Model for Detecting Illegal Tree Felling in the Protected Area of Bagua in Amazonas Using Convolutional Neural Networks

Wilmer Calle Carbajal[a], Julio Raúl Huamán Llantoy[b] and Jymmy Dextre Alarcon[c]
Peruvian University of Applied Sciences, Lima, Peru
{u202213826, u20211a424}@upc.edu.pe, pcisjdex@upc.edu.pe

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Abstract: Illegal logging is a problem that occurs in different regions of Peru, causing deforestation, biodiversity loss, and contributing to climate change.Despite the efforts of organizations and governments to combat this problem, constant detection and monitoring are challenging due to the vast extension of forests and the lack of human resources to effectively monitor all areas.Therefore, the use of a detection model is proposed as a solution to detect illegal logging in real time through chainsaw sound. This model consists of four phases: Input, Analysis, Execution, and Output.Phase 1 focuses on the collection of sounds from recording devices. Phase 2 analyzes and processes the characteristic chainsaw sounds. Phase 3 focuses on the execution of the model. Phase 4 will display the result of the detection as a numerical value 1 or 0 as the case may be.The results of the experimental validation were obtained by using mobile devices to record and send audio to the detection model. These results were positive and acceptable in terms of accuracy in detecting illegal logging activities, achieving a 10% reduction in such activities.

1 INTRODUCTION

Illegal logging is one of the main causes of deforestation in Peru, with serious consequences for the environment and society in different departments of Peru (Praeli, 2021). The lack of surveillance and control has allowed this illegal practice to continue unchecked. In this sense, illegal logging has increased in 2020, reaching 200 thousand hectares, the highest figure in the last two decades (Romero, 2017). This phenomenon has devastating consequences for ecosystems. According to a report by the Ministry of the Environment (Minam) from mid-2020, a loss of 7,119 hectares of forest was recorded in Peru, which represents a 28.7% reduction in deforestation compared to the same period of the previous year according to (Watch, 2023). Furthermore, a new study on illegal logging in the Peruvian Amazon prepared by the Ministry of Justice and Human Rights and the USAID Prevent Project confirms that illegal logging and trafficking of timber forest products are in the process of expansion and its mechanisms for operating are increasingly sophisticated and complex according to (D. H., 2022). For its part, the Amazonian Georeferenced Socio-Environmental Information Network (RAISG), in its study entitled "The Plundered Amazon", confirms that the surface area destined for illegal mining is increasing (Romero, 2017). This activity is linked to increased human activity, which in turn is related to the growth of deforestation in the region according to (Georreferenciada, 2018). Given this problem, other countries such as Brazil implemented forest early warning systems that provide information on changes in forests to national governments through Landsat 7 and 8 satellites for monitoring purposes (Watanabe et al., 2021). Likewise, in Indonesia, they implemented a logging detection system through supervised algorithm techniques with wireless detection sensors that allowed detecting sounds in the environment to then analyze and process (Sboui et al., 2023). On the other hand, in Peru the GeoBosque system has been developed, which makes use of technologies such as remote sensing, GPS and real-time tracking and monitoring technologies and this system sends email alerts if it detects changes in forestation (GEOBOSQUE, 2017). However, these solutions based on satellite data are not very effective due to external factors such as the weather, the environment does not work as expected. Therefore, there are other techniques based on convolutional neural networks that

[a] https://orcid.org/0009-0005-9218-8470
[b] https://orcid.org/0009-0007-8845-0901
[c] https://orcid.org/0000-0002-1686-0510

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are more effective in dealing with climatic factors, this uses real-time data.

Therefore, our proposal is to develop a sound detection model to solve the problem of illegal logging. It consists of 4 phases: data entry, data analysis, model execution and obtaining results which indicate whether it is a logging or not based on the characteristics of the sound with which the model was trained.

The article is organized as follows: Section 2 presents the work related to the problem, Section 3 presents the proposed model for detection, Section 4 explains how the model will be validated, Section 5 presents the results obtained with their discussion, and finally Section 6 mentions the conclusions and future work.

2 RELATED WORKS

In this section, a literature review was carried out to analyze the related works that support the research. A systematic review of the literature (Kitchenham, 2007) was carried out where the following phases were applied: 1) Planning of the review, 2) development and 3) Analysis and results. It began with the definition of the research questions, which are: (P1), What components are used for detecting tree felling? (P2) What algorithms are used for detecting tree felling? (P3) What technologies are used to alert tree felling? (P4) How are illegal logging detection models validated?

They also defined the following keywords: “Tree felling”, “deforestation”, “Machine learning”, “Convolutional Neural Networks” and “sound detection”. Subsequently, searches were carried out in research repositories such as Scopus, Scielo, IEEE Xplore, EBSCO, Re-searchGate and WebOfScience. All articles considered for the research were from journals published after 2020. Finally, for the analysis of the articles, a taxonomy related to the questions formulated for the selection of articles was used (see table 3).

Regarding the components, seven main ones used in the detection of illegal logging have been identified: wired sound sensors, satellite image sensors (Saha et al., 2022; Mayfield et al., 2020) , drones (Sethi et al., 2020), IoT sensors, GPS devices, infrared (IR) sensors, and vibration and tilt sensors (Kumar, 2022). Of all these, wireless sound sensors and vibration sensors stand out as the most effective in detecting ambient sound in monitored areas. These sensors, in combination with IoT technology, allow for more accurate and real-time detection of suspicious activities, such as the use of chainsaws (Kumar, 2022). The ability to analyse and classify the data captured by these sensors makes them key tools for detecting illegal logging, providing an efficient and robust method for identifying and responding to these environmental threats.

Table 1: Classification of articles.

Taxonomy	Sources
Component (P1)	(Sethi et al., 2020), (Saha et al., 2022), (Kitchenham, 2007), (Doblas et al., 2020), (Watanabe et al., 2021), (Sboui et al., 2023), (Kim et al., 2020), (Bogomolov, 2021), (Casallas, 2022), (S., 2022), (Kumar, 2022), (Simiyu and Vikiru, 2017)
Algorithm (P2)	(Sethi et al., 2020), (Saha et al., 2022), (Kitchenham, 2007), (Ball et al., 2022), (Antonelli et al., 2023), (Hethcoat et al., 2021), (Simiyu and Vikiru, 2017)
Technology (P3)	(Saha et al., 2022), (Kitchenham, 2007), (Al-Obaidi, 2017), (Doblas et al., 2020), (Dong et al., 2023), (Antonelli et al., 2023), (Sethi et al., 2020), (Liao et al., 2022), (Kumar, 2022), (Simiyu and Vikiru, 2017)
Validation (P4)	(Doblas et al., 2020), (Ball et al., 2022), (Marmaroli et al., 2023), (Kim et al., 2020), (Hethcoat et al., 2021), (Dominguez et al., 2022), (Kumar, 2022), (Simiyu and Vikiru, 2017)

Regarding the algorithms used in illegal logging detection, we have identified five main ones: Support Vector Machine (SVM) (Saha et al., 2022), Convolutional Neural Network (CNN) (Kitchenham, 2007), Rain-Forest (Antonelli et al., 2023), Refined Algorithm (Watanabe et al., 2021), and Transformers (Sboui et al., 2023). After a review of each one, we conclude that the Convolutional Neural Network (CNN) stands out for its superior effectiveness and precision in the classification, analysis, and prediction of sounds, especially when trained with chainsaw-specific data. This ability of CNN to capture and learn complex features of sound data makes it the most suitable option for the development of an alert system for the detection of illegal logging. Therefore, we will implement a CNN-based model, trained on a dataset of chainsaw sounds, which will be integrated into an application to facilitate the identification and response to illegal logging activities.

Likewise, regarding the ”Technologies”, we found 4 which are: Python (Mayfield et al., 2020), Amazon Web Services (Dong et al., 2023), Tensorflow (Ball et al., 2022), Google Maps (Kim et al., 2020). For our purposes, we will use Tensorflow technology to test the sound classification and prediction model. Additionally, we will use Google Maps to determine the location and show the detected illegal logging. Additionally, we will use Firebase push notification to send alerts, which is how we differentiate ourselves from the other proposals.

Finally, regarding the “Validation”, the most notable were, an intelligent system based on IoT operated by solar energy to monitor illegal logging validated in the field of study. (Kumar, 2022), intelligent IoT remote sensing through terrestrial networks to alert logging (Antonelli et al., 2023), drone sound detection (Dong et al., 2023), classification of domestic animal sounds, the validation was carried out in a real environment with a pig sound (Liao et al., 2022), characterizing soundscapes in various ecosystems using a set of universal acoustic features (Hethcoat et al., 2021; Bogomolov, 2021), for our validation of the problem of illegal logging we will use mobile devices powered by solar panels that record and send data to the model which makes the detection in real time.

3 PROPOSED MODEL

In the present model, 4 phases will be developed to effectively address the problem of illegal logging in Bagua, Amazonas, Peru. These phases include: Data input, which will focus on collecting environmental sounds using recording devices strategically placed in the region. Data analysis, where the collected data will be processed and cleaned to remove background noise and normalize it, preparing it for analysis with convolutional neural networks (CNN) and model execution, which will use CNNs to detect and classify complex patterns in the auditory data, identifying suspicious illegal logging activities. In the final phase, a performance evaluation of the trained model is carried out, using specific evaluation metrics such as precision, recall, and F1-score, among other measures. This structured approach will allow for a robust and effective implementation of the predictive model, providing a valuable tool for forest conservation and the protection of indigenous and local communities.

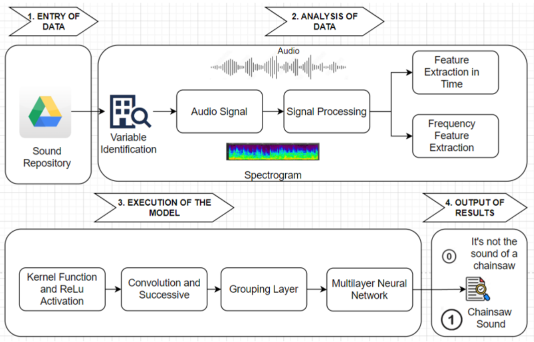

Figure 1: Architecture diagram of the proposed detection model.

3.1 Phase 1: Data Entry

The objective of this phase is to ensure the quality and integrity of the collected audio data. Therefore, two key activities were defined: (1) Select device, Upload files.

It is essential to ensure high-quality audio capture. To do this, a technological tool is used based on discarded cell phones, modified and equipped with solar panels and a Movo VXR10 universal shotgun microphone. These devices are installed in the treetops, from where they send real-time alerts to the phones of people authorized by the community. In addition, they function as a GPS system, providing the exact coordinates of the place where damage to the forest could be occurring. With this information, actions are coordinated with the competent environmental authorities to intervene in a timely manner and mitigate any possible damage in the area.

Next, we will proceed to upload the audio files. This involves transferring the data from the mobile device to a development or processing platform. Various methods can be used for this task, such as USB connection or cloud storage. It is essential to maintain the integrity of the data during the transfer and to organize it in an orderly and secure manner for easy access and manipulation later.

3.2 Phase 2: Data Analysis

The objective of this phase is to improve the data preparation in order to enhance the CNN model's ability to detect and understand the relevant patterns present in the audio files. Therefore, two key activities were defined: (1) Extraction of relevant features, (2) Data normalization.

Regarding the extraction of relevant features, it is

Figure 2: Sensor Components (Mobile).

essential to verify spectrograms or frequency characteristics, in order to obtain crucial information about the acoustic structure of the files and facilitate the identification of significant patterns.

We will then proceed to normalize the data in order to ensure its proper adaptation to processing by the CNN model, thus ensuring consistency and comparability between the different data sets.

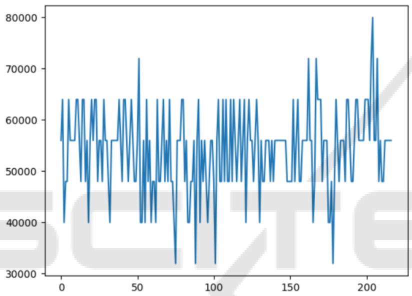

Figure 3: Average chainsaw call duration and wave cycle length.

3.2.1 Phase 3: Execution of the Model

The objective of this phase is to implement and train the convolutional neural network (CNN) architecture, ensuring its ability to detect relevant patterns in the input data. Therefore, two key activities were defined: (1) Definition of the CNN structure, (2) Training the model.

Regarding the definition of the CNN structure, it is essential to determine the number and configuration of the convolutional, pooling, and fully connected layers, crucial aspects for its ability to capture and learn relevant patterns. We will then proceed with training the model using the data prepared in the analysis phase to adjust the network weights and minimize the loss, through repeated iterations where the model learns and adapts to improve its classification ability.

Table 2: Classification of articles.

Layer	Type	Filter size	Outputs	Activation
Input	-	-	32 x 32 x3	-
Convolu -cional 1	Conv2D	3x3	32 x 32 x 32	ReLU
Pooling 1	MaxPoo - ling2D	2x2	16 x 16 x 32	-
Convolu -cional 2	Conv2D	3x3	16 x 16 x 64	ReLU
Pooling 2	MaxPoo - ling2D	2x2	8 x 8 x 64	-
Flattening	Flatten	-	2048	-

	Inputs
	DataSetName: Name of the .WAV file with the data
	test_size: porcentaje of data to be used for the test set
	max_features: Máximum number of selected features (default 2)
	Outputs
	Model Acurracy : Fit Model, View Loss and KPI Plots
	Classification Report: Detaded Classification Report of the model
	Start
1	Define Paths to Files
2	wave = load_wav_16k_mono(CHAISAW_FILE)
3	def load_wav_16k_mono(filename)
4	wave = load_wav_16k_mono(CHAISAW_FILE) nwave = load_wav_16k_mono(NOT_CHAISAW_FILE)
5	POS = os.path.join('data', 'Parsed_Chaisaw_Clips') NEG = os.path.join('data', 'Parsed_Not_Chaisaw_Clips')
6	pos = tf.data.Dataset.list_files(POS+'*.wav') neg = tf.data.Dataset.list_files(NEG+'*.wav')
7	positives = tf.data.Dataset.zip((pos, tf.data.Dataset.from_tensor_slices(tf.ones(len(pos)))))
8	for file in os.listdir(os.path.join('data', 'Parsed_Chaisaw_Clips'))
9	tf.math.reduce_min(lengths) tf.math.reduce_max(lengths)
10	def preprocess(file_path, label)
11	filepath, label = positives.shuffle(buffer_size=10000).as_numpy_iterator().next()
12	data = data.map(preprocess) data = data.cache() data = data.shuffle(buffer_size=1
13	train = data.take(36000) test = data.skip(360000).take(15000)
14	samples, labels = train.as_numpy_iterator().next()
15	model = Sequential()
16	hist = model.fit(train, epochs=4, validation_data=test)
17	plt.plot(hist.history['val_loss'], 'b')
18	plt.plot(hist.history['val_recall'], 'b')
19	hist = model.fit(train, epochs=4, validation_data=test)
20	X_test, y_test = test.as_numpy_iterator().next()
21	yhat = [1 if prediction > 0.5 else 0 for prediction in yhat]
	End

Figure 4: Artificial intelligence algorithm pseudocode.

3.2.2 Phase 4: Output of Results

The objective of this phase is to evaluate the performance of the trained model in the audio classification task, using specific metrics such as precision, recall and F1-score on a test data set, to determine its effectiveness and reliability in detecting illegal tree felling activities. Therefore, two key activities were defined: (1) Performance evaluation, (2) Comparison of results. Regarding the evaluation of the performance of the trained model, specific metrics such as precision, recall and F1-score will be evaluated on a test data set, to determine its effectiveness and reliability in detecting illegal tree felling activities. Finally, we will proceed with the comparison of results with the objectives initially established to determine whether the model meets the expected precision and robustness requirements.

1. Accuracy: Measures the proportion of all correct predictions (both true positives and true negatives) out of the total number of predictions. It is an overall measure of the model's performance.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

2. Precision: Indicates the proportion of predicted positive cases that are truly positive. High precision means that few of the predicted positive cases are false positives.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

3. Recall: Indicates the model's ability to detect all true positive cases in the dataset. A high recall means that few positive cases are missed.

$$Recall = \frac{TP}{TP+FP} \times 100 \quad (3)$$

4. F1-Score: Combines the precision and recall scores.

$$2 \times \frac{precision + recall}{precision * recall} \quad (4)$$

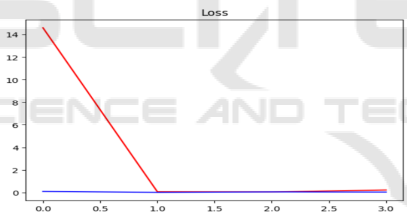

Figure 5: Loss Chart.

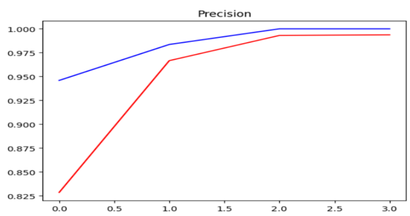

Figure 6: Accuracy Chart.

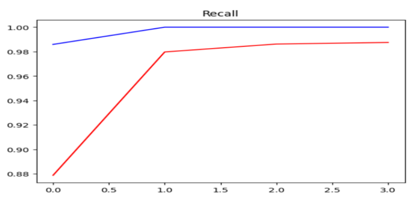

Figure 7: Recall Chart.

Table 3: Classification of articles.

Period	Loss	Recall	Precision
1	14.6007	0.8788	0.8286
2	0.0666	0.9797	0.9667
3	0.0490	0.9862	0.9931
4	0.2184	0.9875	0.9937

The model shows a steady improvement throughout the epochs, especially in the first three. The slight decrease in validation loss and increase in training loss in the fourth epoch could be a sign of overfitting, although the recall and precision values are still perfect.

4 VALIDATION

The model will be validated in collaboration with the Municipality of the Bagua district, located in Peru. The validation will be carried out in a specific area of 500 square meters within the protected area. Monitoring activities were carried out in two different areas. This was done to assess how variations in the environment could affect the detection of logging activity.

To validate the proposed model, two scenarios were carried out. Scenario 1, Scenario 2

Table 4: STAGES.

Stage	Features to Evaluate	Place
Logging Sounds Near Sensor	Model accuracy	Sector 5 of the Municipality of Bagua
Remote Sensor Felling Sounds		

1. Scenario 1: Illegal logging sounds occur at a distance of 60 to 120 meters from the sensor, allowing the model's ability to detect high intensity sounds with minimal interference from ambient noise to be assessed. Audio captured in this environment is characterized by increased clarity and volume. The goal is to measure the model's accuracy under optimal conditions, assess its ability to detect intense sounds, and validate its effectiveness with clear and nearby sounds.

2. Scenario 2: Illegal logging sounds occur at a distance of 130 to 310 meters from the sensor, allowing to evaluate the model's ability to detect lower intensity sounds with a higher probability of interference from ambient noise. Audio captured in this environment, characterized by lower clarity and volume, is crucial to measure the model's ac-

curacy under more challenging and realistic conditions, evaluate its ability to detect low intensity sounds, and validate its effectiveness with distant and less clear sounds.

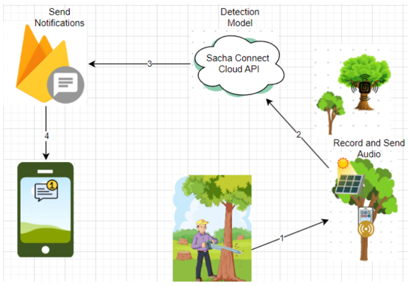

Figure 8: The mobile device is placed in the treetops, records the sounds of the environment and sends the data via the mobile cellular telephone network to detect illegal logging patterns.

Figure 9: Team member Sacha, next to a mobile device, equipped with an audio sensor, an old smartphone.

5 RESULTS

To evaluate the effectiveness of the illegal tree felling detection model, tests were conducted in two different scenarios. These scenarios helped evaluate the model's ability to detect high and low intensity sounds, as well as its performance under different ambient noise interference conditions.

Table 5: Sounds of logging near the sensor.

Sounds of felling	Non-logging sounds	Correctly identified felling sounds	Non-logging sounds correctly identified
350	150	330	140
Total of sounds			500
Effectiveness on Stage			
Accuracy			93%
Precision			96%
Recall			94%

The model showed 93% effectiveness in this scenario, indicating a high ability to detect logging sounds when they occur close to the sensor.

Table 6: Remote sensor felling sounds.

Sounds of felling	Non-logging sounds	Correctly identified felling sounds	Non-logging sounds correctly identified
350	100	280	85
Total of sounds			450
Effectiveness on Stage			
Accuracy			83%
Precision			92%
Recall			82%

The model showed 81% effectiveness in this scenario, indicating a lower ability to detect logging sounds when they occur at greater distances from the sensor, with greater interference from ambient noise.

Comparison of Results.

The comparison between the scenarios showed that the effectiveness of the model decreases with distance and environmental noise interference. In Scenario 1, with logging sounds at a distance of 60 to 120 meters, the model showed an accuracy of 93%. In Scenario 2, with logging sounds at a distance of 130 to 310 meters, the accuracy was 82%. These results indicate that the proximity of the sensor to the sound sources significantly improves the accuracy and effectiveness of the model in detecting illegal logging activities.

Table 7: Manual monitoring vs. monitoring with sensors.

Week	**Manual Monitoring**	**Personal Intervention**	**Monitoring with Sensors**
Week 01	130	2	117
Week 02	120	3	96
Week 03	140	2	127
Week 04	100	2	97
Week 05	135	3	123
Total trees lost	625	12	560
Average	125.00		112.00
Result	**((MM-MS) /MM)** * 100% = 10%		

The comparison between both methods showed a notable improvement in monitoring accuracy when using sensors. In addition, a 10% decrease in illegal logging was observed with the implementation of the sensor system. This shows that we achieved greater efficiency in detecting illegal logging. Early detection and immediate notifications allowed for faster actions to be taken to prevent and mitigate illegal logging, resulting in an effective reduction in the number of trees cut down.

6 CONCLUSIONS AND FUTURE WORK

The illegal logging detection model allowed us to identify illegal logging activities with a high accuracy of 90%, resulting in a 10% reduction in these activities in real-time by detecting chainsaw sounds. The experimental results indicated that the Convolutional Neural Network (CNN) algorithm offers better performance and higher effectiveness compared to other methods. The research focused on identifying chainsaw sounds during logging activities in the forest. The experimental validation was carried out using a Huawei P SMART 2019 mobile device to record and send the audios to the detection model. The model was evaluated with different sounds at close distances of 10 meters and far distances of 110 meters, obtaining positive and acceptable results, with an illegal logging detection accuracy ranging between 80% and 90%.

As future work, it is recommended to implement this model in other municipalities in the Amazonas region, such as Chachapoyas, Utcubamba, and Condorcanqui, to expand the use of the application and strengthen forest protection. In addition, the integration of more sophisticated smart sensors, such as the AR854, is suggested to cover a larger area and achieve a more precise analysis of results. Collaboration with local governments and environmental organizations will be crucial for the success and sustainability of these initiatives. In particular, efforts should be focused on critical points such as Chachapoyas where illegal logging is most prevalent, to maximize the impact of protection measures.

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