

# SoundCatcher: Acoustic Emission with Machine Learning for Root Cause Analysis of Complaint Devices

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## Abstract

Acoustic Emission (AE) profiles, in combination with machine learning (ML) algorithms, can provide valuable quality related information for inhalation devices and formulations. Here, the technique applicability is extended to patient complaint analysis. Acoustic profiles were collected from Dry Powder Inhalers (DPIs) with simulated patient failure modes using an automated delivered dose analytical platform. The acquired AE data was analysed using different ML algorithms including orthogonal projections to latent structures (OPLS) and convolutional neural networks (CNN). Using this approach, ML accurately predicted the level of applied powder residue on internal surfaces of the inhaler device with up to 85% accuracy based on the AE profiles of 123 inhalers. At higher residue levels (>10 mg), the model could also distinguish between the relative position with an accuracy of above 85%. Based on these results, the models developed were applied on a set of 6 devices with unknown and challenging simulated residue levels, giving an accuracy of around 75%. The overall conclusion is that AE combined with ML is a non-destructive analytical approach with the potential of providing valuable information when assessing the root cause for complaint sample returns. Long term, the hope is for the methodology to be evaluated on other device platforms to generalise the approach.

## Introduction

- Currently, few non-invasive techniques exist for analysis of device quality complaints caused by for instance residue buildup inside DPI inhalers
- This work aimed to assess if acoustic emission (AE) and Machine Learning (ML) can be used to detect the root cause of the failure modes leading to complaints – enabling an enhanced response letter to patients

## Methods

- Lactose particles (two levels; low < 5mg, high > 10 mg) were glued in one of three positions inside 120 DPI devices to simulate patient failure modes associated with powder residue buildup.
- Air was purged through the devices at a flowrate of 55 LPM and the acoustic profile collected using an automated analysis platform
- The collected raw audio was manually trimmed to be 4s after onset of the signal.
- Using a Python script developed in-house the raw audio files were transformed into acoustic profiles (MEL/SPEC) using a short time fourier transform.
- Collected AE profiles were analysed using OPLS-DA and CNN machine learning algorithms to determine if one could distinguish between;
  1. Devices with or without lactose residue
  2. The level of residue glued inside device
  3. Where in the device residue is stuck
- For details on AE modelling approaches, refer to [3].

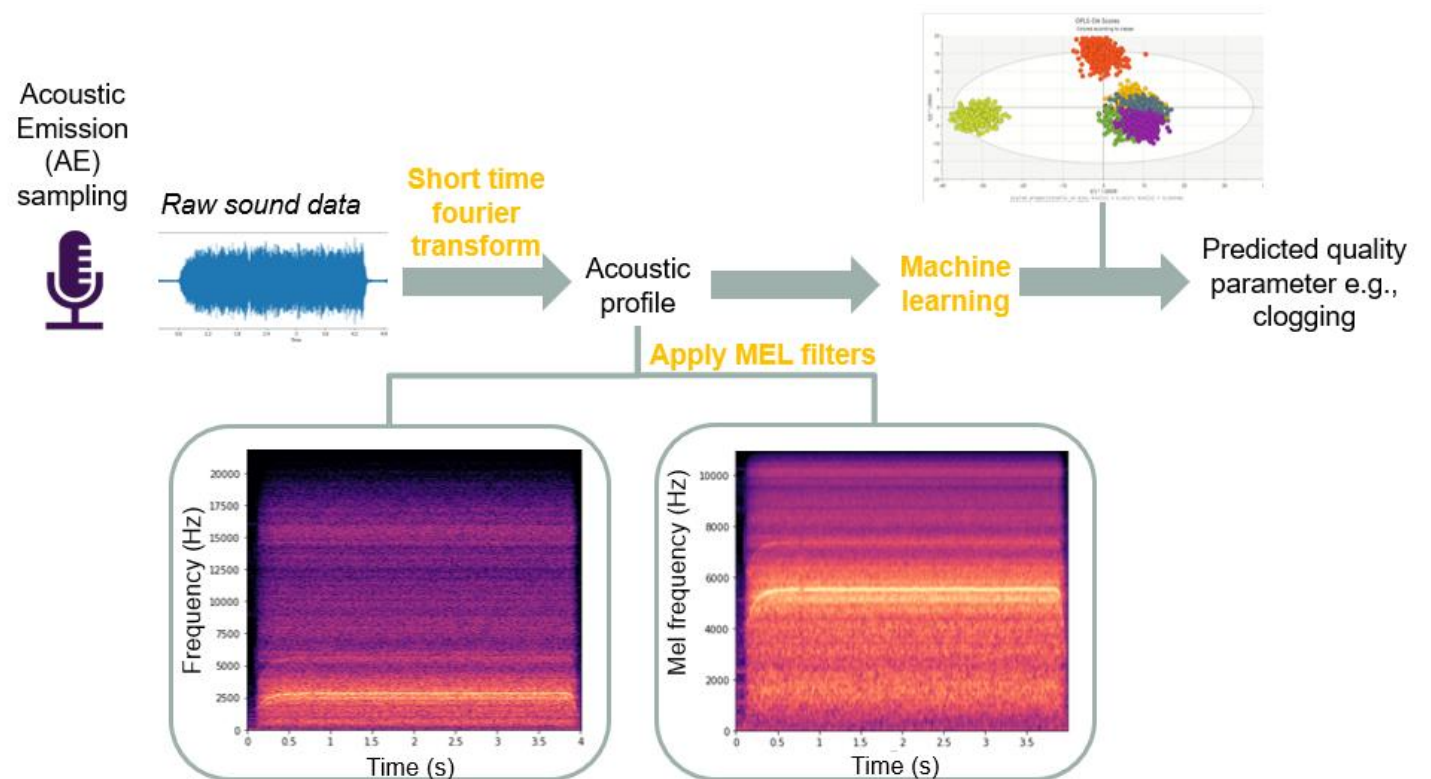


Figure 1. The SoundCatcher tool process for device complaint samples analysis.

## Results

### OPLS-DA screening

OPLS-DA illustrates the feasibility of using AE to detect particles on internal surfaces of DPIs where;

1. OPLS-DA differentiates between AE profiles in simulated failure modes and the reference
2. Higher components/dimensions showing variations between simulated patient failure modes
3. Indications of a non-linear relationship observed looking at residue level

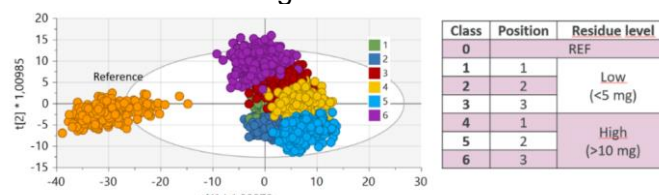


Figure 2. OPLS-DA screening of manipulated configurations and unmanipulated references.

### CNN modelling

The best result in terms of predicting level/amount and position of the residue buildup inside the manipulated DPIs was achieved when using the CNN approach in combination with the MEL spectrograms – see Figure 3. The level of residue is easiest to differentiate, with an accuracy of above 90%, while this drops to around 70% if position predictions are added. If devices with particles glued in position 1 (being most difficult to accurately predict) is removed, the accuracy increases to above 90%. If the flow is increased from 55 to 65 LPM, the accuracy remained fairly constant.

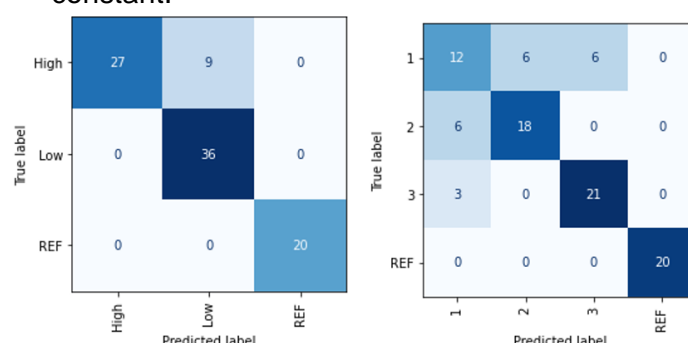


Figure 3. CNN predatory performance illustrated via confusion matrices of the attributes amount of residue (left), and position (right). True label = True manipulation class, Predicted label = Manipulation class predicted by the model. Acoustic data obtained at 55 LPM. For algorithm details see [3].

Device	Position	Level
67	3	Low 4.65mg
87	2	High 15.91 mg
107	2	Low 2.79mg
127	3	High 16.09mg
147	1	Low 2.85mg
167	1	High 16.38mg

Table 1: Predictions of unknown samples. Green = Correct, Red = Not correct.

### Prediction failure modes in unknowns

In an exercise to further challenge the model, 6 devices of unknown (to the analyst) configurations were also analysed at the same experimental conditions as for building the model. The resulting predictions are shown in Table 1. Here, 9 out of 12 manipulations were determined correctly by the model, with, as expected, the accuracy for the level of residue being higher.

## Conclusions

- AE profiles combined with machine learning algorithms can differentiate powder residue levels in inhalers from clean reference inhalers, as well as identifying the level of residue and the relative position of built-up particles.
- The method is non-invasive and has high sensitivity for detecting residue levels even below those generating an effect on the pressure drop across the inhaler.

## References

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