# 1 BACKGROUND: ML ALGORITHMS AND FEATURE EXTRACTION

A variety of recent work has studied classification of environmental sounds using machine learning analysis of audio data collected by embedded devices [6–8], including detection of rain [1, 3–5]. This previous work has considered a menagerie of ML algorithms, from SVMs and decision tree architectures [3, 5, 8] to neural networks [1, 7], as well as statistical (e.g., Bayesian) analysis [1, 8].

## 1.1 Feature Extraction

Prior to algorithm choices, a primary consideration in any machine learning analysis of audio data is feature extraction. Electronic formats for sound- e.g., .wav- record audio as time series data. These recordings themselves and other aggregate data directly extracted from it, such as zero crossing rate (ZCR) and root mean squared energy (RMSE), are generally termed *time domain* audio data. Time domain data is also commonly cast into the *frequency domain* as a *spectogram* via Fourier transformation, especially as a Mel spectogram. Additional manipulation of the Mel spectogram obtains frequency domain features in the form of Mel-frequency cepstral coefficients (MFCCs), which are a dominant feature in ML analysis of audio data.

Both time and frequency domain audio features have been used in previous related work. Features of most effective models for rainfall detection [1–3] include the following:

- F1. Mel-frequency Cepstral Coefficients (MFCCs)
- F2. First Autocorrelation Coefficient (ACC)
- F3. Zero Crossing Rate (ZCR)
- F4. Temporal and Spectoral Entropy Indices ($H_t$ and $H_f$)
- F5. Acoustic Complexity Index (ACI)
- F6. Background Noise (BgN)
- F7. Spectral Cover (SC)

The way these features are used varies significantly depending on the approach. A variety of work has focused on MFCCs, especially neural network based approaches [1, 2]. Approaches using simpler modeling algorithms, such as SVMs and Decision trees, have used F3-F7 [3]. And statistical analysis in previous work "shows the possibility of being able to clearly discriminate all levels of rainfall intensity through the parameters of zero crossing rate and first autocorrelation coefficient" (F1 and F2) [1]. Some related work in environmental sound classification has also considered sophisticated combinations of time- and frequency-domain features , so-called joint signal analysis, to obtain better model performance [6].

Some more recent work has leveraged the power of deep learning to more directly and automatically extract features from "raw" spectograms. This includes approaches to rain detection where the spectogram itself is the feature set [1], and approaches to general environemental sound classification where neural networks are used to automatically extract features from spectograms [6].

## 1.2 ML Algorithms and Performance

Earlier work on rain detection from acoustic signals considered simple ML algorithms such as SVMs and decision trees [3]. Later work, both in rain detection and environmental sound detection more generally, has considered ensemble methods and boosting [6, 8]. As in many other areas, interest has recently grown in neural network approaches to modeling [1, 2, 6], particularly CNNs.

Interestingly, none of these methods seems to significantly outperform the earliest work on rainfall prediction [3] using SVM classifiers and features F3-F7, where accuracy of 93% was achieved, though competitive baseline performance metrics have been reported for essentially all of the previous work discussed so far. More recent work using neural network models has made some contextual advancements, for example successful integration with a low-cost, low-power embedded system [2], and rain detection in challenging urban environments [8].

## 2 RESEARCH PLAN: ML ALGORITHMS AND FEATURE EXTRACTION

Previous approaches to predicting rain using ML analysis of audio data show that the general approach is promising. However, our intended application has several novel aspects and system constraints. Previous related approaches have considered detection of rain events, or rain events amidst a host of other sound classifications in urban settings. But we are interested in the more general problem of precipation phase detection, and operating in remote, alpine settings. And while there has been previous work on the integration rain detection analysis with low-cost embedded systems for audio data collection [2, 5], these works have not considered ML in the edge- i.e., embedding the full process of data collection, feature extraction, and model classification on a low-cost, low-powered platform. We hypothesize that implementing the full detection workflow on-device will be more feasible than communicating streams of audio data over radio for analysis in the system back end.

Thus, with respect to ML algorithm and feature selection, we can't adapt existing models for precipation phase detection from acoustic data. And the computational and power characteristics of our application space recommend the use of simpler ML models. The Arduino platform can easily support implementations of decision trees, including ensembles and even boosting. However implementation of neural networks in low-cost embedded systems is currently a challenge. TensorFlow Lite has been developed for edge devices, for example, but it is only available on one Arduino platform that is not available for purchase at the time of this writing. While implementation on, e.g., embedded Linux platforms would be feasible, this would entail an order of magnitude greater power consumption.

### 2.1 Machine Learning Experiments

We will evaluate SVM, Random Forest (RF), and boosted decision tree (XGBoost) architectures, as well as ensembles of these architectures. We will focus on models using features F1-F7. We evaluate both feature importance of F1-F7, and evaluate performance of models in terms of accuracy and ROC metrics. In our initial exploration we will use the dataset we developed for simulated rainfall and sleet at different intensities.

## REFERENCES


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