National Nuclear Security Administration

Application of Machine Learning on Side Channel Data streams from Advanced Machining Process

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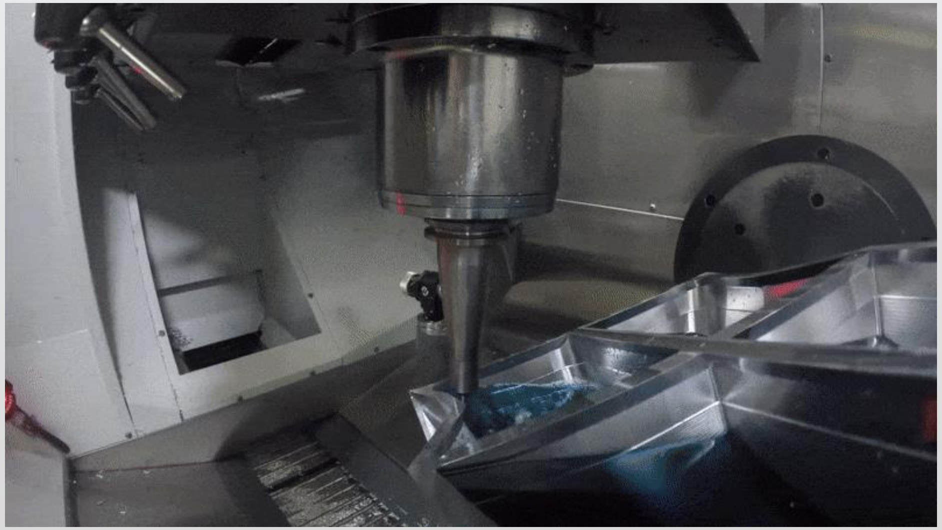
Georgia Tech College of Engineering
George W. Woodruff School of Mechanical Engineering

Consortium for Enabling Technologies & Innovation

Introduction and Motivation

- CNC machining is a very important part of the manufacturing industry
  - Advanced manufacturing technique
  - Allows for complex parts with tight tolerances
- Makerspaces have grown in popularity
  - Provide tools and equipment to non-professional user base for projects
  - Interest in providing variety of manufacturing techniques, so beneficial to include CNC



https://cloudnc.com/cnc-best-practices-3-whats-the-difference-between-3-axis-4-axis-5-axis-milling/

https://trulifeengineeredsolutions.com/products/defense/

https://www.productivity.com/do-more-with-less-5-axis-machining/

https://www.emachineshop.com/sample-parts/

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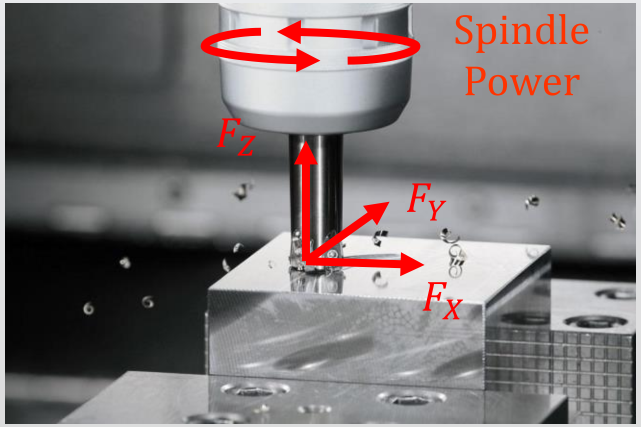
Introduction and Motivation

- Learning to use a CNC machine is difficult
  - Many parameters to define; ideal settings are learned through exhaustive training AND experience
- Staff must dedicate much time to training, watching new users
  - Risk of damage to machine or people
  - Time lost in repairs
- Seek to make makerspaces safer/more efficient by **making CNC easier to learn**
  - Offer feedback about parameter selection
  - Feedback generated through machine learning (ML) models
    - Models classify cut aggressiveness

Introduction and Motivation

- Previous research [1] was able to classify cuts with force-data-based machine learning models
  - Data was taken from force sensors built-in to machine
  - Not cheap!
- Current work has sought to replicate results with acoustic data
  - Goal is for acoustic-data-based models to perform **at least as well** as force-based ones



https://www.canadianmetalworking.com/canadianmetalworking/article/cuttingtools/the-versatility-of-multifunctional-milling-tools

COMPARE

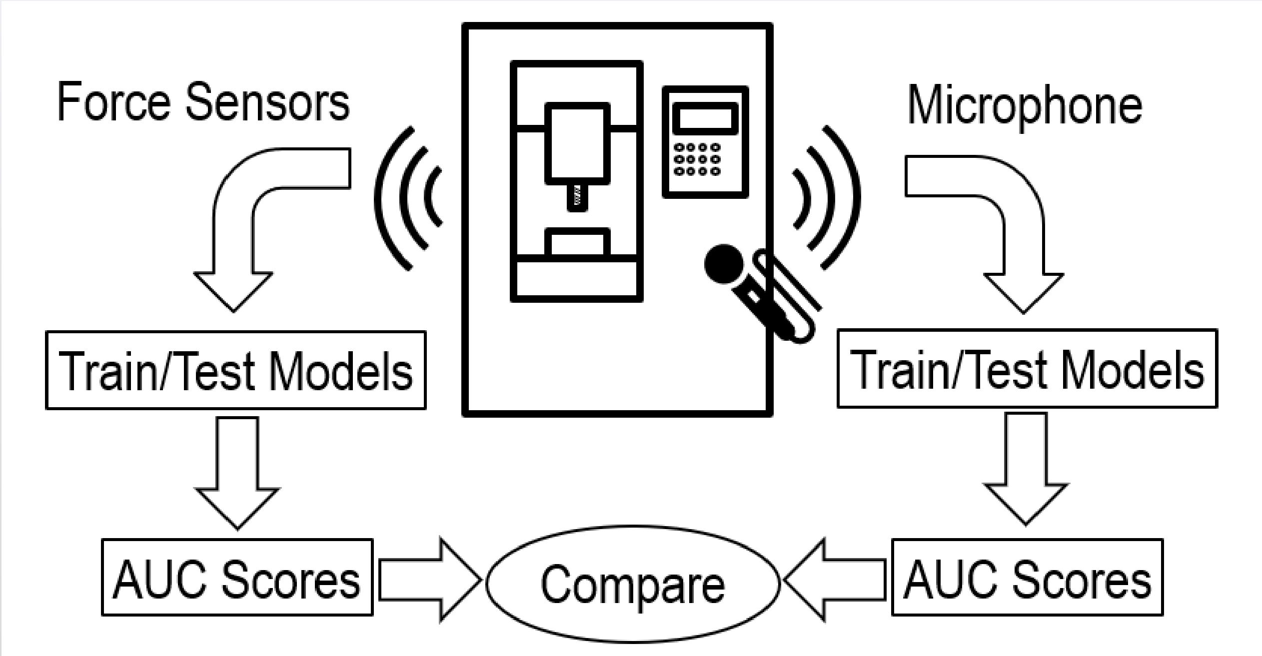
[1] N. Greenfield, “Using Machine Learning to Identify Machining Parameters in Computer Numerical Control,” M.S. Thesis, College of Eng., Georgia Institute of Technology, Atlanta, Georgia, 2022. Available: https://smartech.gatech.edu/handle/1853/67296

Mission Relevance

- This research lays the foundations for sensing machine behavior through side channel data streams
  - Insight into parameters (depth of cut, feedrate, etc.) without direct interaction/measurement
  - Possible data streams include temperature, power consumption, cutting forces, etc.
- Use cases:
  - Identification of operations being performed (e.g., roughing vs. finishing)
  - Detection of material loaded (e.g., something common like aluminum or steel vs. something more exotic like tungsten)
  - Detection of outside interference (detect cyber threats, presence of malware)

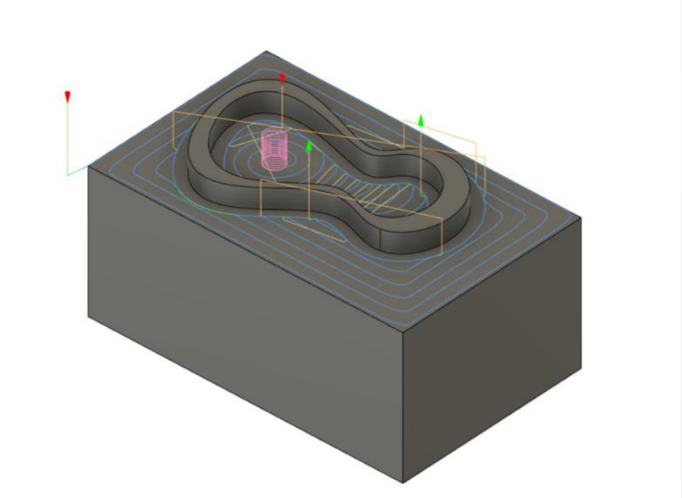
Technical Work Overview

- Experiments performed using EMCO E350 CNC
  - Force data collected using drive axis force sensor & spindle power sensor
  - Acoustic data collected using PCB Piezotronics 130F21 microphone & Raspberry Pi

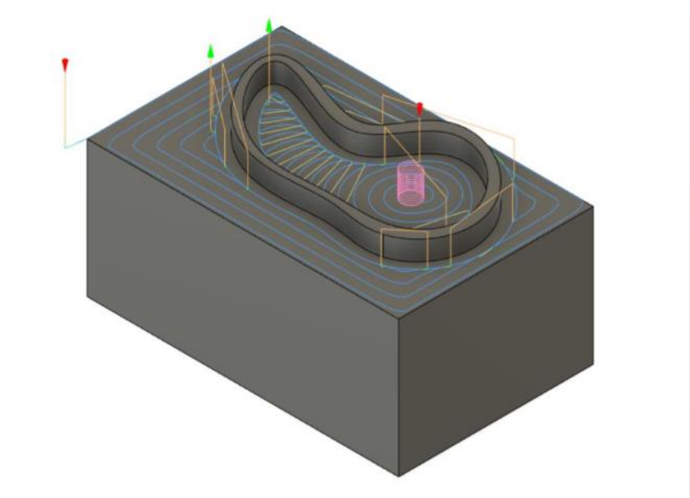


Experiment Setup

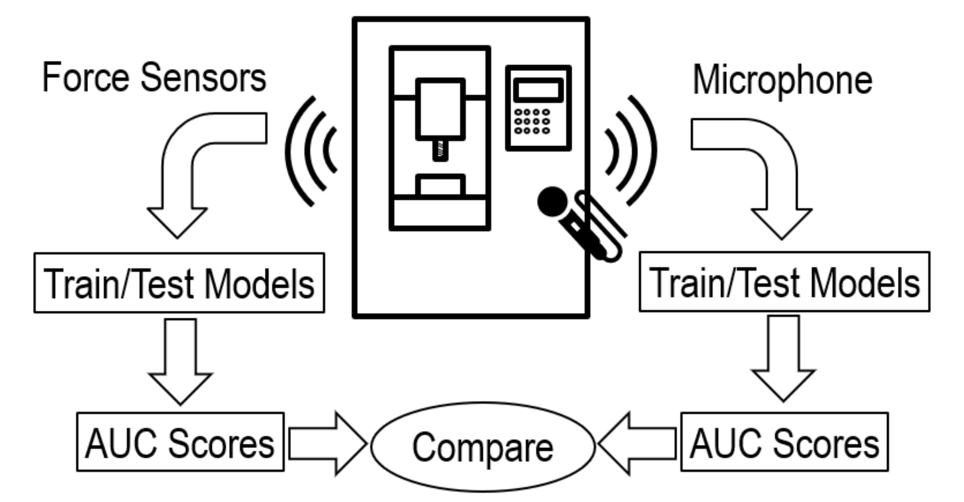
- Three feedrates correspond to three aggressiveness levels
  - Conservative, optimal, aggressive
  - Feedrate controlled with feedrate override on EMCO
- Training and Testing geometry



Training Geometry

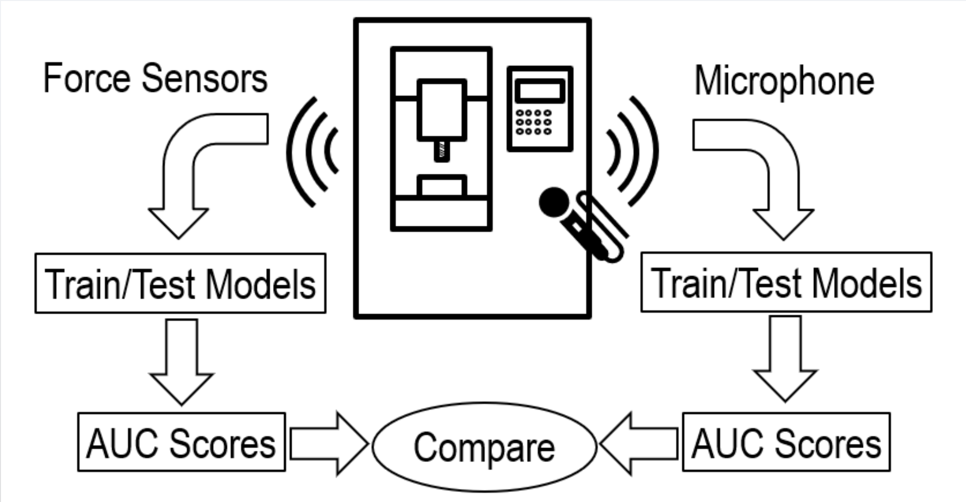


Testing Geometry



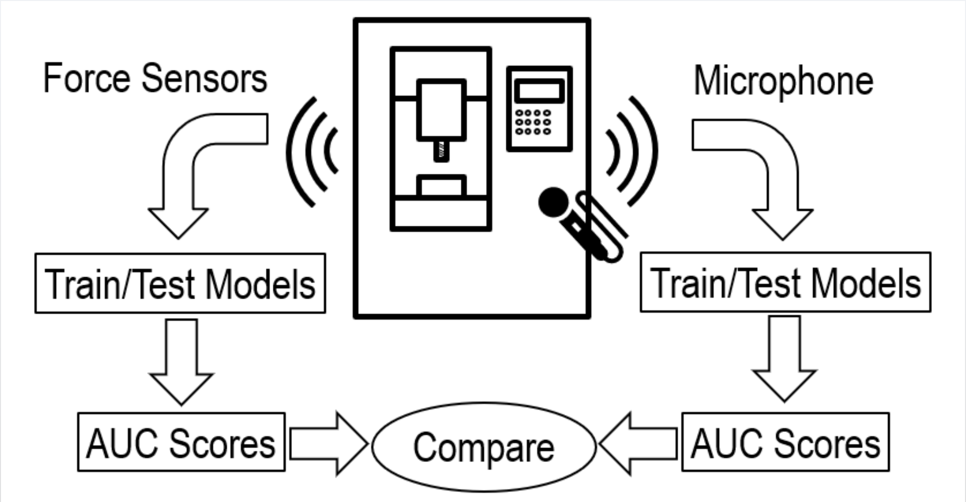
Data Processing

- Force:
  - Continuous Wavelet Transform (CWT) to generate frequency features
    - 630 total features (time domain and frequency)
    - Pearson Correlation & MI Scores to down select
- Acoustic
  - Log-mel spectrogram generated for recorded sound
  - Principal component analysis (PCA) to reduce dimensionality
    - Keeping 20 features



Machine Learning Models

- Models classify aggressiveness into 3 categories: Conservative, Optimal, and Aggressive
- 5 Models Trained on each data source:
  - Multilayer Perceptron (MLP), K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), Logistic Regression (LR)
- Performance evaluated using area under the receiver operating characteristic curve (AUC)
  - Closer to 1 -> better prediction
  - Closer to 0.5 -> random guessing



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Results

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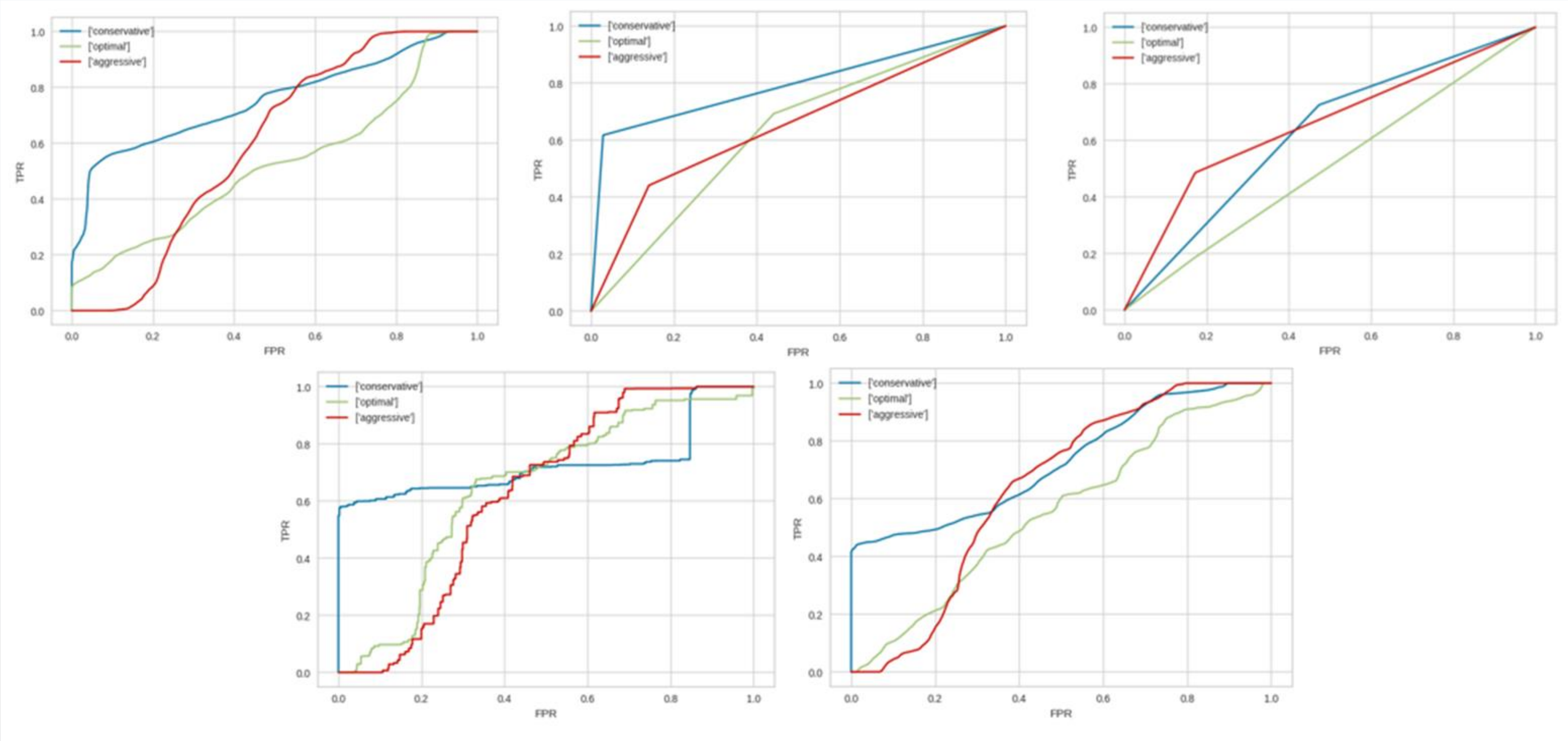
- Force Models



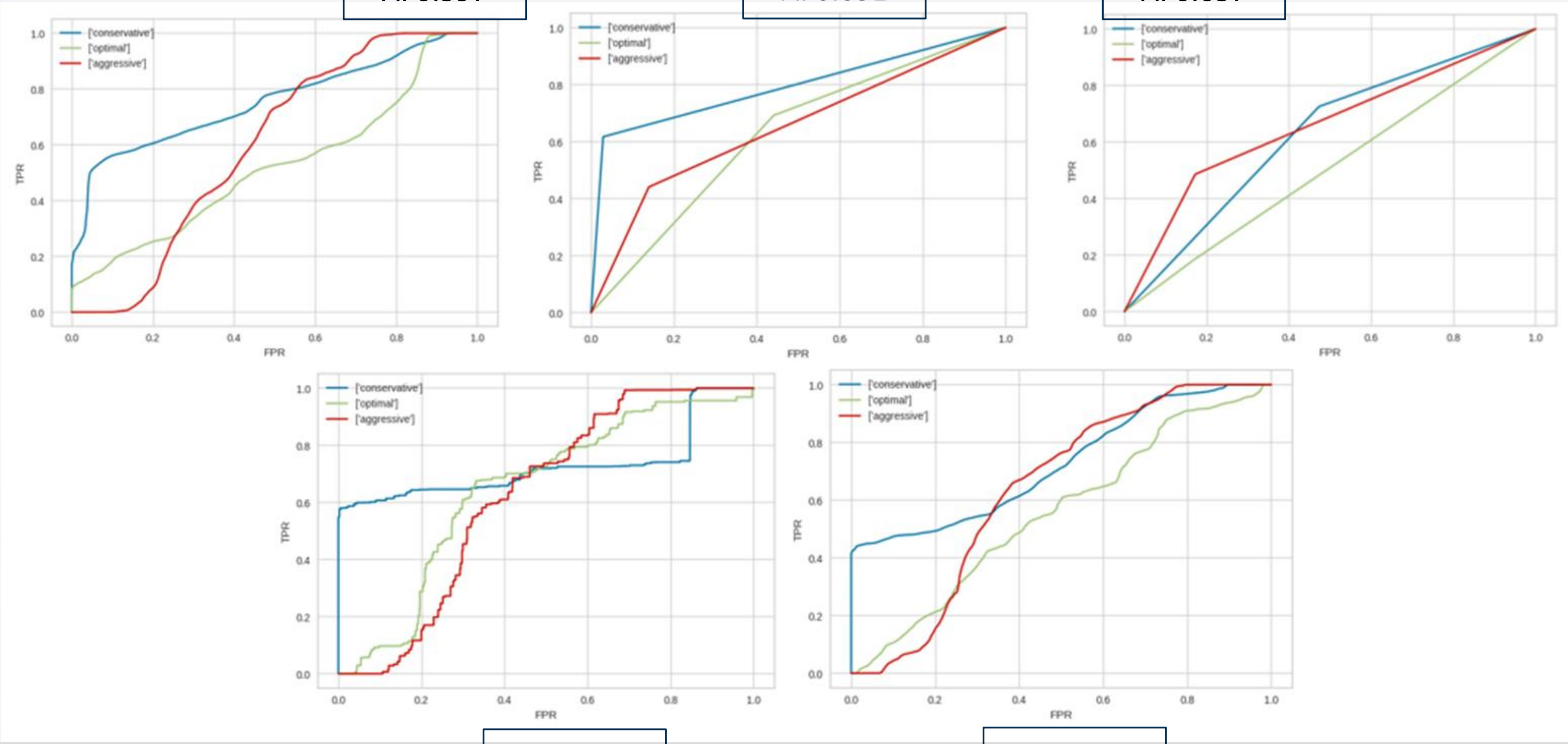
Results

- Force Models

MLP
C: 0.754
O: 0.522
A: 0.597

KNN
C: 0.794
O: 0.626
A: 0.651

DT
C: 0.626
O: 0.507
A: 0.657



RF
C: 0.728
O: 0.646
A: 0.625

LR
C: 0.727
O: 0.555
A: 0.638

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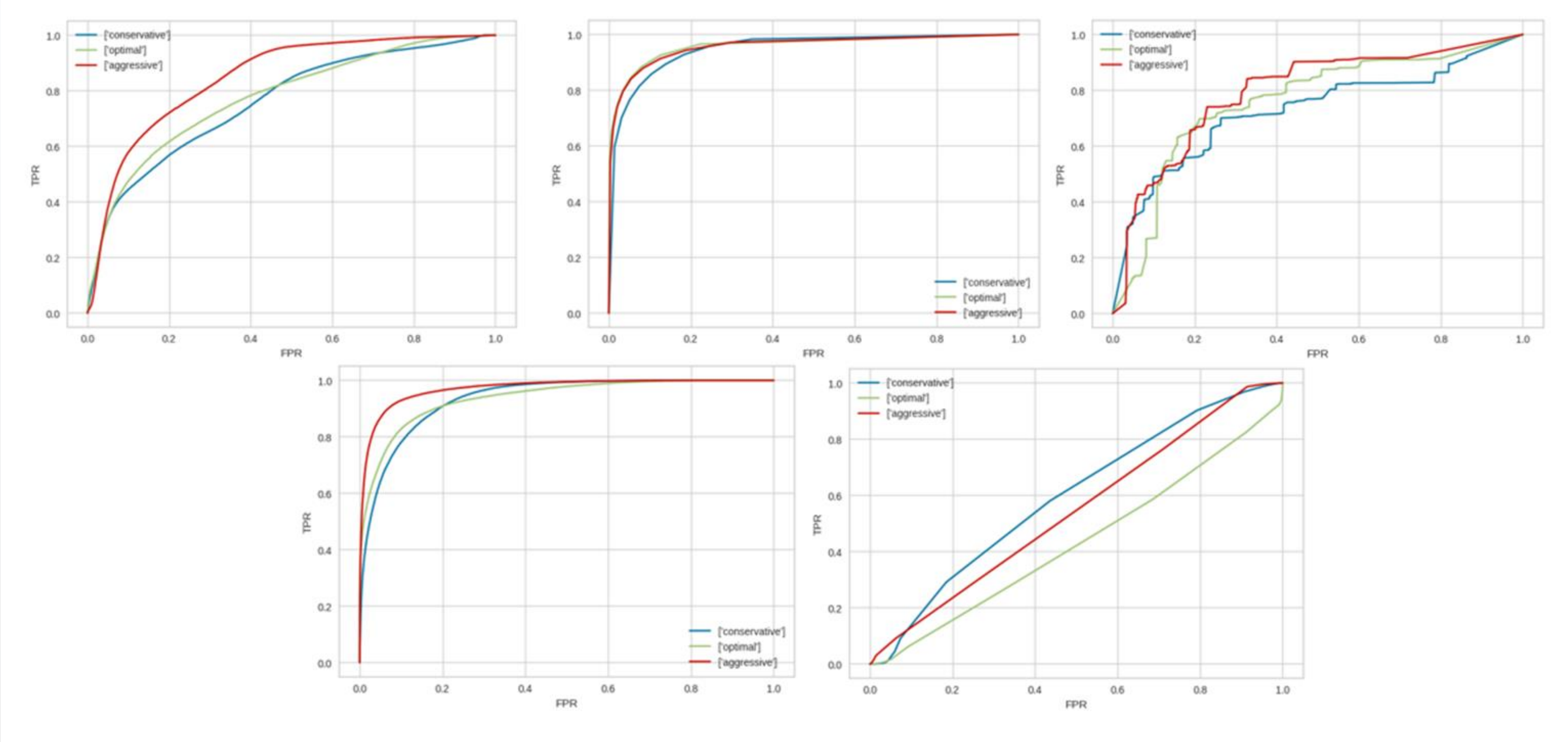
Results

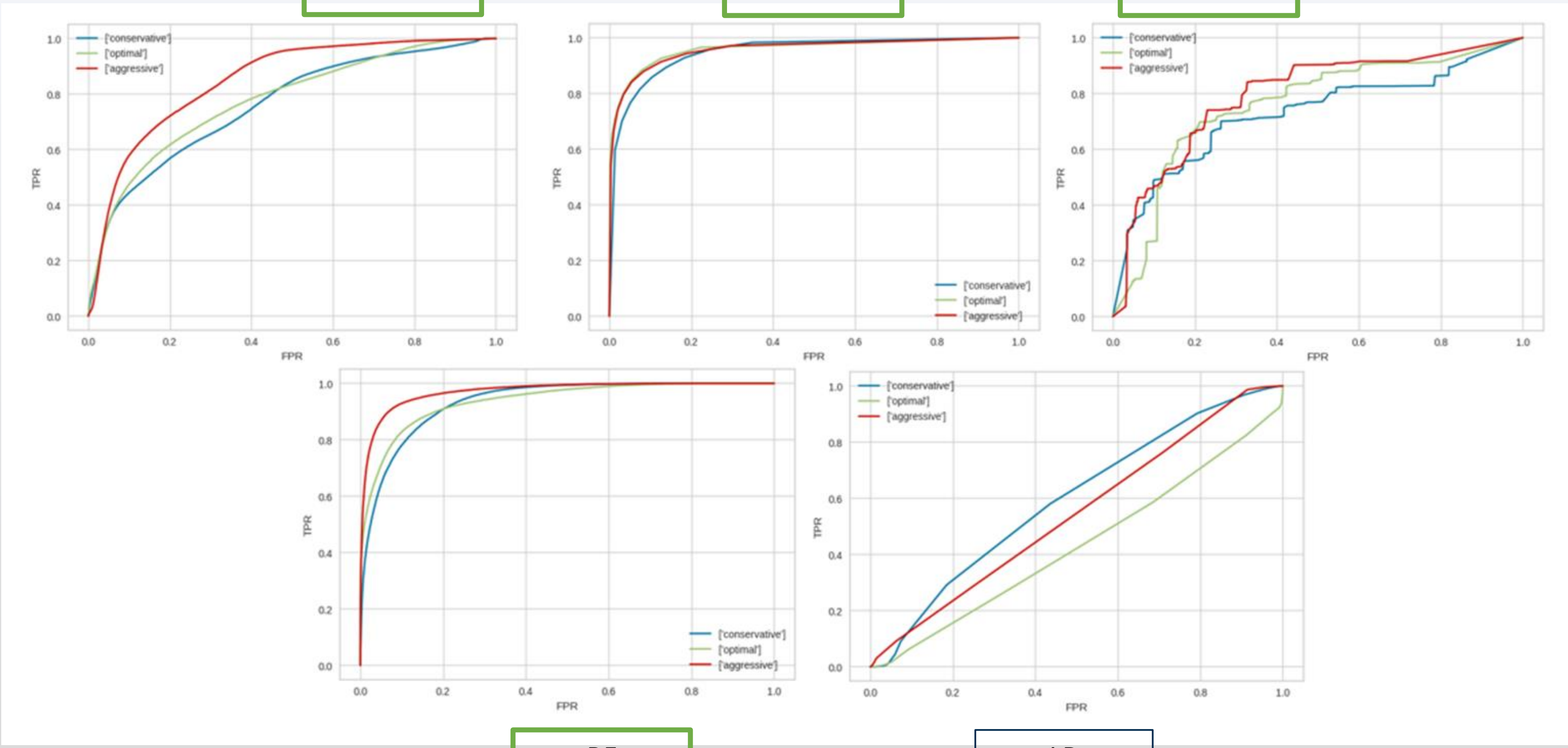
- Acoustic Models



Results

- Acoustic Models

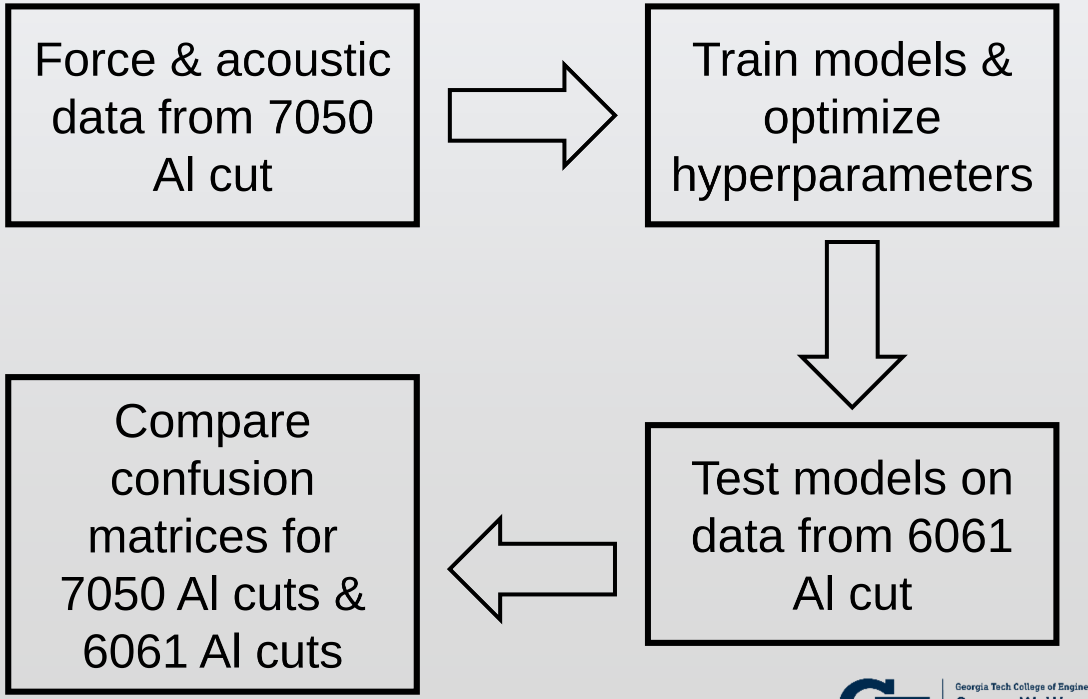
MLP	KNN	DT
C: 0.760	C: 0.949	C: 0.726
O: 0.777	O: 0.959	O: 0.760
A: 0.849	A: 0.957	A: 0.794



RF	LR
C: 0.935	C: 0.595
O: 0.938	O: 0.431
A: 0.971	A: 0.544

Material Identification Investigation

- Does changing the material show up in the model performance evaluation?
  - Change in model’s performance should reflect changed material
- Trained models on 7050 aluminum, tested on 6061 aluminum
  - 7050 selected for higher yield strength, slightly lower machinability
- Wanted to see how classifications shifted
  - How were cuts being misclassified?
  - Looked at **confusion matrices**



Material ID Preliminary Results

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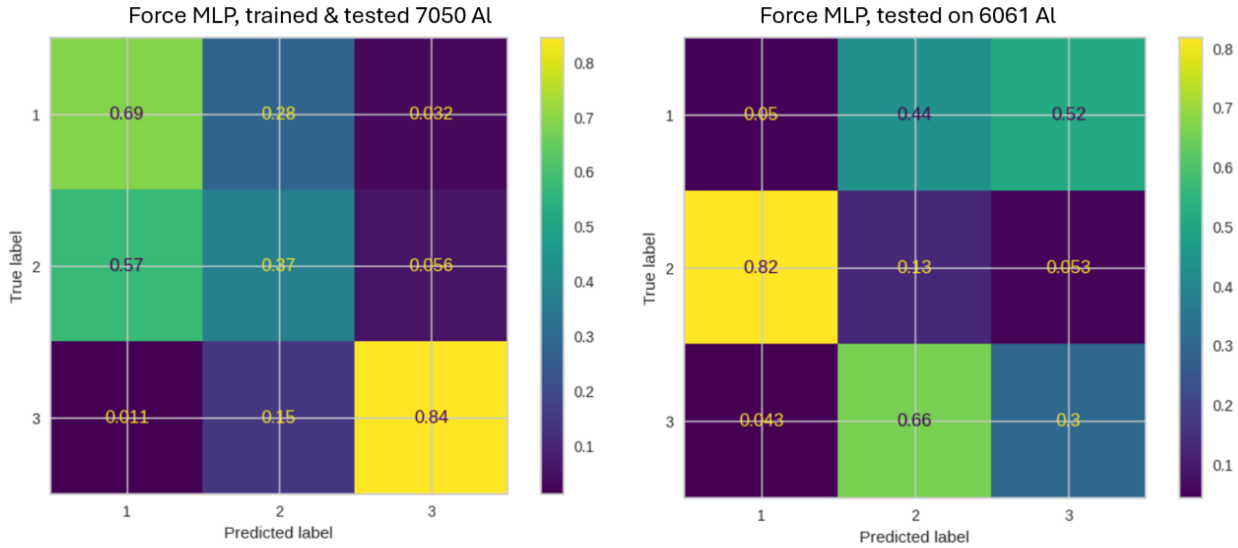
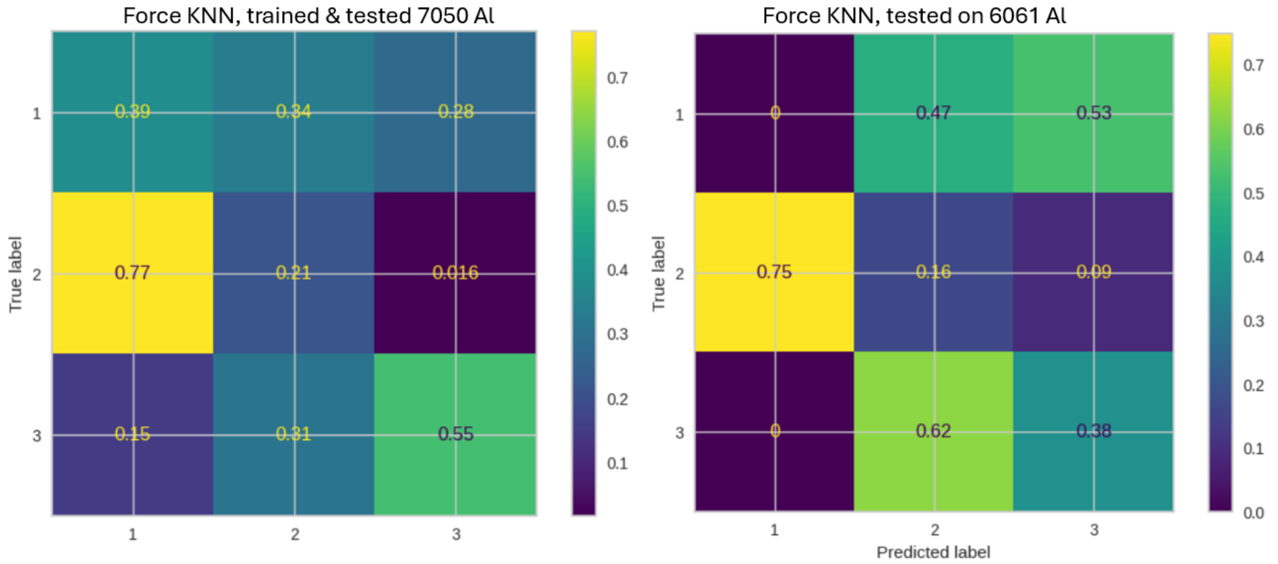
Force Multilayer Perceptron



Force K-Nearest Neighbors



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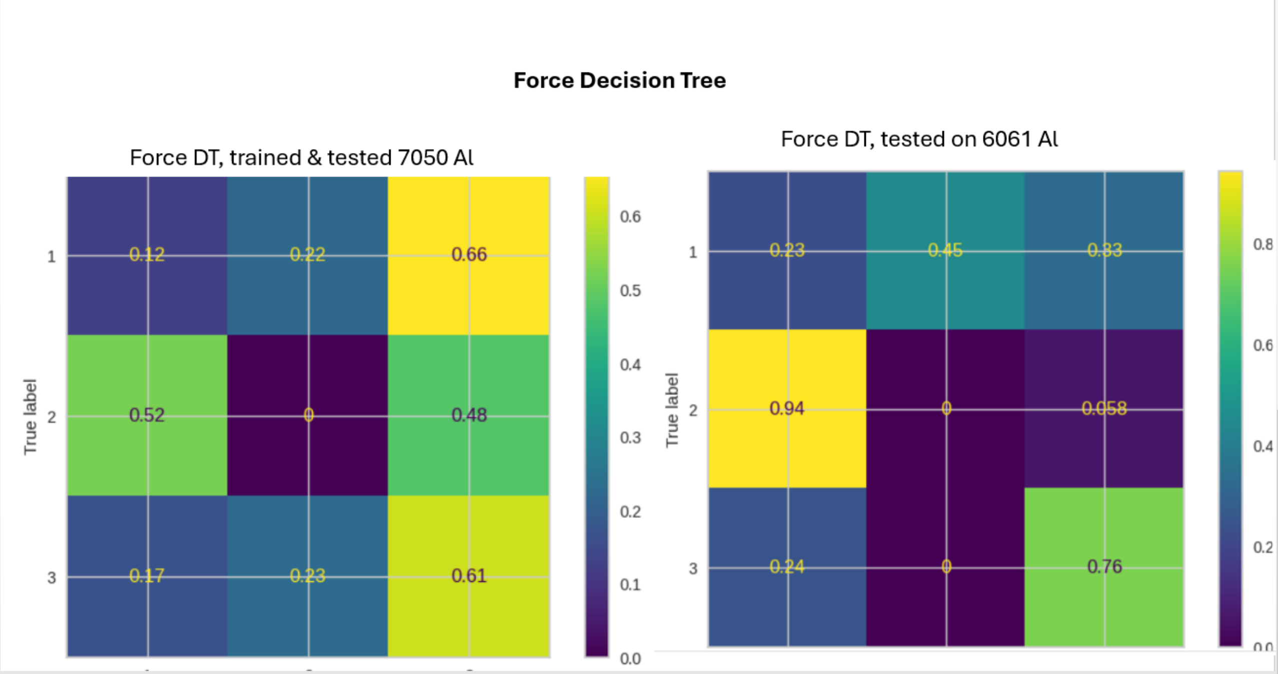

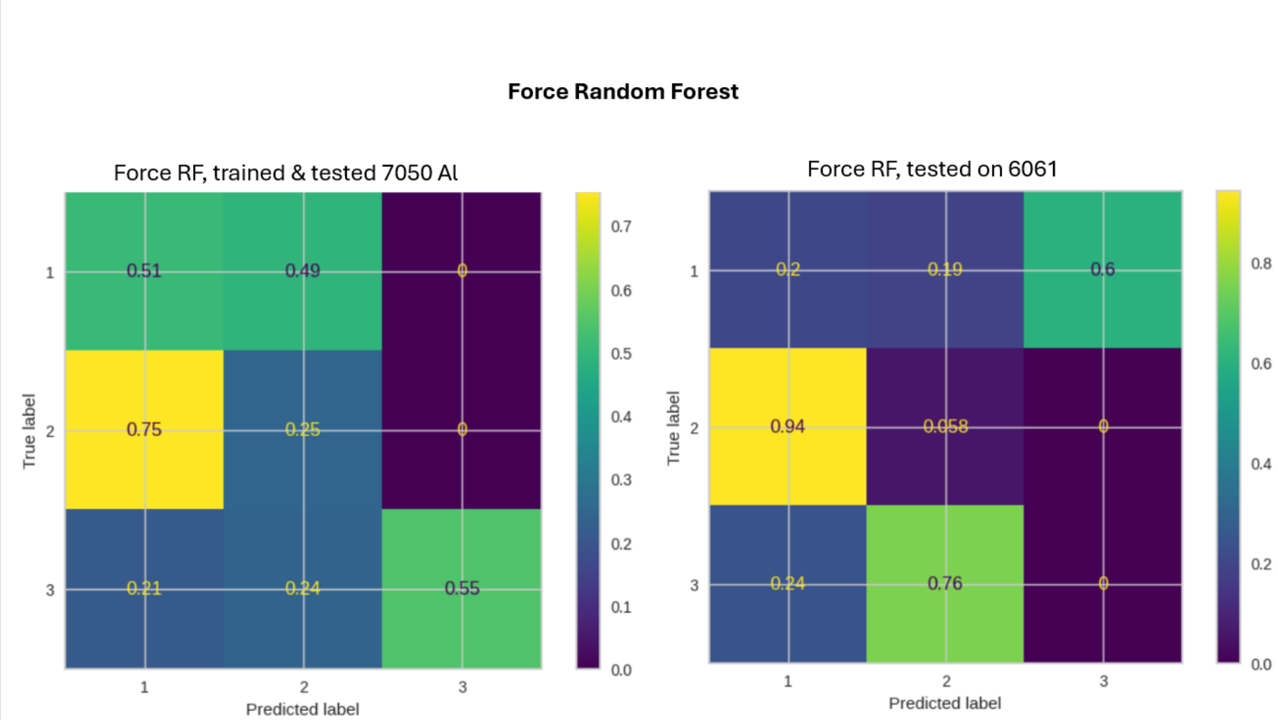

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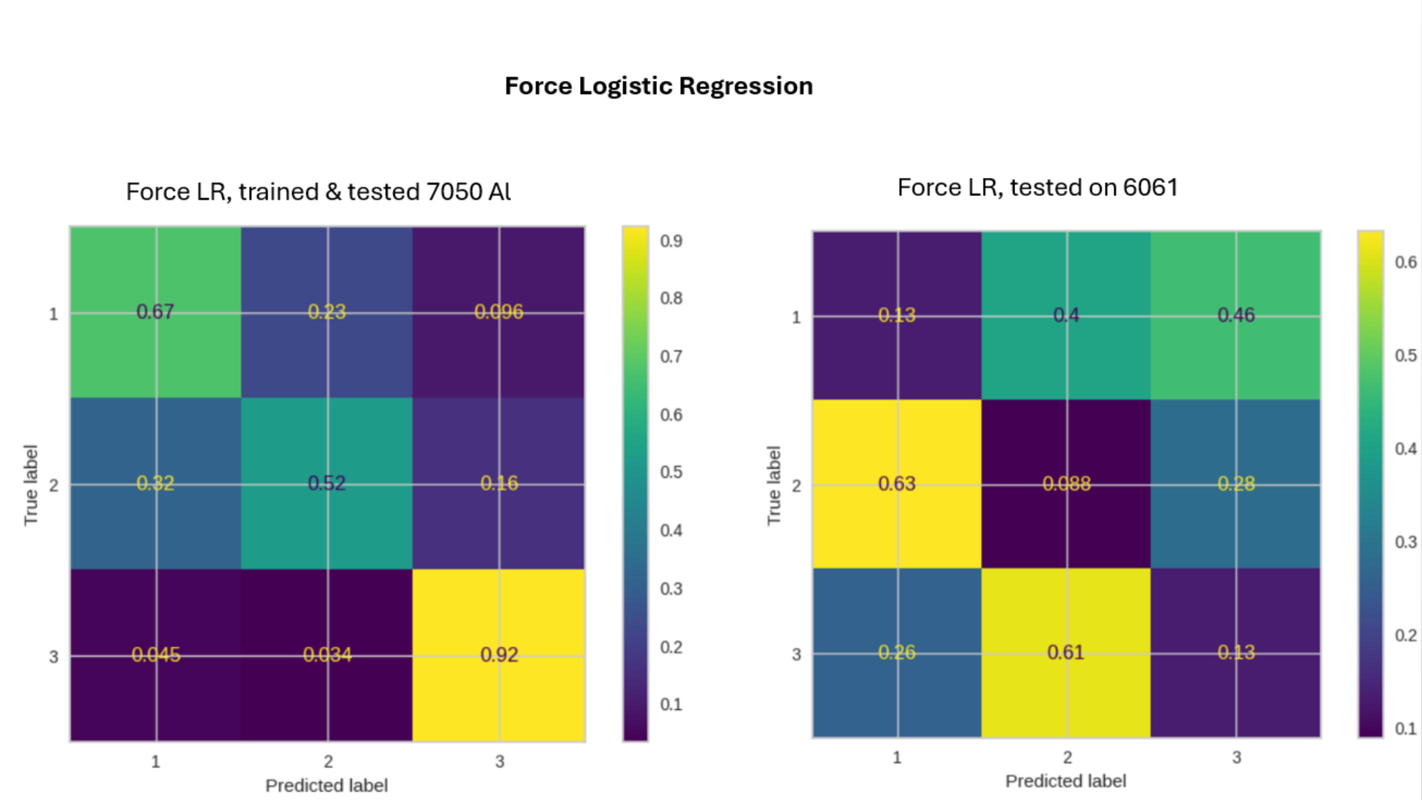
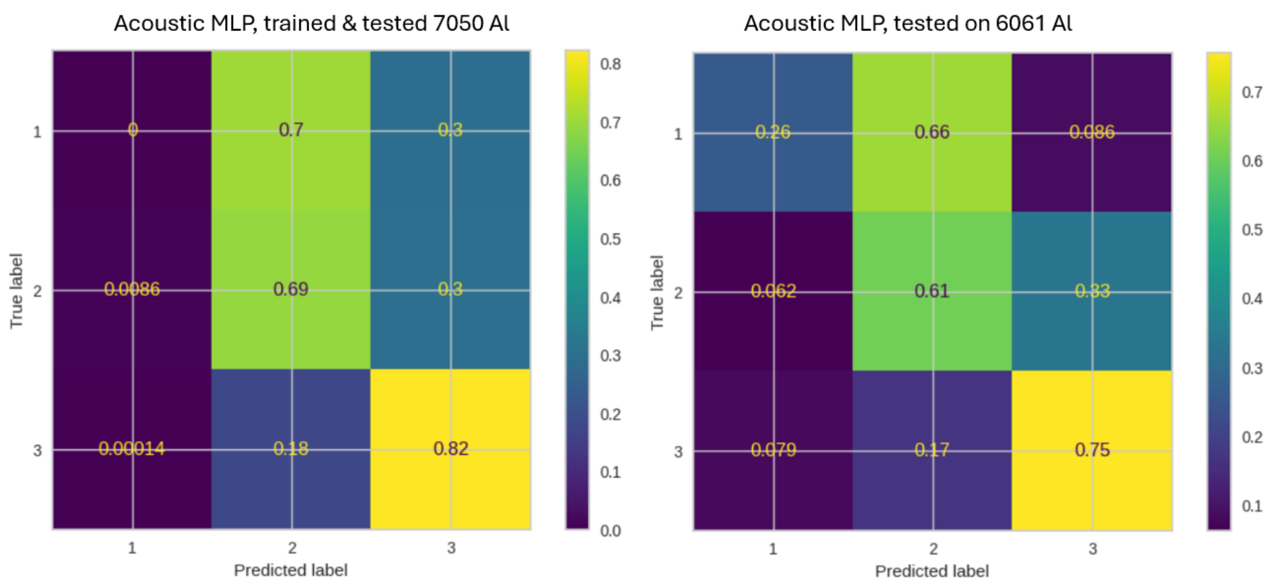
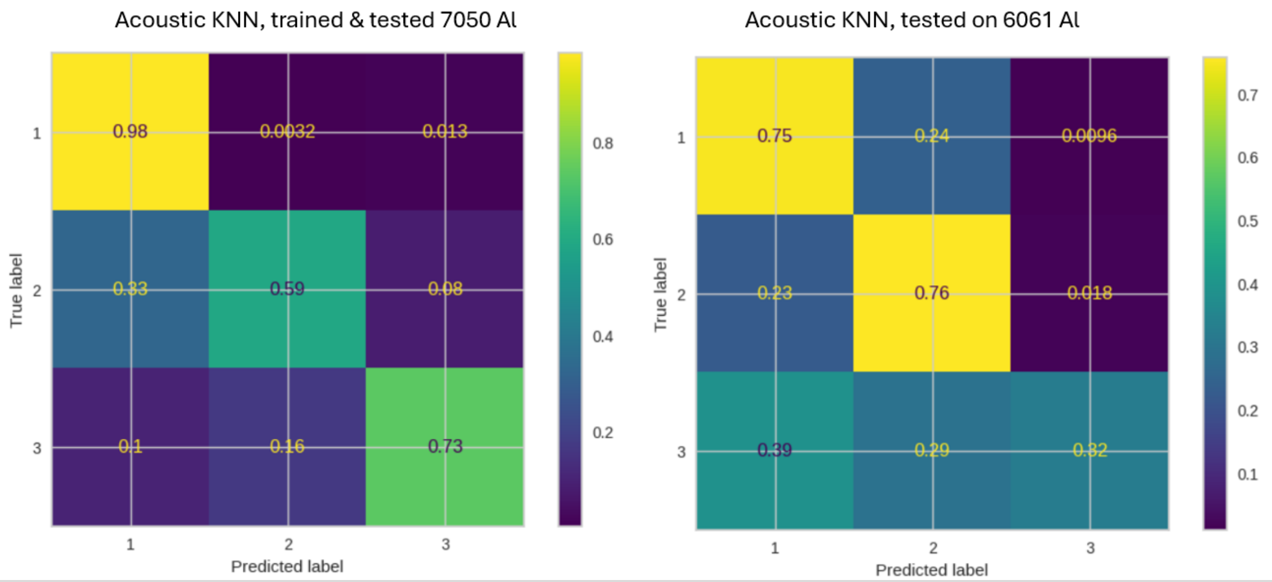


Material ID Preliminary Results

Acoustic Multilayer Perceptron

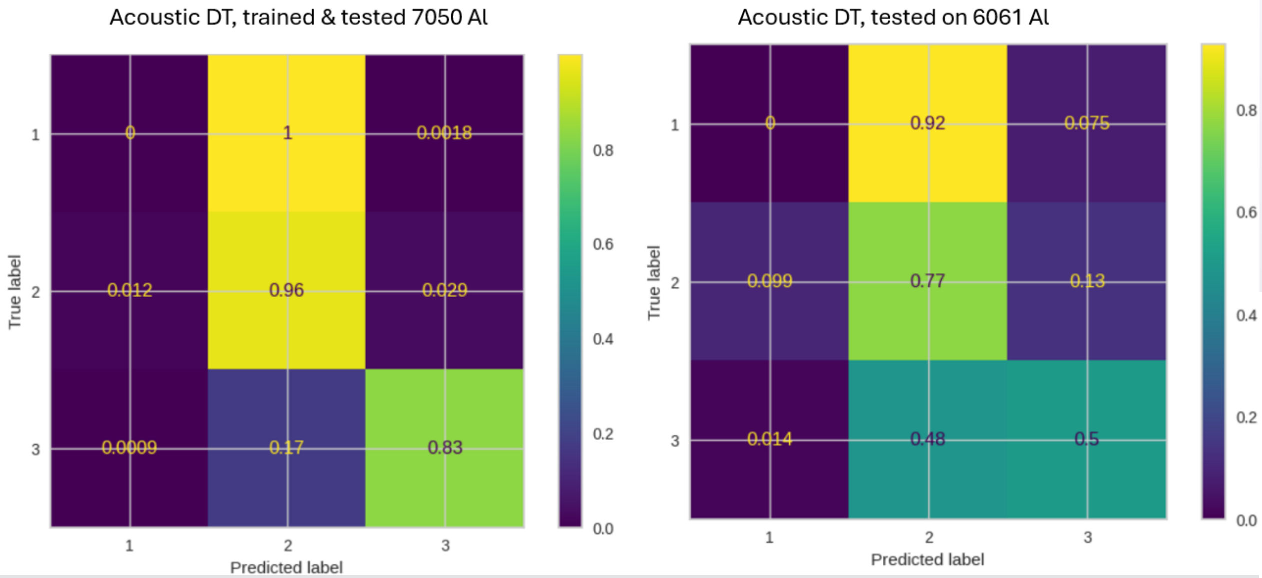


Acoustic K-Nearest Neighbors

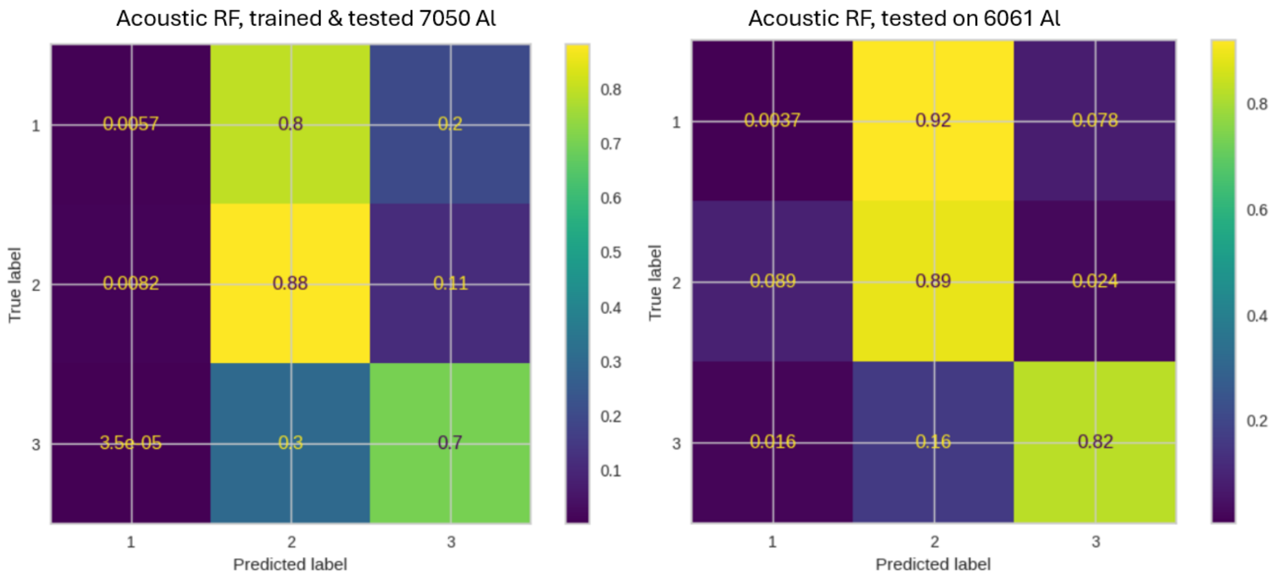


Material ID Preliminary Results

Acoustic Decision Tree



Acoustic Random Forest



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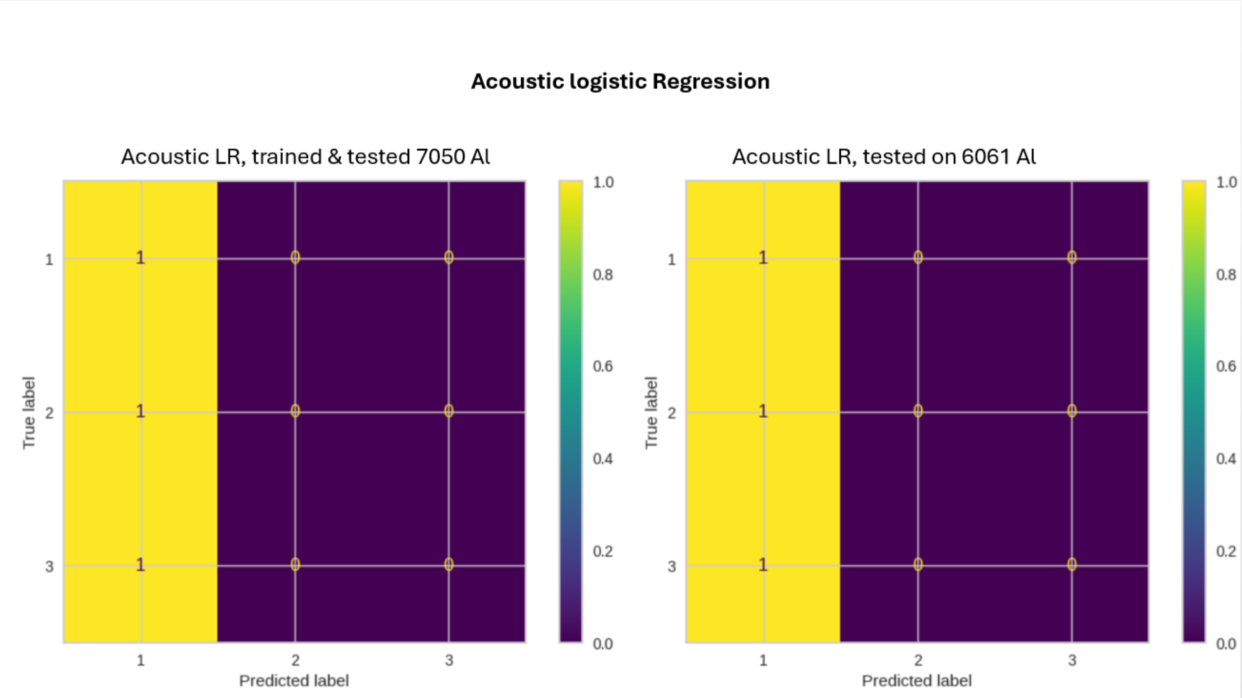

Conclusion & Future Work

- CNC machining is an important manufacturing technique that presents challenges to novice users
- Machine learning can be used to classify cut aggressiveness through side channel data
  - Acoustic models performed at least as well as force models
  - Can offer insights into how machine is being used
- Future work:
  - Investigate effects of tool wear
  - Close loop for user feedback
  - Implement in real-time format

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ACKNOWLEGEMENTS

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PPPL Princeton Plasma Physics Laboratory

Sandia National Laboratories

SRNL Savannah River National Laboratory

NNSA National Nuclear Security Administration

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