Machine Learning for Acoustic Anomaly Detection

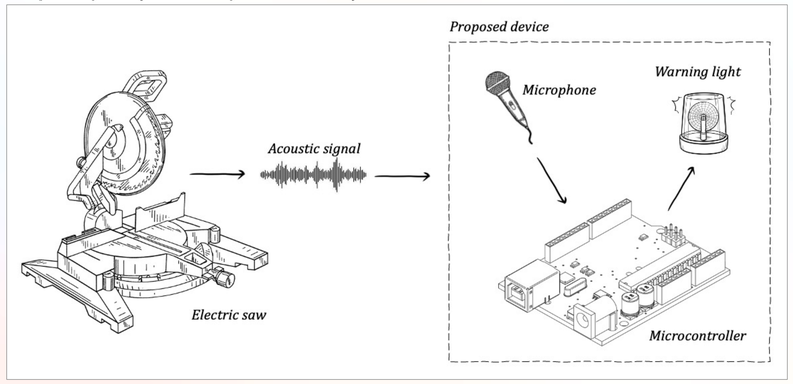
Alex Renaudin

Introduction

Ensuring user safety during power saw use is an important, yet inherently difficult, task. Machinery faults are primarily identified aurally by the trained ear of the human operator. However, this relies on operator experience without room for human error. Thus, the question was posed:

How can machine learning automate acoustic anomaly detection?

Proposed system functionality to warn user of anomalous saw behaviour

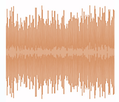


Project Description

- Existing work using machine learning for acoustic fault detection focuses largely on automotive applications.
- Very few models are deployed and tested in the field.
- The aim is to develop a machine learning solution to perform acoustic anomaly detection on an electric saw.
- The machine learning model needs to successfully classify the two types (classes) of saw cuts.
- A deployable microcontroller solution is proposed.

Class 1: Satisfactory

Class 2: Anomalous



Gantt chart of project timeline showing key stages

No.	Stage	Semester 1					Semester 2		
		Mar	Apr	May	Jun	Jul	Aug	Sep	Oct
1	Literature review								
2	Research proposal								
3	Data acquisition								
4	Feature extraction								
5	Model development								
6	Model testing								
7	Results & reporting								

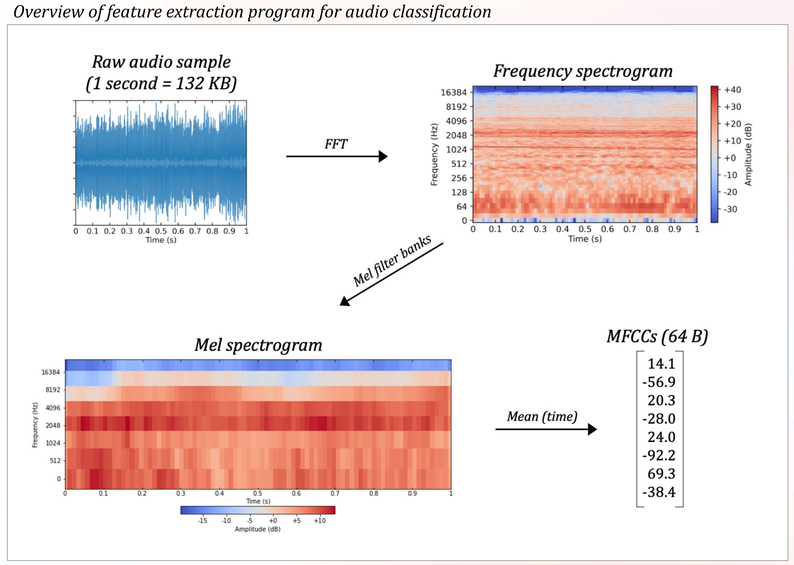
Midyear break

Dataset & Feature Extraction

A novel dataset was needed train the model, which was collected experimentally via field recordings of the saw. A custom program was developed to process the audio and extract key features, thus reducing the size and complexity of the raw data.

The feature extraction program pre-processes the audio into second-long clips and converts the signal into the frequency domain via a fast Fourier transform. Then, the Mel frequency cepstrum coefficient (MFCC) algorithm is employed, which utilises mathematical transforms to represent the audio as a compact numerical array.

Overview of feature extraction program for audio classification



Results

- Collected a high-quality experimental dataset of saw cut audio recordings.
- Dataset includes strong representation of anomalous samples (18%).
- Development of a custom feature extraction program to characterise audio.
- Three types of machine learning architectures explored:
  1. Support Vector Machine (SVM)
  2. K-Nearest Neighbours (KNN)
  3. Linear Classifier
- Final model using SVM algorithm with 20% testing split on dataset.
- Iterative optimisation of both programs to improve overall performance.
- Investigated deployment using Arduino and Raspberry Pi microcontrollers.

Model Performance

Model performance was averaged over 1000 runs and assessed by the following:

- **Accuracy** – percentage of correct predictions.
- **Precision** – accuracy of positive predictions.
- **Recall** – proportion of actual positives identified.
- **F1 score** – measure of both precision and recall.

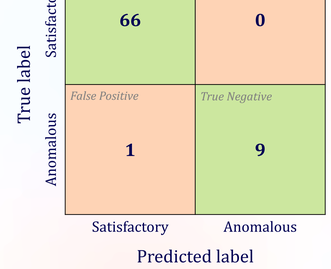
Average **overall model accuracy was 97.98%** with a standard deviation of 1.48%.

Class	Precision (%)	Recall (%)	F1 score (%)	Support (samples)
Satisfactory	98.14	96.90	98.84	66
Anomalous	99.57	87.48	91.52	10

SVM Python program output

```
Running 1000 SVM models with a 20% split...

Complete! Mean model performance metrics:

   Size of dataset          = 377 samples
   Overall accuracy         = 97.98%
   Standard deviation       = 1.48%

   Satisfactory: Precision = 98.14%
                 Recall    = 96.90%
                 F1 score  = 98.84%
                 Support   = 66 samples

   Anomalous:    Precision = 99.57%
                 Recall    = 87.48%
                 F1 score  = 91.52%
                 Support   = 10 samples
```

SVM Confusion Matrix



Conclusions

Overall, the SVM model demonstrated strong performance in identifying anomalous saw cuts, suggesting high suitability for safety and maintenance applications. Deployment onto a microcontroller was ultimately unsuccessful due to budget and time constraints, however, this remains a promising opportunity for future work.

Some areas of weakness and/or difficulty included:

- Model installation was unsuccessful on Raspberry Pi MCU.
- Slightly inferior performance classifying anomalous samples as compared to satisfactory samples.
- Results may not be extendable to different saw set-ups due to dataset homogeneity.

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