevant. Upon detecting the chainsaw sound, the robot autonomously navigates towards the source and transmits its location to law enforcement agencies for appropriate action. Additionally, the robot is equipped with ultrasonic sensors to facilitate navigation and obstacle avoidance as it moves through the forest terrain.

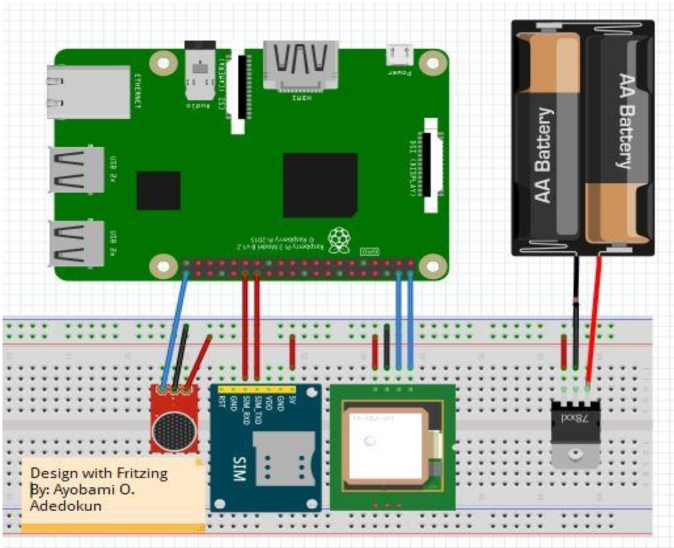

Fig. 2. System Schematic Diagram using Fritzing.

3.1.1 Raspberry Pi

The Raspberry Pi is a compact, affordable single-board computer, roughly the size of a credit card, designed to provide accessible computing experiences for individuals of diverse backgrounds and skill levels [12]. It has major features of the motherboard in an average computer but not with internal storage or peripherals. In setting up Raspberry computer, there is a need for an SD card that will be inserted into the provided space. The SD card should have been preloaded with operating system for the computer to boot. Raspberry computers are compatible with Linux operating system. The amount of memory needed is reduced and creates an environment for diversity. Also, there are several models of The Raspberry Pi in the range of Raspberry Pi 1 to 4. However, for this research, the Raspberry Pi 4 was chosen due to its exceptional features. The Raspberry Pi 4B is powered by a Broadcom BCM2711 processor, offering quad-core Cortex-A72 performance at 1.8GHz. It comes in various configurations, with up to 8GB of LPDDR4-3200 SDRAM. Featuring dual-band wireless connectivity and Bluetooth 5.0 support, it provides fast networking options. The device includes USB 3.0 and USB 2.0 ports for peripheral connections. Equipped with micro-HDMI ports, MIPI DSI and CSI interfaces, and stereo audio ports, it supports versatile display and camera setups.

Fig. 3. Raspberry Pi 4B

As shown in Fig. 3,the Raspberry Pi 4B, an essential and flexible single-board computer used for diverse applications and to load an AI chainsaw sound model trained on Edge Impulse onto a Raspberry Pi 4, the model is first exported in a compatible format while ensure the Raspberry Pi is set up with the necessary dependencies and operating system. Transfer the exported model to the Raspberry Pi and load it into memory using appropriate libraries. Finally, integrate the model into your application running on the Raspberry Pi for real-time detection of chainsaw sounds.

3.1.2 Microphone

A high-sensitivity sound detection module is capable of detecting sounds ranging from 48 to 66 dB as shown in Fig. 4. This module plays a vital role in detecting chainsaw sounds or any tree-cutting activities within the forest.

Fig. 4. Microphone

The output signal from the microphone module undergoes processing through an analog-to-digital converter before being sent for further analysis by the Raspberry Pi. This component serves as a critical element in the proposed design, facilitating the detection and monitoring of illegal logging activities in real-time.

3.1.3 Ultrasonic Sensor

The utilization of ultrasonic sensors in the robot enhances its intelligence, enabling it to automatically detect obstacles ahead and navigate around them by adjusting its direction. This design feature empowers the robot to traverse unknown environments safely by actively avoiding collisions, a fundamental necessity for any autonomous mobile robot operating in dynamic settings [13].

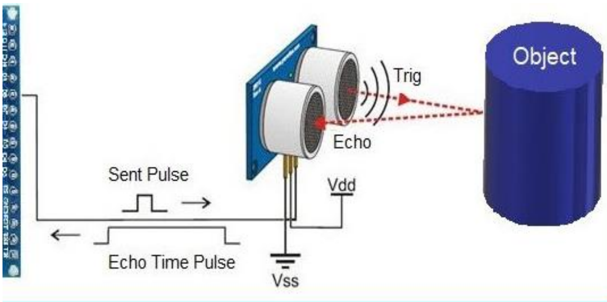

Fig. 5. Ultrasonic Sensor Operation.

As shown in Fig. 5, to initiate the measurement process, the Trig pin of the HC-SR04 ultrasonic sensor is set to a high state for a duration of at least 10 microseconds. Subsequently, a sonic beam comprising eight pulses of 40 kHz each is emitted from the sensor. Upon reaching a surface, the beam is reflected back and captured by the receiver connected to the Echo pin of the HC-SR04. It is noteworthy that the Echo pin is already set to a high state when the high signal is sent. The duration taken for the beam to return is recorded in a variable and subsequently converted into distance through appropriate calculations in the equation 1 [13]:

$$D = \frac{t \times S}{2} \tag{1}$$

where D is the distance and t is the time and S is the speed of the sound in air in 343m/s

3.1.4 Subscriber Identity Module (SIM) 800

The SIM800 module shown in Fig. 6 utilizes the AT command set, which consists of standard commands for controlling and configuring modem-like devices. These commands facilitate sending of text messages, making phone calls, and accessing the internet. To transmit data or messages, users issue specific AT commands to the module, which then encodes the information and sends it over the GSM network to the intended recipient. Conversely, when receiving data or messages, the module decodes the information and provides it for further processing by the host system [14].

Fig. 6. SIM 800 GSM Module

Leveraging the GSM network infrastructure, the module ensures seamless communication, making it a valuable component in applications such as remote monitoring, telematics, and IoT devices. Its simplicity and compatibility with standard AT commands have led to its widespread adoption in numerous projects and applications.

3.1.5 Global Positioning System (GPS) Module

The GPS module shown in Fig. 7 is a wireless chip module combined on the mainboard of a mobile phone or machine [15]. It can communicate with the global satellite positioning system in Nigeria. It can locate and navigate according to the condition of a wireless network signal. The GPS module plays a crucial role in sending coordinates of areas where chainsaw activity is detected.

Fig. 7. GPS Module

Upon detecting chainsaw sounds, the system activates the GPS module to determine the precise location of the incident. The module then transmits the coordinates, allowing authorities to pinpoint the exact area of illegal logging activity. This capability enables swift and targeted responses to combat deforestation and protect forest ecosystems.

3.2 Data Collection and AI Model Training with Edge Impulse

3.2.1 Audio Data Collection

The system is designed to detect illegal logging activities by recognizing chainsaw sounds using a microphone, processing the audio data through a machine learning model, and transmitting the GPS coordinates of the detected activity via GSM. The microphone was installed on the Raspberry Pi 4 to capture ambient sound. Raw audio data was collected in real-time, which included natural forest sounds and various mechanical noises. This data served as the input for the chainsaw sound detection model.

3.2.2 Training the Chainsaw Detection Model

Training the chainsaw sound detection model with Edge Impulse involves several steps [16]. Initially, a dataset containing audio samples of chainsaw sounds is collected and labelled appropriately. As shown in Figure 8, these samples are then uploaded to the Edge Impulse platform for processing and model training [17].

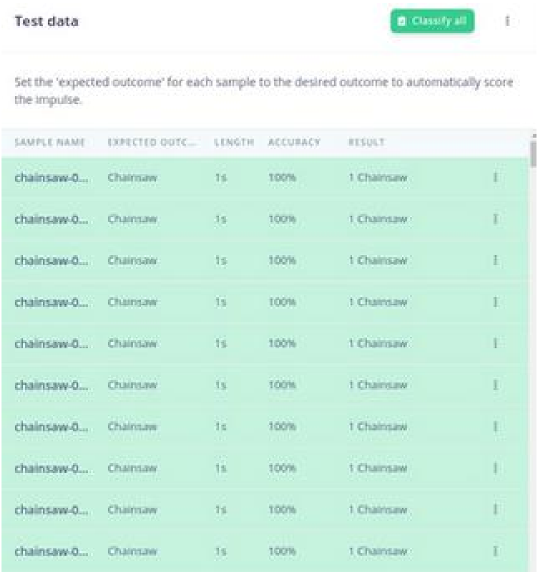

Fig. 8. Trained Data Testing on Edge Impulse

Through machine learning techniques, the platform analyses the audio features and trains a robust chainsaw sound detection model. Once trained, the model undergoes validation to ensure its accuracy and effectiveness in identifying chainsaw sounds. After successful training and validation, the trained model is exported in a format compatible with deployment on Raspberry Pi 4. The exported model file is transferred to the Raspberry Pi, where it is loaded into memory and integrated into the detection system.

Using Python programming, the Raspberry Pi is programmed to capture audio input from a high-sensitivity microphone and process it through the trained model for real-time detection of chainsaw sounds. The system then takes appropriate actions based on the detected chainsaw activity, such as sending alerts or recording the incident location using GPS coordinates. Overall, this integration enables the Raspberry Pi 4 to effectively monitor and combat illegal logging activities in forested areas.

4. Results and Discussion

As shown in Fig. 10 is the complete robot design and construction. The robot design makes use of a highly sensitive microphone to detect chainsaw sounds or tree-cutting activities related with illegal logging.

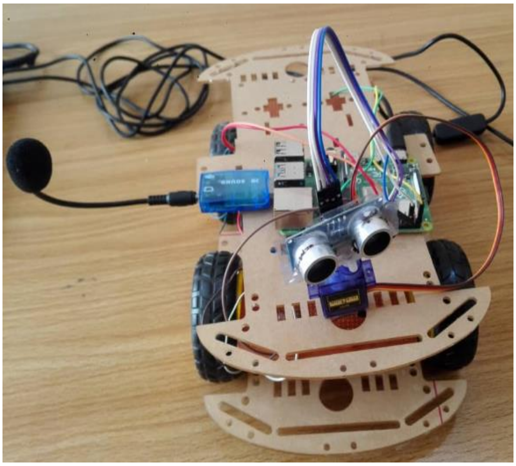

Fig. 10.: Robot Design and Construction

Upon detecting such sounds, the robot autonomously navigates towards the source, utilizing obstacle avoidance sensors to ensure safe traversal. Once in proximity to the logging activity, the robot transmits its location coordinates to relevant authorities for intervention. This functionality allows the robot to effectively monitor and combat illegal logging activities in forested areas solely based on audio detection capabilities.

The system was deployed in a controlled forest environment to assess its effectiveness in detecting chainsaw sounds and transmitting real-time location data. Key performance indicators such as audio detection accuracy, latency, and overall reliability were evaluated to determine the system's performance. Specifically, audio detection accuracy measured the system's ability to correctly identify chainsaw sounds, while latency was assessed by tracking the time taken to detect sounds and transmit GPS coordinates via Global System for Mobile Communications (GSM). The reliability of the system was evaluated by monitoring its continuous operation in the field without significant errors. The developed AI-enabled Raspberry Pi robot was thus tested across these parameters, and its performance was measured by examining detection accuracy, false positive rate, system latency, and the dependability of GPS and GSM transmissions. The results of these evaluations are presented in the following section.

4.1 Audio Detection Accuracy

The primary function of the system is to accurately detect chainsaw sounds. The model was tested using a dataset comprising 500 audio samples, with 250 chainsaw sounds and 250 background sounds (wind, animals, birds, vehicles, humans). The system was evaluated on its ability to correctly classify chainsaw sounds.

Table 1. Audio Detection Accuracy

S/N	Performance Metric	Obtained Value
1	True Positives (TP)	230
2	False Positives (FP)	15
3	True Negatives (TN)	235
4	False Negatives (FN)	20
5	Precision	0.939
6	Recall	0.920
7	F1-Score	0.929
8	Accuracy	0.93

As shown in Table 1, the system achieved a precision of 93.9%, meaning that of all the chainsaw sounds detected, 93.9% were correctly identified. The recall rate of 92.0% indicates that 92.0% of actual chainsaw sounds were detected by the system. The overall accuracy of 93% demonstrates that the model performs reliably in distinguishing between chainsaw and background sounds.

4.2 False Positive Rate

Despite efforts to minimize false positives, the system occasionally misclassified background sounds as chainsaw activity. The false positive rate (FPR) was computed using:

$$FPr = \frac{FP}{FP + TN} \tag{2}$$

$$FPr = \frac{15}{15+235} = 0.06$$

This 6% false positive rate is deemed acceptable, considering the challenging environmental noise conditions typically present in forested areas.

4.3 System Latency Evaluation

The system's latency, measured from the moment a chainsaw sound was detected to the time an SMS with GPS coordinates was sent, was another key performance indicator. Multiple trials were conducted to measure the average latency. From the table, let DT be detection time, GPSRT be the GPS retrieval time and SMSST be the Short Message Service (SMS) sending time.

Table 2. System Latency

Test	DT (ms)	GPSRT (ms)	SMSST (ms)	Total Latency (ms)
1	350	200	500	1050
2	370	220	490	1080
3	345	210	520	1075
4	360	205	510	1075
5	355	215	495	1065
Avg	**356**	**210**	**503**	**1070**

In Table 2, the average total latency from detection to SMS transmission was approximately 1070 milliseconds (1.07 seconds), which is within [18] acceptable limits for real-time detection and reporting of illegal logging activities.

CONCLUSION

In conclusion, the integration of AI-enabled robotics presents a promising solution for monitoring and combating illegal logging activities in forested areas. The system, equipped with a microphone for detecting chainsaw sounds, GPS for location tracking, and GSM for real-time data transmission to law enforcement, was rigorously tested in a controlled forest environment. The results demonstrated that the system effectively identified chainsaw sounds with a detection accuracy of 93%, a 6% false positive rate, and an average latency of 1.07 seconds from detection to GPS data transmission. Additionally, the GPS and GSM modules were found to be highly reliable, with a 98% success rate in transmitting location data. Moving forward, further research to test the system using various environmental conditions and development in this field hold the potential to significantly impact forest conservation efforts worldwide.

REFERENCES

1. Food and Agriculture Organization of the United Nations, "Global Forest Resources Assessment Country Report: Nigeria," 2015. [Online]. Available: http://www.fao.org/3/a-au190e.pdf. [Accessed: Feb. 18, 2024].
2. SFM Tropics, "Status of Tropical Forest Management: Nigeria," in Sustainable Forest Management, pp. 112-119, 2005.
3. S. Wang, K. Wang, X. Wang, and Z. Liu, "A Novel Illegal Logging Monitoring System Based on WSN," Advanced Materials Research, vol. 518-523, pp. 1417-1421, 2012. doi: 10.4028/www.scientific.net/AMR.518-523.1417.
4. K. Eman, G. Mesko, and G. B. Fields, "Crimes Against the Environment: Green Criminology and Research Challenges in Slovenia," Varstvoslovje: Journal of Criminal Justice and Security, vol. 11, pp. 574-592, 2009.

5. W. B. Wood, "Tropical deforestation: balancing regional development demands and global environmental concerns," Global Environmental Change, vol. 1, no. 1, pp. 23-41, 1990.
6. B. Haq, M. A. Jamshed, K. Ali, B. Kasi, S. Arshad, M. K. Kasi, and M. Ur-Rehman, "Tech-Driven Forest Conservation: Combating Deforestation With Internet of Things, Artificial Intelligence, and Remote Sensing," IEEE Internet of Things Journal, 2024.
7. O. N. Chisom, P. W. Biu, A. A. Umoh, B. O. Obaedo, A. O. Adegbite, and A. Abatan, "Reviewing the role of AI in environmental monitoring and conservation: A data-driven revolution for our planet," World Journal of Advanced Research and Reviews, vol. 21, no. 1, pp. 161-171, 2024.
8. J. H. Seo and H. B. Park, "Forest environment monitoring application of intelligence embedded based on wireless sensor networks," KSII Transactions on Internet and Information Systems (TIIS), vol. 10, no. 4, pp. 1555-1570, 2016.
9. A. Raihan, "Artificial intelligence and machine learning applications in forest management and biodiversity conservation," Natural Resources Conservation and Research, vol. 6, no. 2, p. 3825, 2023.
10. K. Nguyen-Trong and H. Tran-Xuan, "Coastal forest cover change detection using satellite images and convolutional neural networks in Vietnam," IAES International Journal of Artificial Intelligence, vol. 11, no. 3, p. 930, 2022.
11. R. M. Prakash, M. Aravind, A. G. Krishna, and K. J. Prakash, "Forest Fire Monitoring using Internet of Things and Machine Learning," in 2024 4th International Conference on Pervasive Computing and Social Networking (ICPCSN), pp. 486-490, May 2024. IEEE.
12. S. Karthikeyan, R. A. Raj, M. V. Cruz, L. Chen, J. L. A. Vishal, and V. S. Rohith, "A Systematic Analysis on Raspberry Pi Prototyping: Uses, Challenges, Benefits, and Drawbacks," IEEE Internet of Things Journal, vol. 10, no. 16, pp. 14397-14417, 2023.
13. M. A. Baballe, I. B. Mukhtar, S. H. Ayagi, and F. M. Umar, "Obstacle Avoidance Robot using an ultrasonic Sensor with Arduino Uno," Global Journal of Research in Engineering & Computer Sciences, vol. 3, no. 5, pp. 14–25, 2023. doi: 10.5281/zenodo.10015177.
14. P. Flescher, N. Benjamin, N. Astoyao, and A. Robert, "Design and Development of GSM/GPS Based Vehicle Tracking and Alert System for Commercial Inter-City Bus," in IEEE 4th International Conference on Adaptive Science & Technology (ICAST), 2012.
15. L. J. B. Andrews, D. Sarathkumar, and R. A. Raj, "IoT Based Surveillance Camera with GPS Module," in 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), pp. 1-3, Feb. 2023. IEEE.
16. Edge Impulse for Illegal Logging. Available online: https://studio.edgeimpulse.com/public/126774/ (accessed on: Feb. 18, 2024).
17. T. A. Teixeira et al., "Development of a Monitoring System against Illegal Deforestation in the Amazon Rainforest Using Artificial Intelligence Algorithms," Engineering Proceedings, vol. 58, p. 21, 2023. doi: 10.3390/ecsa-10-16188.
18. N. Kouzayha, M. Jaber, and Z. Dawy, "Measurement-based signaling management strategies for cellular IoT," IEEE Internet of Things Journal, vol. 4, no. 5, pp. 1434-1444, 2017.