

# A machine learning framework for acoustic rainfall classification applied to two distinct soundscapes

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**Abstract**—Traditional rain gauges face coverage and maintenance limitations in tropical areas. Opportunistic acoustic sensing offers a scalable alternative; however, models often struggle with environmental adaptability and data imbalance. This study proposes a Machine Learning framework for rainfall classification across two contrasting soundscapes: Fortaleza’s semi-urban and Amazonian forest. The pipeline extracts 102 features followed by site-specific dimensionality reduction. To handle data skewness, we apply undersampling and stochastic augmentation. Classifiers such as Random Forest, Extreme Gradient Boosting, and Support Vector Machine are evaluated. Results indicate that integrating acoustic feature engineering with rigorous dataset curation enables reliable rainfall classification in complex environments.

**Keywords**—Acoustic monitoring, Rainfall classification, Machine learning

## I. INTRODUCTION

Traditional rain gauges are often subject to mechanical failures and to high maintenance costs limiting their deployment in tropical regions [1]. In urban centers like Fortaleza, Brazil, sparse rain gauge networks fail to monitor intense convective rainfall, which frequently triggers flash floods [2], [3]. In this context, opportunistic acoustic sensing emerges as a scalable, low-cost alternative for environmental monitoring [4], [5].

Building on Power Spectrum Density (PSD)-based baselines for the Amazon [1], this study proposes a framework using 102 off-the-shelf acoustic metrics combined with an empirical feature selection workflow. We evaluate two contrasting sound scenarios from audio recordings: i) a semi-urban scenario at the Ceará State University (UECE) campus in Fortaleza, and ii) an Amazon rainforest scenario at the Mamirauá Sustainable Development Institute (IDSM). By independently analysing these soundscapes, we address methodological adaptability to continuous technophony and biophonic interferences using Random Forest (RF), Extreme Gradient Boosting (XGB) and Support Vector Machine (SVM) [6].

Our main contributions are summarized as follows:

- **Cross-soundscape evaluation:** Assessment of acoustic rainfall classification using Machine Learning (ML) methods

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across contrasting semi-urban (UECE) and rainforest (IDSM) environments.

- **Large-scale feature selection:** Extraction of 102 off-the-shelf acoustic metrics and empirical dimensionality reduction for each site.
- **Structured processing pipeline:** Implementation of 10-second audio segmentation [7], data curation, class balancing, and stochastic augmentation to mitigate the *accuracy paradox* in rare events [6].
- **Comparative experimental matrix:** Benchmarking against PSD baselines and evaluating 5-class and 3-class.

The remainder of this paper is organized as follows: Section II describes the adopted materials and methods; Section III presents the experimental results and related discussions; and Section IV provides concluding remarks and perspectives for future work.

## II. MATERIALS AND METHODS

### A. Study areas and data collection

To validate the methodological adaptability of the proposed acoustic processing pipeline, data were independently collected and evaluated across two contrasting Brazilian soundscapes. This approach allows the analysis of the model’s performance under acoustic and climatological extremes. The primary dataset was acquired at a semi-urban UECE, located in Fortaleza, Brazil. In this environment, the soundscape is dominated by anthropophony (vehicular traffic and human activity) and wind-induced geophony, alongside a mild presence of local biophony, such as birds, cicadas, and dogs. Climatologically, the region averages 1,430 mm of annual precipitation concentrated between February and May [3]. Despite long dry spells, the city is highly susceptible to extreme convective rainfall, which frequently triggers severe and sudden urban floods, leading to significant impacts on the quality of life in several areas of the region [2].

Drastically contrasting with UECE, the second and baseline dataset is an expanded dataset of Xavier *et al.* [1] from a secondary rainforest at the IDSM in Tefé, Brazil. Receiving approximately 2,500 mm of annual rainfall [8], IDSM dataset is dominated by intense biophony (e.g., bird, insect and amphibian vocalizations) and a dense multi-layered canopy that fundamentally alters the acoustic signature of raindrop impacts. Regarding the rain gauges, the IDSM tipping-bucket was set in an open field area 1 m above the ground and approximately 15 m away from the acoustic recorder [1] and the UECE recorder, as shown in Fig. 1, was collocated next to the tipping-bucket on a meteorological tower.

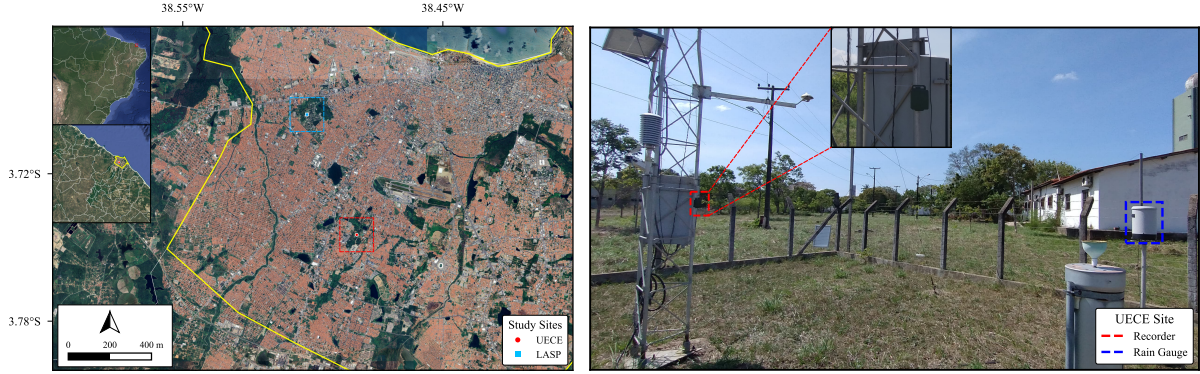


Fig. 1. Location and experimental setup of the primary study area at UECE. The Laboratory of Applied Signal Processing (LASP), where the data analyses were conducted is also indicated. The IDSM measurement site location is available in [1].

Acoustic data were acquired using Song Meter Micro recorders (Wildlife Acoustics, MA, USA; SNR: 73 dB) [1] capturing 1-minute .wav files (16-bits) every 5 minutes. IDSM recordings were downsampled from 48 kHz to 24 kHz, using Python’s *Librosa* library [9], to match UECE’s sample rate. Ground-truth labels were provided by synchronized tipping-bucket rain gauges (0.2 mm resolution) located at the Funceme/UECE automatic weather station. Table I summarizes the hardware and campaign periods. The synchronized acoustic data were categorized according to the World Meteorological Organization (WMO) five distinct classes: No Rain ( $0 \text{ mm}\cdot\text{h}^{-1}$ ), Light ( $< 2.5 \text{ mm}\cdot\text{h}^{-1}$ ), Moderate ( $2.5$  to  $10.0 \text{ mm}\cdot\text{h}^{-1}$ ), Heavy ( $10.0$  to  $50.0 \text{ mm}\cdot\text{h}^{-1}$ ), and Violent ( $> 50.0 \text{ mm}\cdot\text{h}^{-1}$ ).

TABLE I:  
SUMMARY OF STUDY SITES AND HARDWARE CONFIGURATIONS

| Site | Coordinates (S, W)  | Campaign Period | Rain Gauge                     |
|------|---------------------|-----------------|--------------------------------|
| IDSM | 3.35326°, 64.73370° | 02/23 - 01/24   | PluviDB (DualBase, SC, Brazil) |
| UECE | 3.74513°, 38.57811° | 12/24 - 08/25   | Campbell Scientific TB4MM      |

### B. Data curation and signal processing

Organizing a set of raw rainfall audio recordings into a structured ML dataset requires specific processing to handle class imbalances, sensor failures, and labeling inconsistencies, among other issues. As detailed in Table II, the “No Rain” class dominates data in both sites. This imbalance reflects the natural sparsity of precipitation events, where dry periods significantly outlast rainfall [7].

TABLE II:  
OVERALL DATA COMPOSITION OF STUDY SITES  
(TOTAL SAMPLES: 42,013 FOR UECE; 55,838 FOR IDSM).

| Precipitation | Site 1: Semi-Urban (UECE) |           |          | Site 2: Rainforest (IDSM) |           |          |
|---------------|---------------------------|-----------|----------|---------------------------|-----------|----------|
|               | Samples                   | Total (%) | Rain (%) | Samples                   | Total (%) | Rain (%) |
| No Rain       | 29,510                    | 70.24     |          | 50,187                    | 89.88     |          |
| Unlabeled     | 11,587                    | 27.58     |          | 4,217                     | 7.55      |          |
| Light         | 299                       | 0.71      | 32.64    | 517                       | 0.93      | 36.05    |
| Moderate      | 328                       | 0.78      | 35.81    | 591                       | 1.06      | 41.21    |
| Heavy         | 249                       | 0.59      | 27.18    | 262                       | 0.47      | 18.27    |
| Violent       | 40                        | 0.10      | 4.37     | 64                        | 0.11      | 4.46     |
| Total Rain    | 916                       | 2.18      | 100.00   | 1,434                     | 2.57      | 100.00   |

For Site 1 (UECE), the skewed distribution of rainy periods aligns with Fortaleza’s historical climatology. Rare extreme

events ( $> 50.0 \text{ mm}\cdot\text{h}^{-1}$ ) represent only 4.37% of historical occurrences but possess the highest urban impact [2]. This physical sparsity justifies the use of synthetic data augmentation in the subsequent stages of the pipeline.

Instrumentation reliability also impacted data quality, with significant portions marked as “Unlabeled” due to mechanical or data-logging errors. We also identified physical ambiguities in the tipping-bucket mechanism, such as wind-induced false tips and post-event dripping (audible in  $0 \text{ mm}\cdot\text{h}^{-1}$  readings). To ensure dataset integrity, we removed all unlabeled data, conflicting instances, and off-season records (August and December for Site 1). This exclusion did not introduce bias, as the unlabeled data was concentrated in January and December, consisting predominantly of redundant “No Rain” instances. The full curation logic is documented at [10]. Training models on these skewed distributions would lead to the *accuracy paradox*, biasing predictions toward the majority class [6], [11]. Consequently, we developed a multi-stage curation pipeline (Fig. 2). First, we applied random undersampling to the “No Rain” class .wav files to achieve a 1:1 global ratio between dry and wet states. Each site’s balanced dataset (.wav files) was then partitioned via stratified sampling [6] into training (80%), validation (10%), and test (10%) sets to prevent data leakage (see Table III). It is worth noting that the data distributions are constrained by the partitioning rules of *Scikit-learn* [12].

TABLE III:  
SPLIT DATASET COMPOSITION (1-MINUTE .WAV FILES).

| Site | Split      | (%) | No Rain | Light | Moderate | Heavy | Violent |
|------|------------|-----|---------|-------|----------|-------|---------|
| UECE | Train      | 80  | 715     | 239   | 252      | 192   | 32      |
|      | Validation | 10  | 90      | 30    | 31       | 24    | 4       |
|      | Test       | 10  | 89      | 30    | 32       | 24    | 4       |
| IDSM | Train      | 80  | 948     | 352   | 407      | 149   | 40      |
|      | Validation | 10  | 119     | 44    | 51       | 19    | 5       |
|      | Test       | 10  | 119     | 44    | 51       | 19    | 5       |

To increase temporal resolution, we performed deterministic signal segmentation across all splits. Using *Librosa* [9], 1-minute recordings were sliced into 10-second segments with a 50% sliding overlap at a 24kHz sample rate resulting in 1D acoustic arrays for each segment. Crucially, segmenting after the file-level split ensures overlapping segments from the same recording remain within the same split, avoiding temporal data leakage while learning localized acoustic signatures [7].

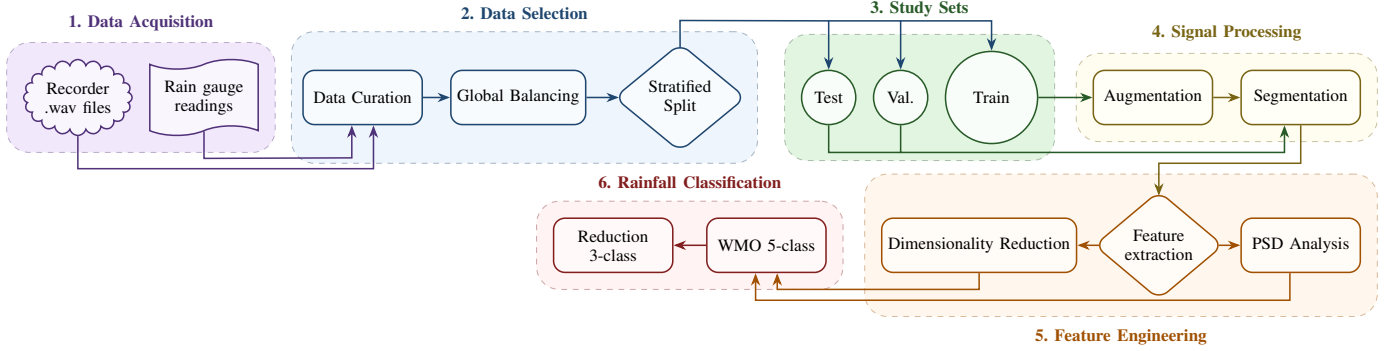


Fig. 2. End-to-end data curation, signal processing, feature engineering and rainfall classification data flow.

Parametric data augmentation was applied exclusively to the training set before segmentation to ensure robust generalization. We implemented an intra-class balancing strategy where all underrepresented rain classes (“Violent”, “Heavy”, and “Light”) were synthetically augmented to match the sample count of the majority rain class ( $N_{max}$ ). Using *NumPy* [13], we applied stochastic transformations to the 1D arrays to prevent overfitting and simulate physical conditions like wind-induced acoustic attenuation. These included randomized circular time shifts, dynamic gain scaling ( $0.7\times$  to  $1.2\times$ ), a 20% probability of additive Gaussian noise ( $\sigma$  between 0.1% to 2% max amplitude), and a 30% probability of a 100 ms random cutout.

Table IV details the composition of the final dataset. In the training partitions, the rain classes were balanced to be equiprobable, which increased the total volume of rain samples and shifted the initial 1:1 ratio relative to the “No rain” class. This expansion also caused a slight deviation from the original 80/10/10 split. Crucially, the validation and test sets remained unaugmented, preserving the 1:1 “No Rain” to “Rain” baseline to ensure an unbiased evaluation of model performance. Detailed sample counts for all processing stages are provided in [10].

 TABLE IV:  
FINAL DATASET COMPOSITION (10-SECOND SEGMENTS).

| Site  | Split      | (%) | No Rain | Light | Moderate | Heavy | Violent |
|-------|------------|-----|---------|-------|----------|-------|---------|
| UECE  | Train      | 83  | 7,865   | 2,772 | 2,772    | 2,772 | 2,772   |
|       | Validation | 9   | 990     | 330   | 341      | 264   | 44      |
|       | Test       | 9   | 979     | 330   | 352      | 264   | 44      |
| IDSMS | Train      | 84  | 10,423  | 4,477 | 4,477    | 4,477 | 4,477   |
|       | Validation | 8   | 1,309   | 484   | 561      | 209   | 55      |
|       | Test       | 8   | 1,309   | 484   | 561      | 209   | 55      |

### C. Feature engineering and rainfall classification

As there is no established consensus on which acoustic indicators best characterise rainfall intensity, we adopted an exploratory approach. We extracted 102 off-the-shelf acoustic metrics from each segment using *scikit-maad* [14], *Librosa* [9], *PyWavelets* [15], *NumPy* [13] and *SciPy* [16] libraries. This high-dimensional feature space encompasses ecoacoustic indices (e.g., ACI, ADI, NDSI), spectral moments, Mel-Frequency Cepstral Coefficients (MFCCs) and multi-resolution wavelet decompositions. To reduce dimensionality

and isolate the most discriminative metrics, we implemented a two-stage empirical selection workflow: (i) calculation of ANOVA F-value (ANFV), using only the training data, to identify the 10 features with the greatest statistical separation between classes; and (ii) combinatorial testing of these leading metrics to determine the smallest subset that maximises Macro F1-Score (MF1S). Due to space constraints, the complete list of extracted metrics, the specific feature subsets, and the hyperparameters are available at our repository [10] to ensure full reproducibility.

To evaluate the proposed pipeline, we established a comparative experimental matrix. First, a baseline model trained exclusively on PSD was implemented to benchmark our approach against Xavier’s methodology [1]. Second, we tested two distinct classification strategies. The first consists of a five-class scheme that encompasses all WMO precipitation categories. The second strategy adopts a reduced three-class scheme, in which adjacent intermediate categories were merged: the heavy and violent classes were grouped into the *heavy* category, while light and moderate were combined into the *moderate* category.

The initial evaluation included linear and gradient-based models (Stochastic Gradient Descent (SGD) and Logistic Regression (LR)). However, given the non-linear transitions between intensities, we also evaluated tree-based ensembles, RF and XGB [6]. Despite the robustness of these algorithms, bioacoustic literature suggests that the acoustic signature of rain is heavily dependent on the surface material and the environment [4]. Our analysis found that the SVM model yielded the best *F1-macro* results, as its kernel-based approach better accommodated the decision boundaries of each soundscape. Notably, the optimal SVM configuration (Nu-SVC, Poly kernel,  $degree = 3$ ,  $\nu = 0.5$ ) was identical for both sites, with full hyperparameter grids detailed in [10].

Finally, due to the natural class imbalance in rainfall data (Section II-B), accuracy was discarded as a primary metric [6]. Instead, model comparison was based on MF1S, while Precision-Recall Area Under the Curve (PR-AUC) was used to assess the classification of minority classes, such as “Violent” rain. The end-to-end data flow is illustrated in Fig. 2.

## III. RESULTS AND DISCUSSION

Before presenting the data, it is worth highlighting the steps that preceded the final classification. Initially, a dimensionality

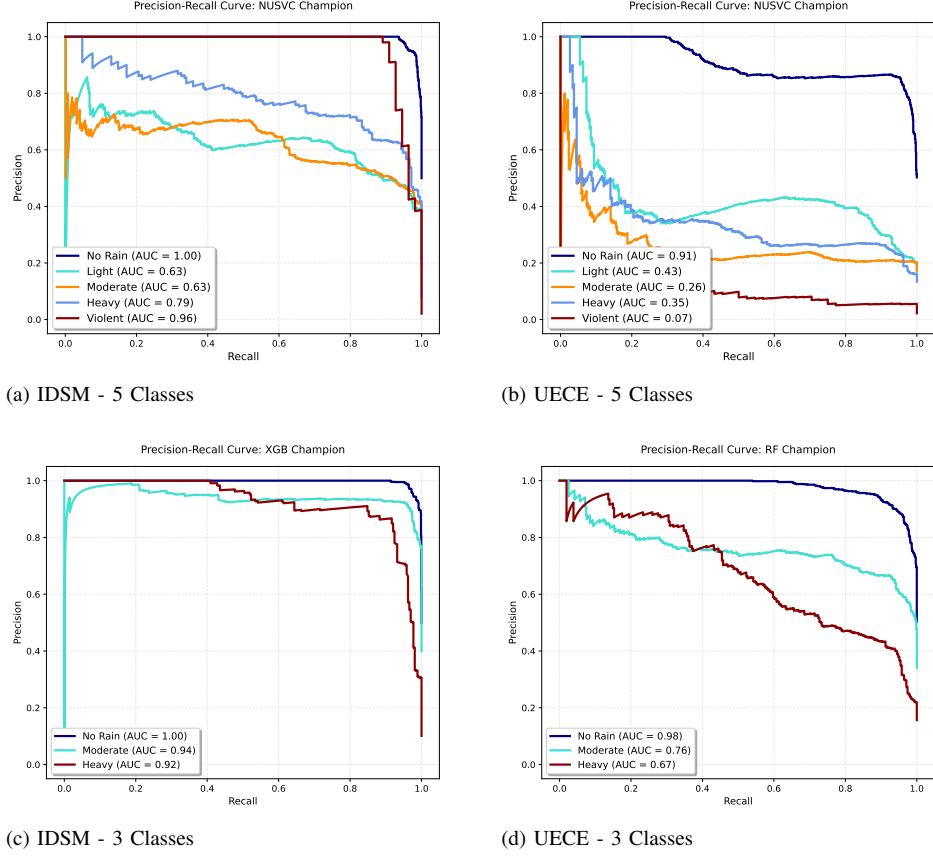


Fig. 3. Precision-Recall curves for the 5-class and 3-class scenarios in the IDSM and UECE environments.

 TABLE V:  
CONFUSION MATRIX RESULTS FOR 5-CLASS AND 3-CLASS SCENARIOS.

| True Class       | Predicted (%) |       |          |       |         |
|------------------|---------------|-------|----------|-------|---------|
|                  | No Rain       | Light | Moderate | Heavy | Violent |
| IDSM - 5 Classes |               |       |          |       |         |
| No Rain          | 89.38         | 9.01  | 1.60     | 0.00  | 0.00    |
| Light            | 0.00          | 47.52 | 51.45    | 1.03  | 0.00    |
| Moderate         | 0.00          | 18.72 | 70.94    | 10.34 | 0.00    |
| Heavy            | 0.00          | 11.00 | 10.05    | 78.95 | 0.00    |
| Violent          | 0.00          | 0.00  | 0.00     | 30.91 | 69.09   |
| UECE - 5 Classes |               |       |          |       |         |
| No Rain          | 99.80         | 0.00  | 0.20     | 0.00  | 0.00    |
| Light            | 62.12         | 16.06 | 6.67     | 15.15 | 0.00    |
| Moderate         | 42.23         | 13.78 | 14.96    | 28.15 | 0.88    |
| Heavy            | 31.44         | 5.30  | 26.89    | 25.76 | 10.61   |
| Violent          | 2.27          | 15.91 | 29.55    | 52.27 | 0.00    |
| IDSM - 3 Classes |               |       |          |       |         |
| No Rain          | 95.19         | 4.81  |          | 0.0   |         |
| Moderate         | 0.67          | 95.79 |          | 3.54  |         |
| Heavy            | 0.00          | 8.33  |          | 91.67 |         |
| UECE - 3 Classes |               |       |          |       |         |
| No Rain          | 96.06         | 3.13  |          | 0.81  |         |
| Moderate         | 19.82         | 65.13 |          | 15.05 |         |
| Heavy            | 4.55          | 36.04 |          | 59.42 |         |

reduction strategy using ANOVA was applied, followed by hyperparameter optimisation. Subsequently, an exhaustive search was carried out, considering 1,023 combinations of the best selected metrics. For the analyses discussed in this

section, only the best-performing scenario achieved by each classifier was considered.

Initially, analysis of the results for the five classes showed that the dimensionality reduction strategy, combined with the isolation of the most discriminative features, led to a significant improvement in performance. When compared to the exclusive use of the PSD in [1], the proposed model achieved significant improvements for the XGB and RF classifiers, as detailed in Table VI.

 TABLE VI:  
RESULTS COMPARISON OF THE EVALUATED METHODOLOGIES  
(MACRO-AVERAGE).

| Site | Model              | F1    | PR-AUC | Precision | Recall | Accuracy |
|------|--------------------|-------|--------|-----------|--------|----------|
| UECE | RF (our strategy)  | 46.3% | 44.7%  | 46.2%     | 48.5%  | 64.9%    |
|      | RF (PSD only)      | 30.5% | 30.8%  | 32.1%     | 35.7%  | 41.8%    |
|      | XGB (our strategy) | 44.5% | 42.8%  | 45.2%     | 46.2%  | 65.1%    |
|      | XGB (PSD only)     | 18.7% | 31.4%  | 32.3%     | 27.9%  | 46.9%    |
| IDSM | RF (our strategy)  | 74.9% | 81.3%  | 72.6%     | 79.8%  | 80.9%    |
|      | RF (PSD only)      | 47.9% | 48.9%  | 46.4%     | 60.5%  | 53.2%    |
|      | XGB (our strategy) | 73.4% | 79.5%  | 71.3%     | 78.3%  | 80.5%    |
|      | XGB (PSD only)     | 47.3% | 50.9%  | 44.4%     | 59.1%  | 54.5%    |

In the subsequent phase, the effectiveness of feature engineering combined with automated hyperparameter optimization was evaluated across three different classifiers. The objective was to determine which algorithm would yield the best performance in classifying the five rainfall categories. Initially, the SVM emerged as the superior model in both evaluated environments, with the detailed five-class results presented in Table VII.

TABLE VII:  
RESULTS OF COMPARING THE CLASSIFICATION MODELS - 5 CLASS  
(MACRO-AVERAGE).

| Site | Model | F1    | PR-AUC | Precision | Recall | Accuracy |
|------|-------|-------|--------|-----------|--------|----------|
| UECE | RF    | 46.3% | 44.7%  | 46.2%     | 48.5%  | 64.9%    |
|      | XGB   | 44.5% | 42.8%  | 45.2%     | 46.2%  | 65.1%    |
|      | SVM   | 45.4% | 46.9%  | 47.9%     | 45.8%  | 65.9%    |
| IDSM | RF    | 74.9% | 81.3%  | 72.6%     | 79.8%  | 80.9%    |
|      | XGB   | 73.4% | 79.5%  | 71.3%     | 78.3%  | 80.5%    |
|      | SVM   | 81.6% | 78.8%  | 80.9%     | 83.4%  | 83.4%    |

However, due to the specific acoustic challenges of the UECE dataset, classifiers confused adjacent classes (*heavy-violent* and *light-moderate*), as factors such as wind and city noise masked the physical boundaries of the sound of rain. To improve robustness, these intermediate classes were merged (*light+moderate*  $\rightarrow$  *moderate* and *heavy+violent*  $\rightarrow$  *heavy*), reducing the problem to a three-class scenario. Under this reduced assumption, although the SVM showed performance gains, it was ultimately outperformed in both environments. Specifically, the RF classifier achieved the most significant improvements on the UECE dataset, while the XGB stood out on the IDSM dataset, with each emerging as the best model for the three-class configuration in their respective environments. The overall performance metrics for the three-class scenario are presented in Table VIII. For a more in-depth analysis of hits and misses, Table V details the confusion matrices comparing the 3-class and 5-class approaches, and their respective PR-AUC curves can be viewed in Fig. 3.

TABLE VIII:  
RESULTS OF COMPARING THE CLASSIFICATION MODELS - 3 CLASS  
(MACRO-AVERAGE).

| Site | Model | F1    | PR-AUC | Precision | Recall | Accuracy |
|------|-------|-------|--------|-----------|--------|----------|
| UECE | RF    | 75.2% | 80.6%  | 75.9%     | 74.6%  | 80.5%    |
|      | XGB   | 74.9% | 78.3%  | 77.0%     | 73.6%  | 79.9%    |
|      | SVM   | 73.4% | 76.6%  | 75.1%     | 72.3%  | 79.3%    |
| IDSM | RF    | 92.2% | 94.9%  | 91.4%     | 94.6%  | 94.8%    |
|      | XGB   | 93.4% | 95.4%  | 92.8%     | 94.2%  | 95.0%    |
|      | SVM   | 88.1% | 84.9%  | 88.5%     | 88.2%  | 92.7%    |

In summary, the comparative analysis between the two scenarios highlights the greater classification complexity associated with the UECE environment. This behaviour is attributed to the open-field propagation conditions (semi-urban area) and the 24 kHz sampling rate used in signal acquisition. In contrast, the IDSM environment, having no such technical constraints, achieved significantly better performance. It is observed that the data quality in the UECE scenario imposed a limitation on the learning process, resulting in very similar metrics across all the classifiers evaluated. Further details regarding the source code used to generate the results, the confusion matrices for the experiments, and the PR-AUC plots can be found in [10].

#### IV. CONCLUSION

Accurate precipitation monitoring remains a critical challenge for tropical urban centers, where extreme rainfall frequently overwhelms drainage infrastructure and triggers severe socio-environmental risks. Traditional meteorological

instruments often lack the micro-local resolution or cost-efficiency required for dense urban deployment. By validating the acoustic processing pipeline in two environments, this study demonstrates that opportunistic sensing fills analysis gaps. Expanding to a 102-dimensional feature space, coupled with site-specific dimensionality reduction (retaining 10 features) and simplification to 3 classes, allowed the models to isolate rain signals amidst intense noise. Our strategy achieved F1-Scores of 93.4% using XGB for IDSM and 75.2% using RF for UECE, proving its effectiveness against the complex challenges of the dataset. Furthermore, in the 3-class scenario, the models achieved maximum accuracies of 95.0% and 80.5% in the forest and urban environments, respectively. Ultimately, this framework demonstrates that machine learning applied to acoustic data can provide insightful meteorological information in regions lacking conventional infrastructure. Future research shall explore the implementation of a cascade classification framework and anomaly detection techniques to evaluate potential improvements in overall classification performance, as well as shall address aspects related to computational complexity for cloud and edge computing implementations of these methods.

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