# Introduction

Community noise flight testing for aircraft noise certification requires extensive equipment and personnel to achieve efficient and effective results. The certification requirements are regulated by government agencies such as the Federal Aviation Administration (FAA) in the United States with FARS Part 36 (REF), the European Aviation Safety Agency in the European Union with ICAO Annex 16 (REF), and the Civil Aviation Administration of China in the People’s Republic of China. The required flight testing involves flying a test aircraft at low altitude over a test site, typically a rural airport. A site at the end of the runway is instrumented with acoustic sensors to record the noise levels of the aircraft during a flyover. The noise data are recorded for various configurations comprised of different airframe configurations and engine power settings to simulated take-off, approach, and landing noise levels. The noise data are processed for comparison to the allowable limits established by the regulations where exceeding the limits risks failing the certification test.

To ensure the best possible data for the noise certification tests, aircraft companies seek test sites with low background or ambient noise levels. In addition, test personal may be assigned to monitor the microphone signals for noise contamination that would increase the measured and recorded noise levels of the aircraft. Typical sources of the environmental noise contamination include bird chirps and other wildlife/livestock vocalizations, insect noises, the sound of traffic, and aircraft sounds from flights other than the test airplane. The noise monitors can alert testing staff to the presence of noise contamination such that corrective action can be taken. These actions include voiding the condition and requesting a repeat run, requesting a delay in the arrival of the test aircraft, and proactive removal of biological sources. This approach is costly due to:

* Travel costs for the monitors.
* Specialized workstation computers and software for the monitoring workstations.
* Storage, shipping, setup, and networking support for the workstation computers.
* Validation and testing of the analysis applications, especially the communications with other data acquisition systems at the test.

Also, human monitors can be subjected to:

* Mental fatigue of the monitors from the repetitive menial task, resulting in a reduction of the quality and consistency of the classification over time.
* Inconsistencies and subjectivities of the classification from monitor to monitor.
* Limited ability or knowledge to accurately account for noise contamination corrections available to analysis staff at post-acquisition data reduction.
* Limited post-test review opportunities for training and enhancements.

An automated system is desired that can minimize the costs and overcome the limitations of the existing solution. The goal of the automated monitoring system would be to detect, or classify, the presence of environmental noise contamination in the acoustic signals as they are acquired. Furthermore, from that classification, it would also provide guidance whether the contamination has corrupted the data, whether the flight condition should be repeated, or to react and remove the noise sources before the airplane is on-condition and thus avoid repeating the condition. The work presented here is limited to the first step in the creation of such an automated system by studying the feasibility of machine learning algorithms to detect biological noise contamination is recorded acoustic signals that contain only ambient noise and aircraft noise. Thus, this work is limited to creating and evaluating different feature sets derived from the signals and supervised classification algorithms on recorded data. The fully developed automated system would remove the need for the multiple work stations and staff providing significant cost reductions for the community noise fly-over capability. The automated system also could provide increased accuracy and consistency of the classification thus increased efficacy of the test for further significant cost reductions. The detector should alert community noise test crews of the presence of environmental noise contamination continually, in real-time, allowing them to respond by either removing the sources from the measurement area before the arrival of the airplane or by declaring the on-condition recording out of tolerance and requesting a repeat of the condition

The remainder of this paper is outlined as follows. The next section describes overall process of creating a machine learning algorithm for contamination detection including the signal processing algorithms for feature generation and lists the machine learning algorithms investigate here. This is followed by a description of example aircraft flyover noise and contamination noise recordings used to train and test the detection algorithms. Then a discussion the results of detection algorithms on the example data is provided. Finally, this paper finishes with a discussion of conclusions of the results and recommendations for additional work.

# Methods (Procedure?)

(Including previous work)

## Any signal preprocessing

## Feature creation

## Algorithm training and testing

Use cross-validation to estimate the performance

Metrics: accuracy, false-positive rate, false-negative rate (confusion matrix)

## Steps

Load data files

Apply any preprocessing

Execute selected feature creation routine

Train selected machine learning algorithm

Record algorithm performance (confusion matrix, accuracy)

# Data

49 aircraft flyover signatures, 10 ambient signatures, and 7 contamination signatures provided by Boeing

Boeing Test & Evaluation provided 49 aircraft flyover signatures, seven contamination signatures, and 10 ambient signature recordings in standard wave file format. All data were recorded on scientific grade instrumentation with a usable bandwidth from 5 Hz to 20 kHz with a sampling rate of 51.2 kHz. Aircraft consisted of turboprop and turbofan aircraft used for commercial flights such as the Bombardier Q400 turboprop, the Boeing 737, the Airbus A350 and others. All aircraft recording were individually reviewed and trimmed to only include the portion of the recording with an audible aircraft noise signature without any contamination. The ambient recordings were individually review to ensure no contamination or other noise sources were present. The contamination signals were individually reviewed and trimmed to only include the portion of the recordings with an audible contamination signature such as a bird call or road noise. All recordings from Boeing Test & Evaluation were anonymized by normalization by an unknown factor to make the absolute noise levels meaningless and labeled only as turboprop, turbofan, contamination, and ambient.

Six additional contamination recordings of wildlife vocalizations from the National Parks Service (NPS) provided as public domain data are added to the data set to provide a greater variety of contamination examples. The original recordings from the National Parks Service are provided in the mp3 file format. The recordings included crickets, bison, common raven, sparrow, Steller’s jay, and yellow-rumped warbler vocalizations and were simple audio recording with no known information about the calibration of the recording instrumentation. The Steller’s jay signature was recorded at a sampling rate of 16 kHz and the remaining five were recorded at 44.1 kHz. All of the NPS data is resampled to match the sampling rate of the aircraft signatures provided from Boeing Test & Evaluation.

Describe how signals where split into test blocks (each test block is an observation is statistical terminology)

Describing process of creating contaminated signals

Superimposed contamination signals on aircraft signals digitally

Controlled the signal to noise ratio on a block by block basis

# Results

Investigated feature and model performance in two phases

1. Broad investigation of widely varying feature sets and model types
2. Deep investigation of the top 2 or 3 models from previous phase

The broad investigation is designed to gather information regarding the general performance of various feature sets and models without extensive hyperparameter optimization or robustness testing with the goal being to down select the top 2 or 3 performing models to continue to study and characterize. The deep investigation is meant to optimize various hyperparameters and stress test the models for various simulated situations that could occur.

# Conclusions

Summarize test cases considered

What worked, what didn’t

What would we recommend?

Next steps, future work

Any other algorithms to consider

Deeper exploration of parameter values for the methods that worked

How to address moving to streaming or online predictions for aircraft flyover use case

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# References

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