Intelligent Monitoring of Engineering Systems

Group 6: Intelligent Monitoring of a Bicycle Tire Pressure

CONTENT

Group 6

Intelligent Monitoring and Multiclass classification of a Bicycle Tire Pressure

Our goal in this project

Problem Statement

Classifying tire pressure based on accelerometer data have limitations in accuracy and generalization

Challenges

Limited ability to accurately differentiate tire pressure levels

Motivation

Development of machine – learning based new tire pressure measurement methodology

Goal

To develop a classification model that can accurately predict tire pressure based on accelerometer data

Team structure

Signal pre-processing

- Aakash Abhani
- Arnav Bhamburkar
- Yash Parab

Neural network

- Yash Patil
- Omkar Kunjir
- Rohit Jain

Deliverables

De-noised signal

Network architecture

Optimised network

Validation

Generalization

Use cases

Signal pre-processing for neural network input

Challenges	Processing technique
Different system response and noise frequencies	FFT analysis for noise and peak frequencies
Cover all signals required for processing	Butterworth bandpass filter 05 Hz to 40Hz of order 8
Isolate peaks for training neural network	Bump (peak) extraction
Datasets with different sampling frequency	Sampling frequency standardization (200 Hz)
Datasets recorded by different cyclists	Cyclist weight standardization
Paucity of training datasets	Individual bump as a single training set

Neural network input parameters

11 Z-acceleration features about bump peak

Bump peak frequency & cyclist weight

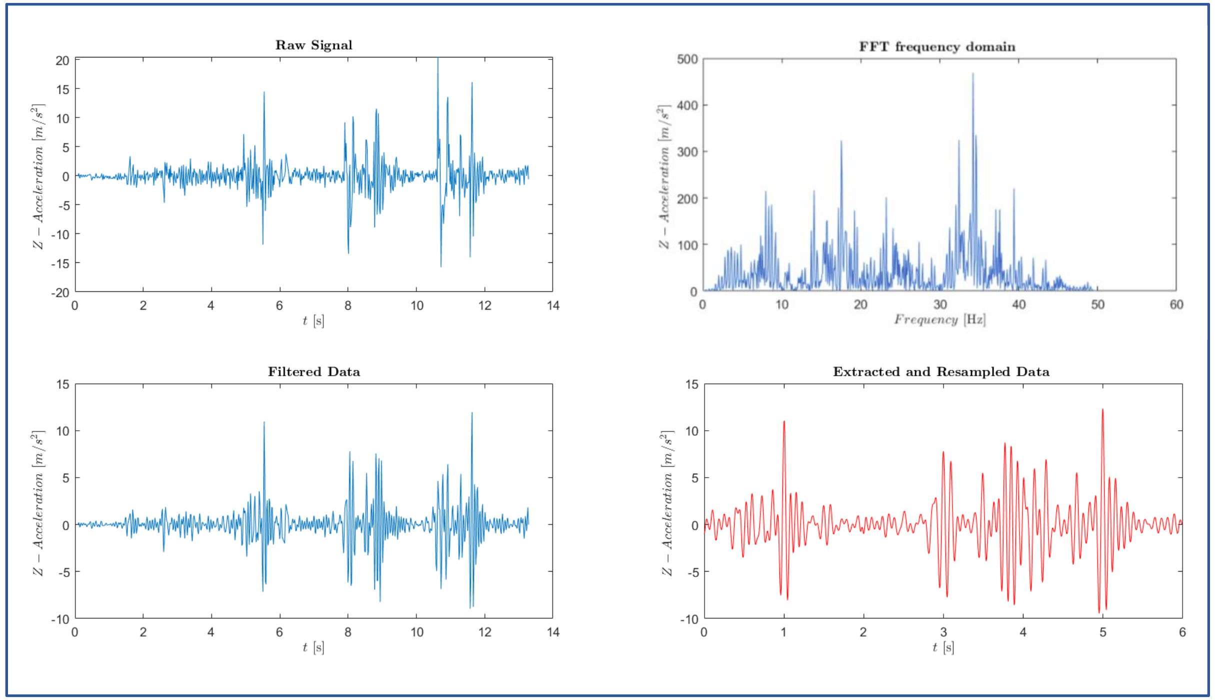


Chart 1: Illustrative signal processing for one group and one tire pressure

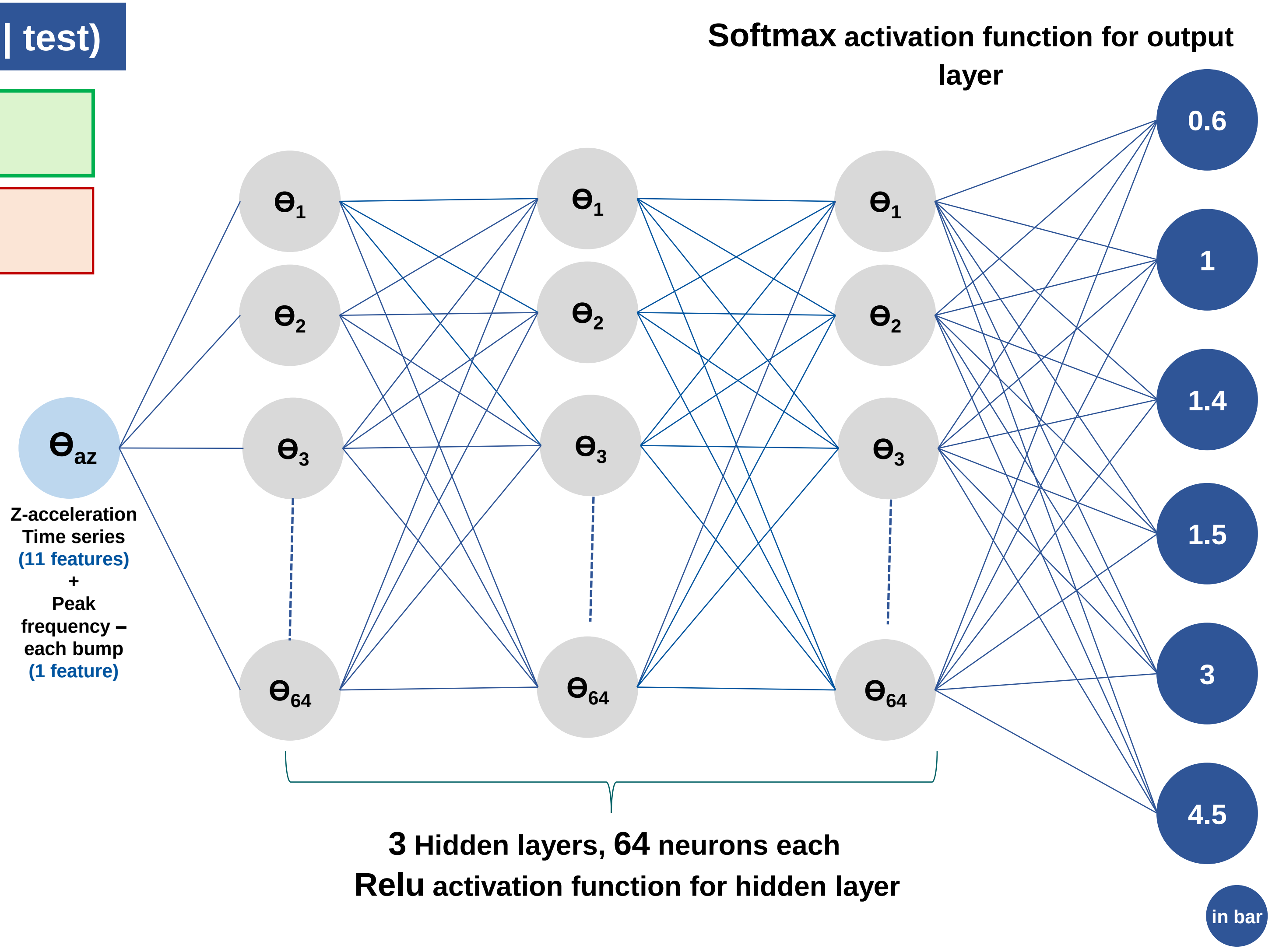
FF Neural network architecture is ~47% accurate, slighty better than SVM

Network classifiers tried (accuracy: validation | test)

1. Feed forward neural network (46.9% | 46.7%)
2. Support vector machines (46% | 43.3%)

Selected neural network architecture (FFNN)

- Number of layers and neurons: [12, **64, 64, 64**, 6]
- Maximum **10000** iterations
- **PCA** with 99% variance
- Regularization strength (λ): **1e-4**
- Data standardization



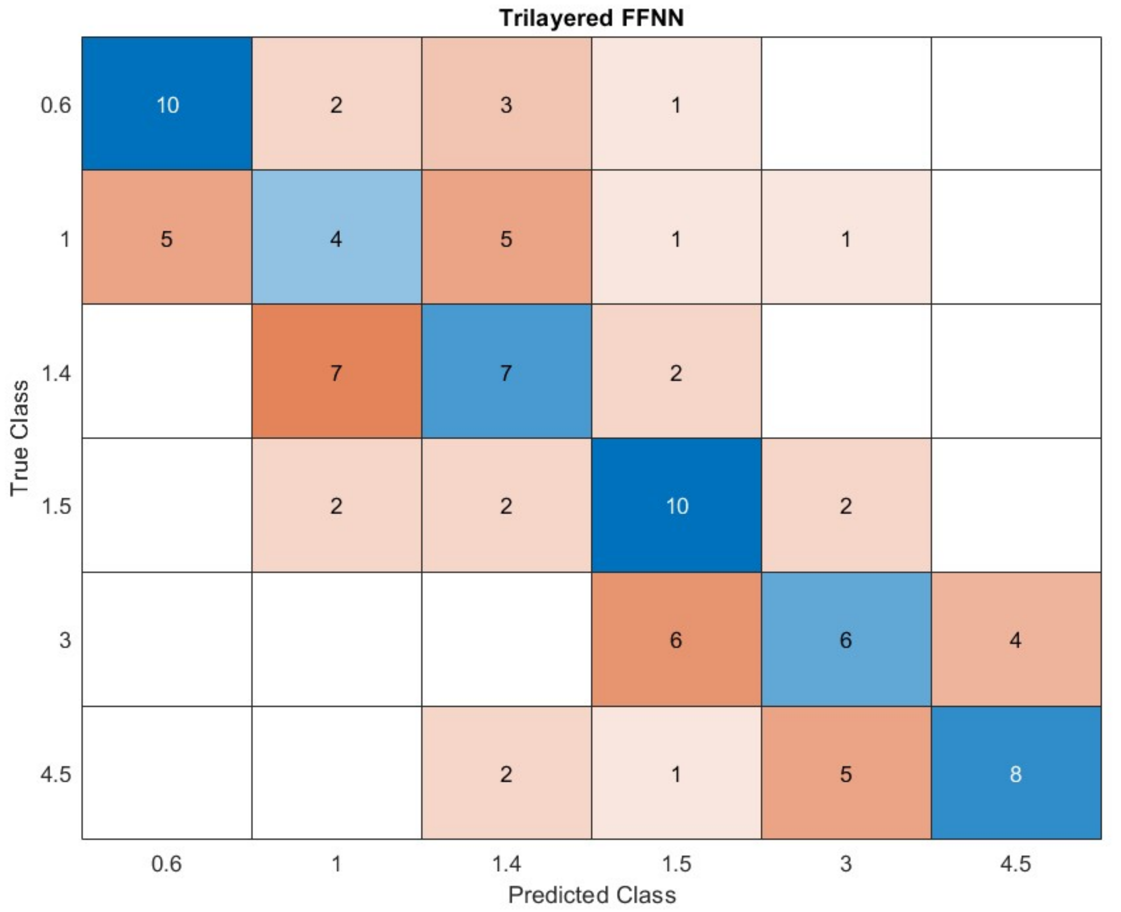
~47% accuracy is achieved for Training + Validation dataset

5-Fold Cross Validation

- 7 groups * 6 pressure classes * 3 Individual bumps each = 126 datasets → (~75%) 96 training & validation datasets

	Class	Precision	Recall	F1 score	Accuracy
Fat damped bike	0.6 bar	0.67	0.63	0.65	62.5%
	1.0 bar	0.27	0.25	0.26	25.0%
	1.4 bar	0.37	0.44	0.40	43.8%
Trekking undamped bike	1.5 bar	0.48	0.63	0.54	62.5%
	3.0 bar	0.43	0.38	0.40	37.5%
	4.5 bar	0.67	0.50	0.57	50.0%
Accuracy					**46.9%**

Confusion Matrix



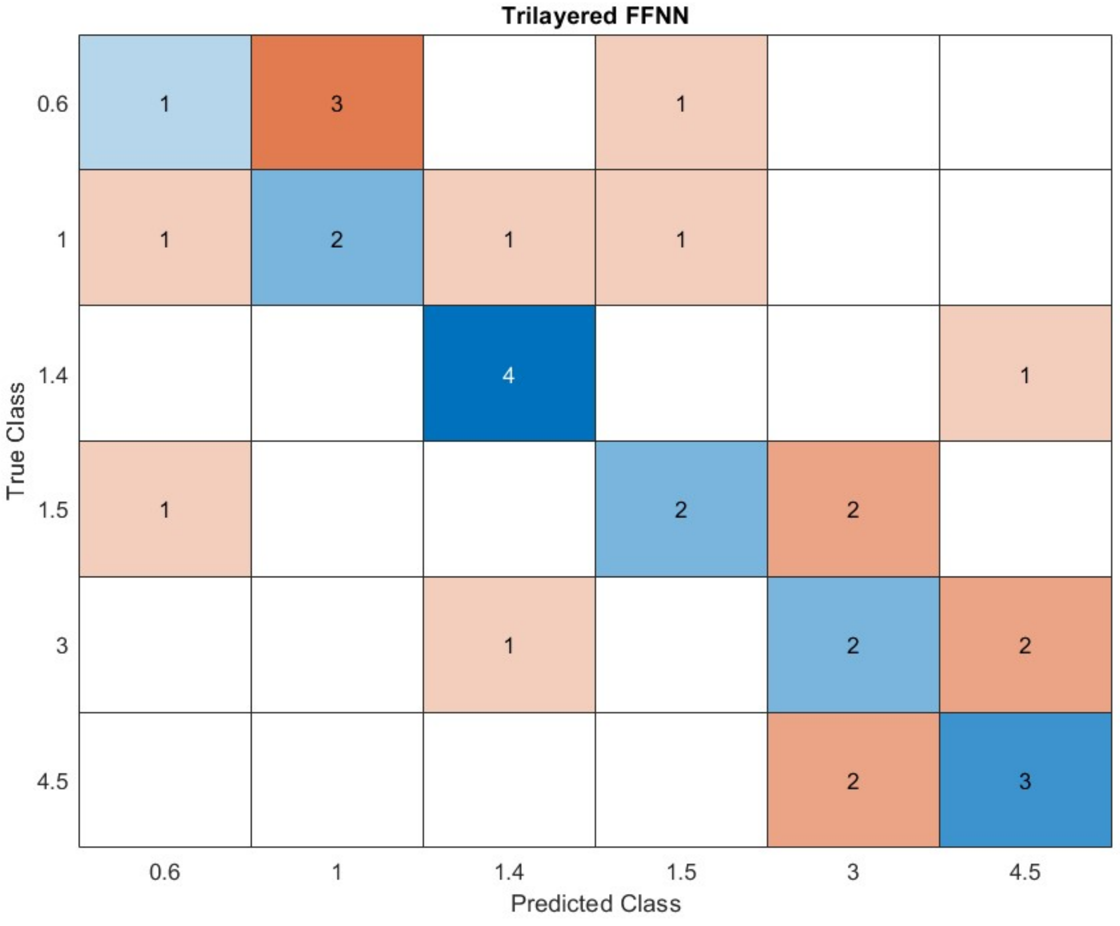
Generalization ability can be measured to ~47% accuracy

Testing

- (~25 %) 30 testing datasets.
- Generalization accuracy similar to validation.

	Class	Precision	Recall	F1 score	Accuracy
Fat damped bike	0.6 bar	0.33	0.20	0.25	20.0%
	1.0 bar	0.40	0.40	0.40	40.0%
	1.4 bar	0.67	0.80	0.73	80.0%
Trekking undamped bike	1.5 bar	0.50	0.40	0.44	40.0%
	3.0 bar	0.33	0.40	0.36	40.0%
	4.5 bar	0.50	0.60	0.55	60.0%
Accuracy					**46.7%**

Confusion Matrix



Pressure classes not sufficiently distinguishable

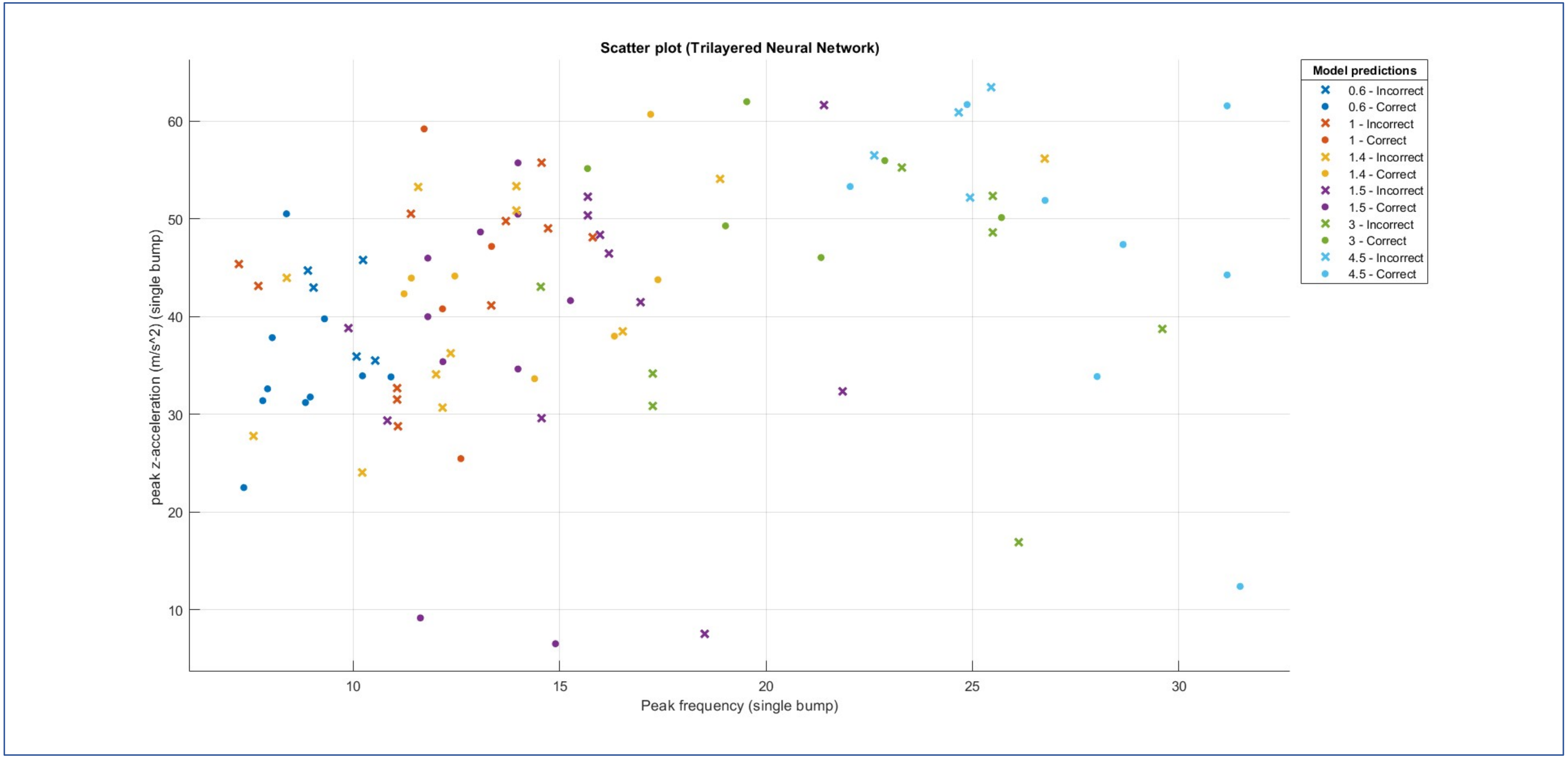


Chart 2: 2D visualization of model predictions with respect to peak z-acceleration and peak frequency for each bump.

What can be further done?

Conclusion

- With the available data, classification model is ill-equipped & accuracy (~47%) is insufficient. Thus, generalization isn't working in this case.
- Furthermore, robust sensor mounting would reduce noise & improve reproducibility

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Potential improvements

- Creating additional run-time filters (dynamic) to eliminate noise due to different set-up, rider → standard & efficient filter strategy
- Regression/ Classification model with advanced network architecture – CNN, LSTM for higher accuracy. Open-source pre-trained networks - AlexNet, GoogLeNet, ResNet-50 can be used for this.

Direct applications

Automotive calibration

- Driver behavior analysis with data driven models.
- Road load prediction for design & analysis

Intelligent TPMS

- Real time monitoring: improve fuel efficiency & prevent accidents
- Tire wear & performance prediction

Extended applications

Smart Wearables

- Activity recognition
- Fall detection
- Sleep stage classification

Structural health monitoring

- Bridges, buildings, and other infrastructure to assess structural integrity, potential defects or damages

Biomedical

- Physiological signals like ECG, EEG, etc.
- Disease diagnosis, progression monitoring and treatment strategies

Material Characterization

- Analyze the response of materials to external stimuli and predict material properties.

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- (136) Principal Component Analysis (PCA) [Matlab] – YouTube
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Thank you for your attention!