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The Commonwealth's Flagship Campus

Drill bit fault detection and classification

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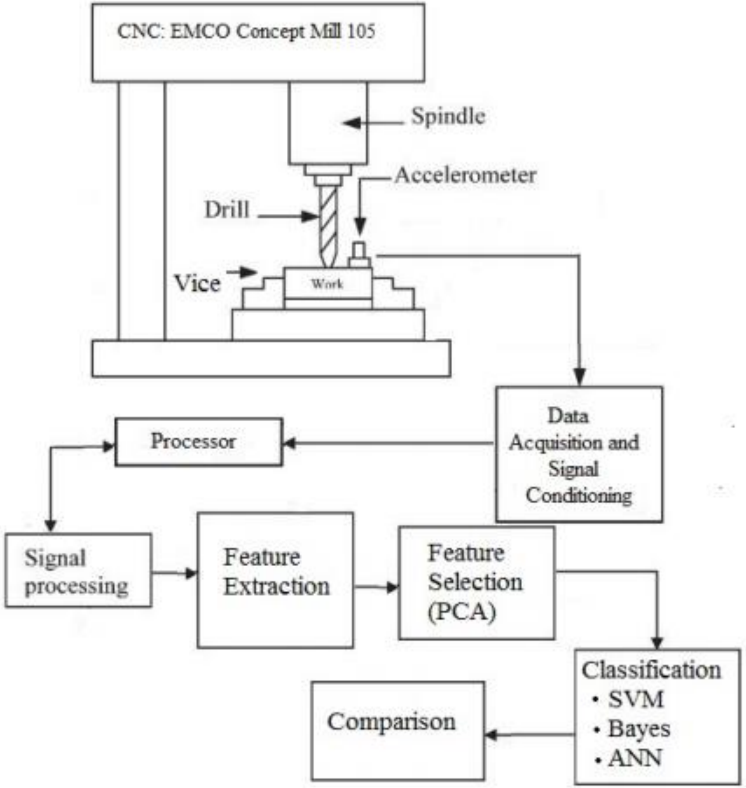
Data flow chart



Data flow chart

Preprocessing

- Digital signal filtering
- Feature Extraction
- Feature Selection
- Feature Reduction
- Feature combination

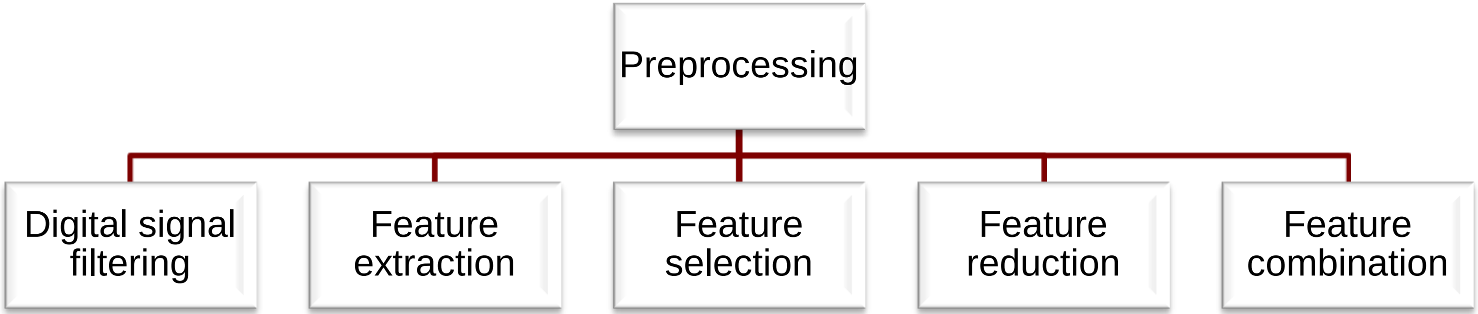
Modelling

- kNN
- ANN
- Decision Tree
- SVM
- Naïve Bayes

Training and Testing

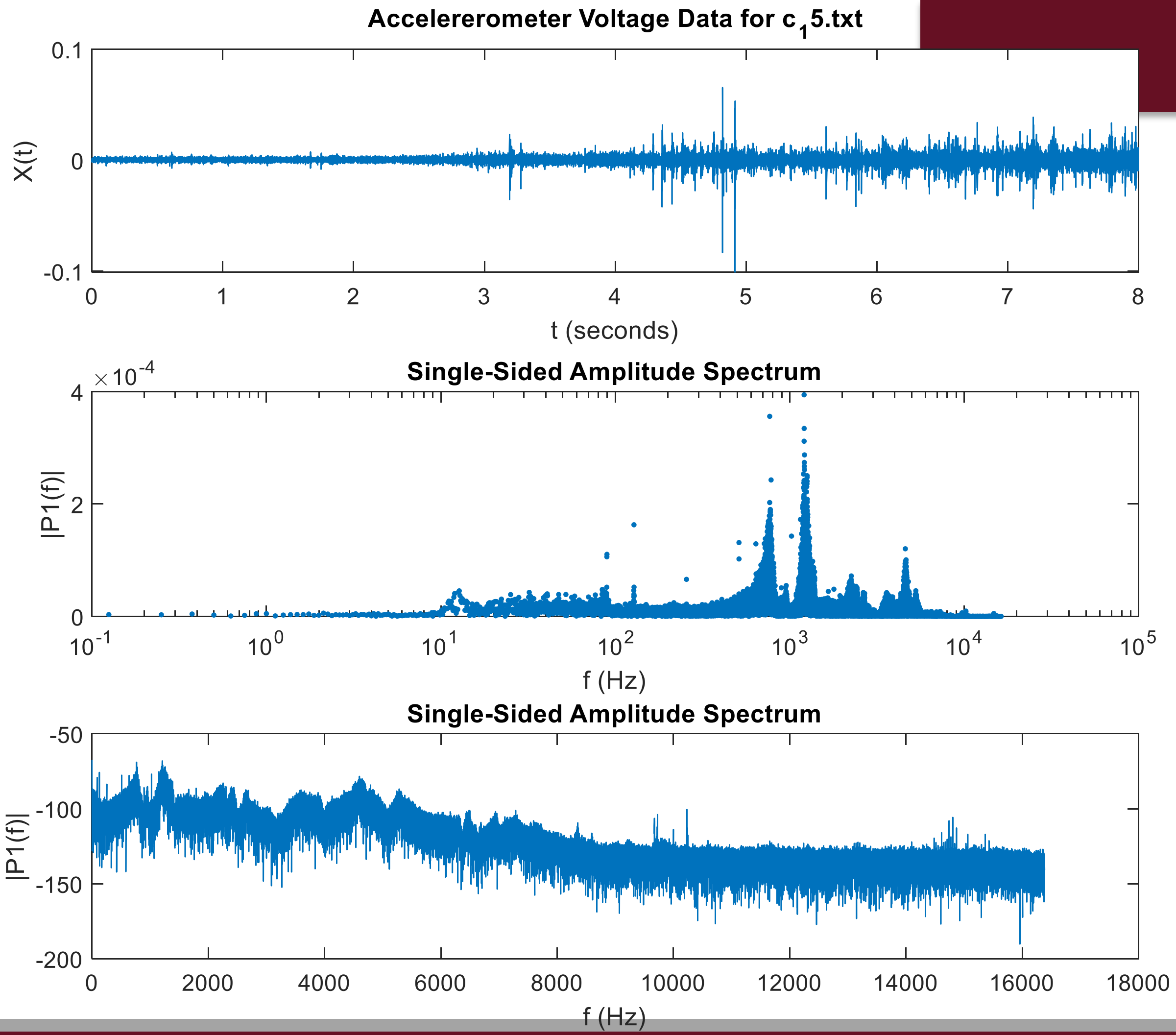
- Fault detection
- Fault Classification
- Individual fault detection

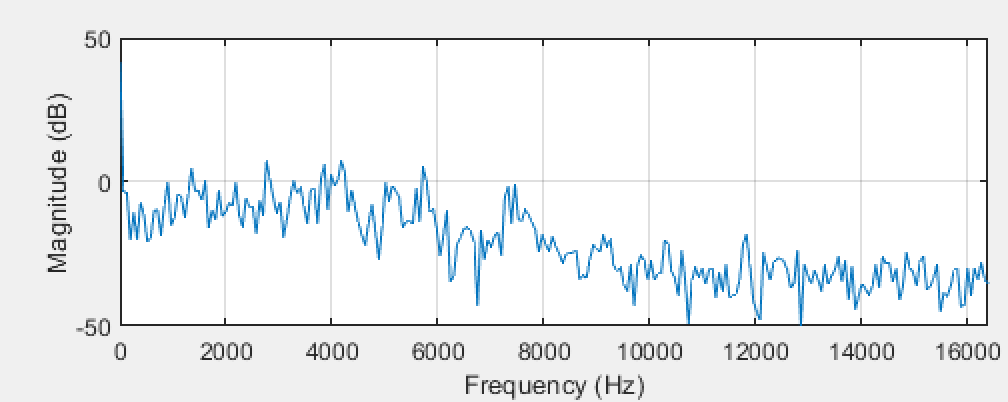
Data preprocessing methods

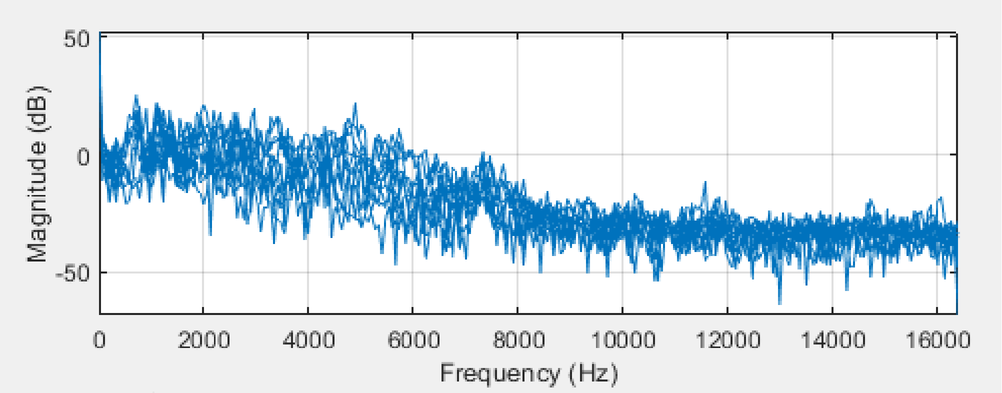


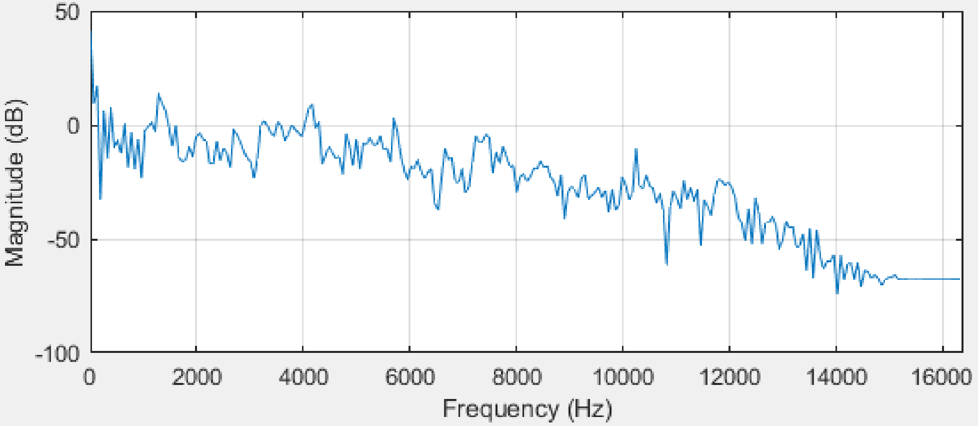
Digital signal filtering

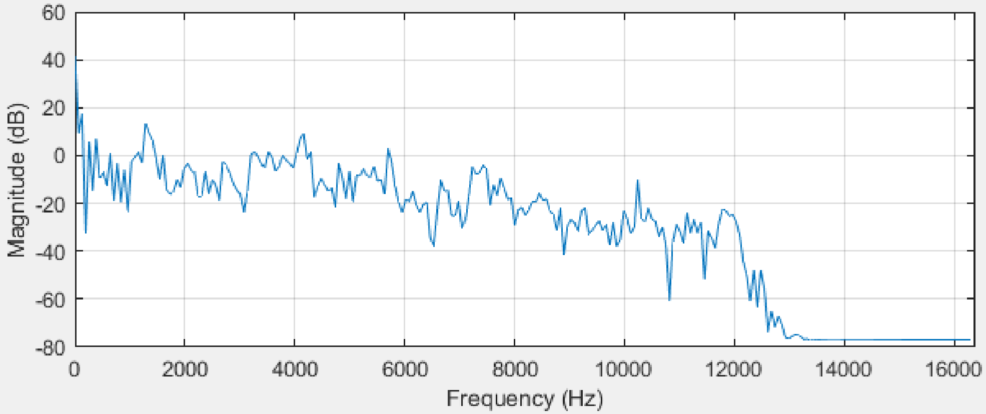
- Remove process noise which doesn’t add value to the data
- Cutoff range of frequencies with low amplitudes
- Lowpass butterworth filter of order 20 used for digital filtering


Acceleromerometer Voltage Data for $c_1$5.txt
X(t)
t (seconds)
Single-Sided Amplitude Spectrum
|P1(f)|
f (Hz)
Single-Sided Amplitude Spectrum
|P1(f)|
f (Hz)


50
0
-50
Magnitude (dB)
0
2000
4000
6000
8000
10000
12000
14000
16000
Frequency (Hz)


50
0
-50
Magnitude (dB)
0
2000
4000
6000
8000
10000
12000
14000
16000
Frequency (Hz)

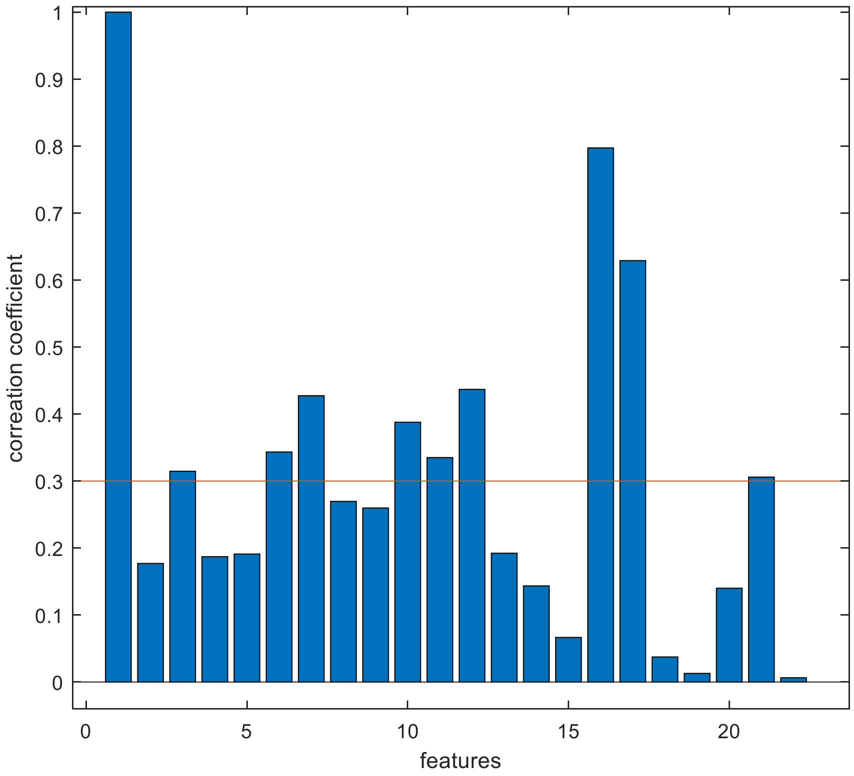

Magnitude (dB)
50
0
-50
-100
0
2000
4000
6000
8000
10000
12000
14000
16000
Frequency (Hz)


Magnitude (dB)
60
40
20
0
-20
-40
-60
-80
0
2000
4000
6000
8000
10000
12000
14000
16000
Frequency (Hz)

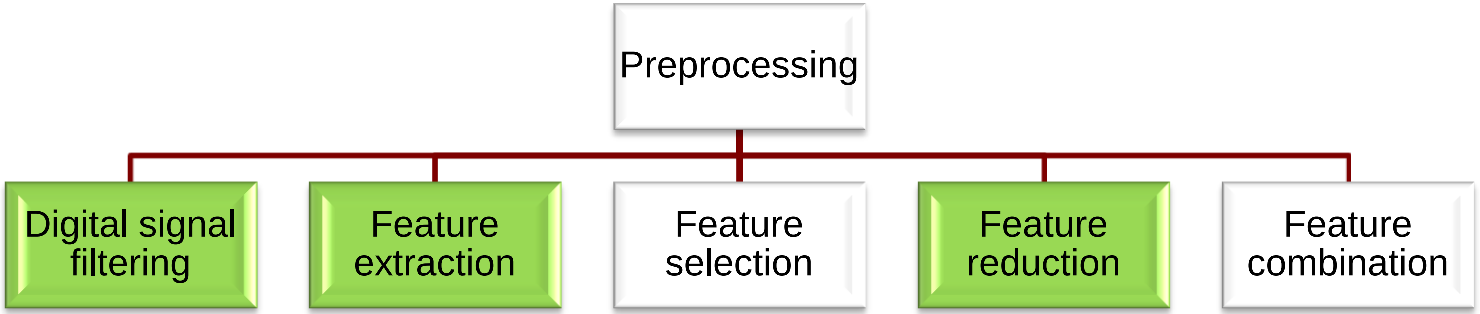
Feature extraction

- Time domain
  - Mean
  - Peak
  - Root mean square
  - Variance
  - Kurtosis
  - Crest factor
  - Shape factor
  - Skewness
- Frequency domain
  - 256 points divided into 8 bins
- Morlet waves
  - Standard deviation
  - Wavelet entropy
  - Kurtosis
  - Skewness
  - Variance

Feature reduction



- Preprocessing
  - Digital signal filtering
  - Feature extraction
  - Feature selection
  - Feature reduction
  - Feature combination

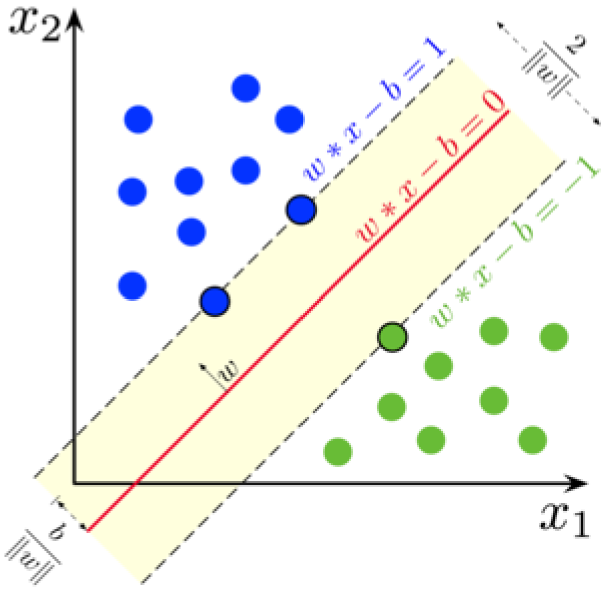


- Steady state: 12kHz
- Penetration: 20kHz

- Time domain (8)
- Frequency domain (8)
- Morlet waves (5)

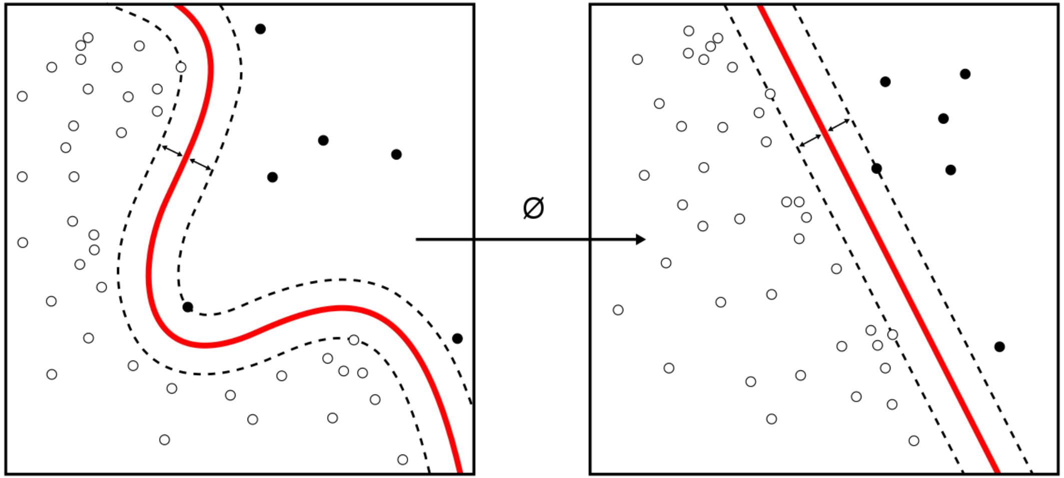
- Fault correlation > 30%

Support vector machine (SVM)



Support vector machine (SVM)	
Kernel Function	Linear
Box Constraint	0.1
Coding Matrix	Onevsone & onevsall
Standardization	False

Naive Bayes classifier



$$p(C_k \mid \mathbf{x}) = \frac{p(C_k)\, p(\mathbf{x} \mid C_k)}{p(\mathbf{x})}$$

$$\text{posterior} = \frac{\text{prior} \times \text{likelihood}}{\text{evidence}}$$

k-nearest neighbor classifier (kNN)

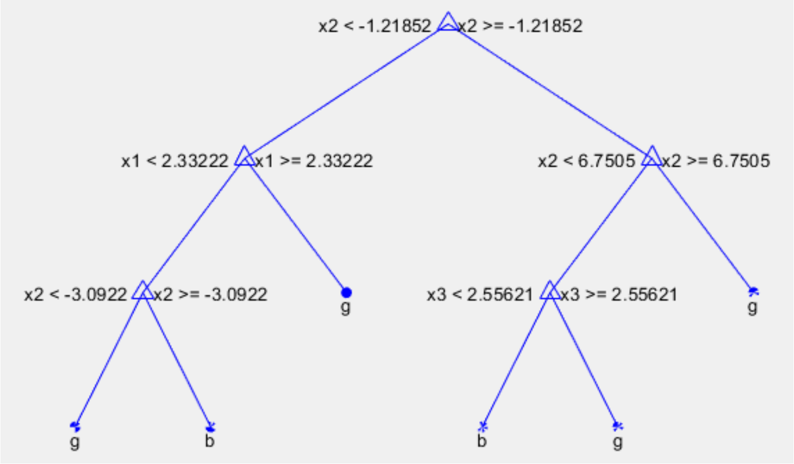
- **kNN**: classification method in which a new object is classified based upon its distance to the nearest training samples of known classification.
  - Strengths: ability to classify nonlinear, multimodal, unlabeled samples based upon similarity to training samples

Design of kNN classifier	
Number of nearest neighbors (k)	3
Distance measurement metric	Euclidean
Equal or weighted voting	Weighted
Distance weight	Squared-inverse

Decision tree classifier

- **Decision tree**: network of binary decision-branches that originate from an initial root node. Branches lead to class labels (“leaves”) at endpoints.
  - Strengths: simple and intuitive, can classify data of multiple types.
- Problem of deep decision trees overfitting data.
  - Can address this by limiting size of the decision tree.
  - Simple, shallow, generalized decision trees can be more robust.

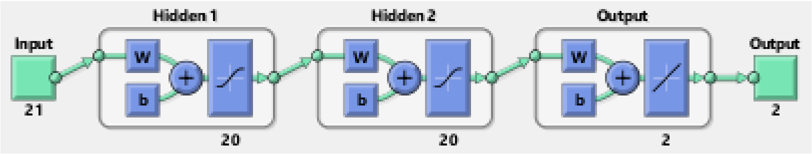
Design of decision tree classifier	
Split predictor technique	CART
Maximum number of splits	5



Neural network classifier (ANN)

- **Artificial neural network**: receives input data and implements weight, biases, and transfer functions to deliver an output.
  - Strengths: recognizing patterns in noisy, complex data and determining their nonlinear relationships.
- ANN candidates: recurrent, feedforward

Design of ANN classifier	
Neural network type	Feedforward
Number of layers	3 (*2 hidden*)
Neurons per hidden layer	20
Transfer function for hidden layers	Tangent-sigmoid
Transfer function for output layer	Pure-linear
Training method	Levenberg-Marquardt
Performance metric	Mean squared error



Classifier training and testing

- 5-fold cross validation for establishing training and testing sets.
- Accuracy determined by comparing the output of the classifier to the known label
- Results from each fold were combined to determine overall accuracy for the classifier

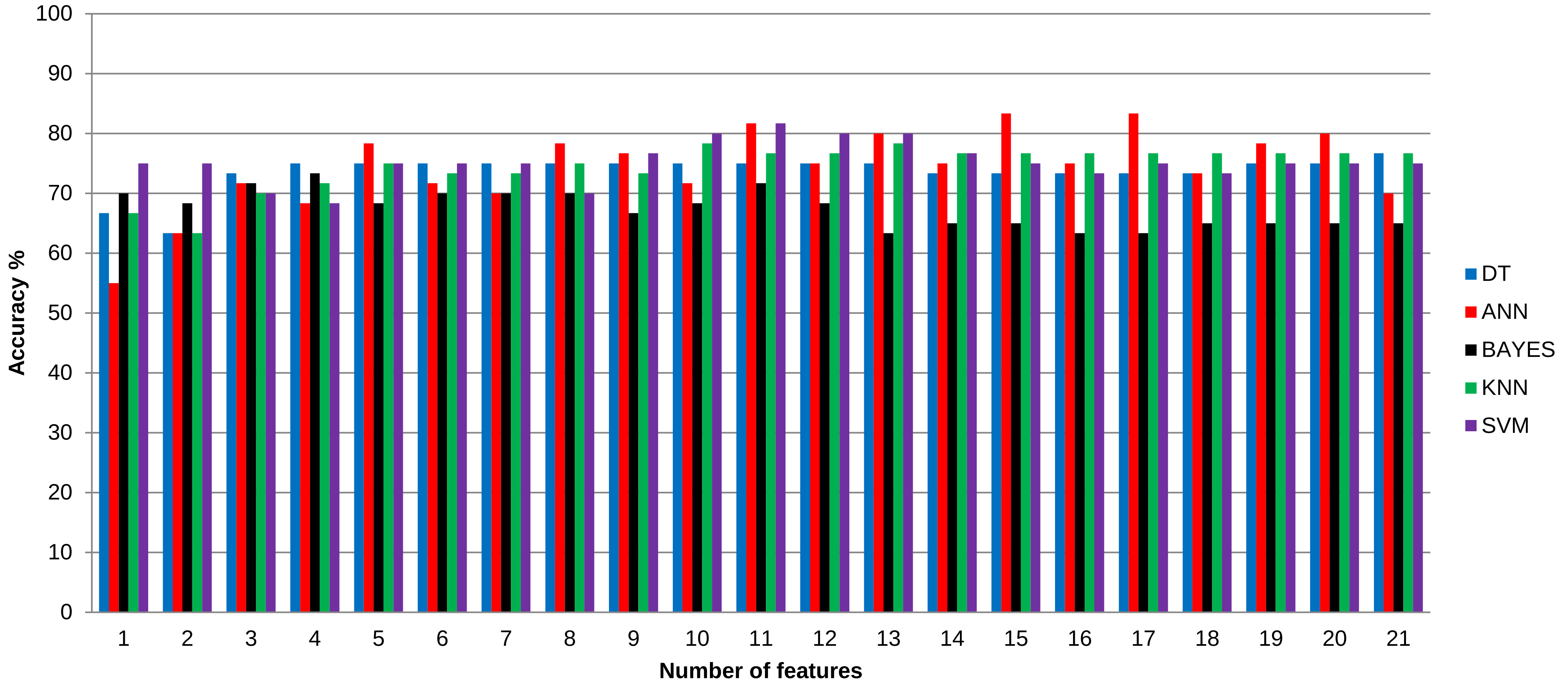
Classifier training and testing

Modes for training

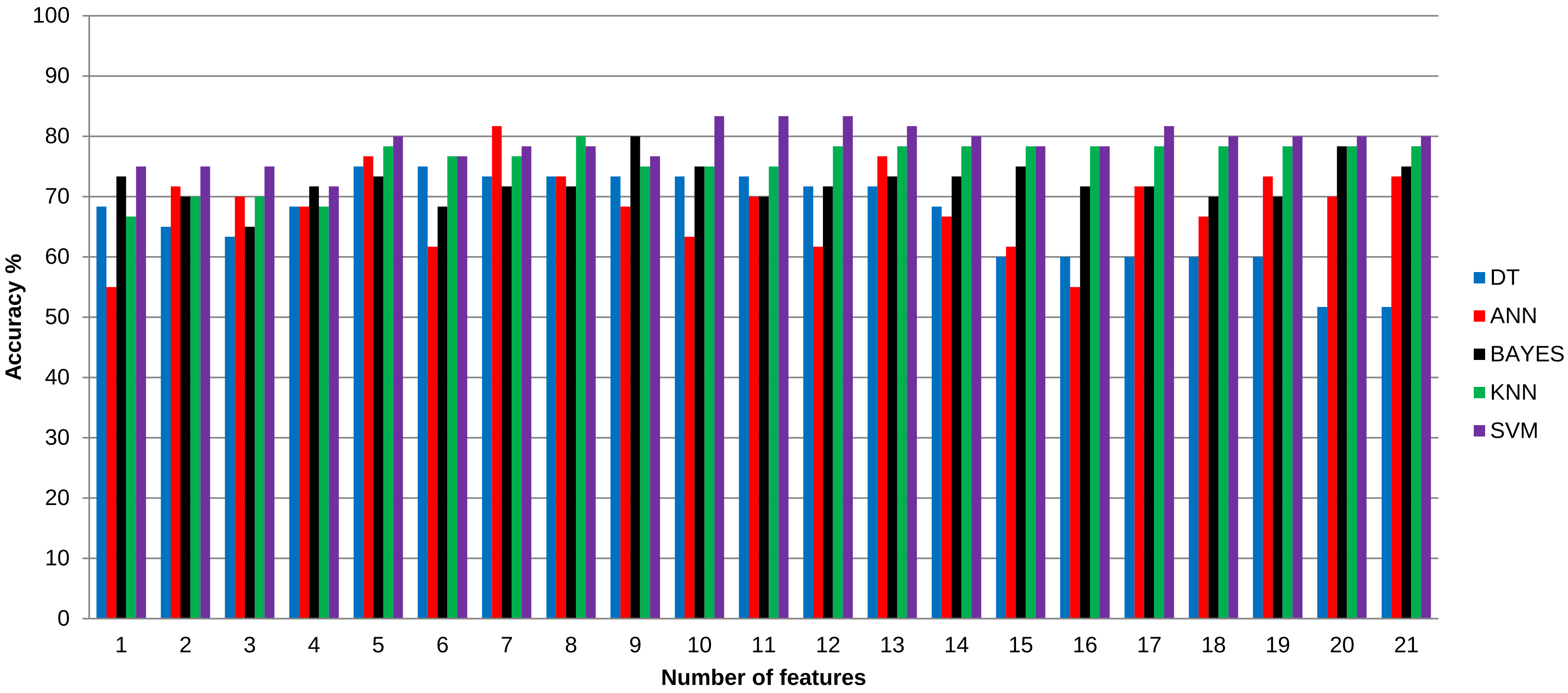
- Fault detection (binary)
- Fault classification (multiclass)
- Individual fault detection (binary)

Fault detection results

Fault detection (penetration)



Fault detection (steady-state)



Fault classification results

Fault classification (penetration)

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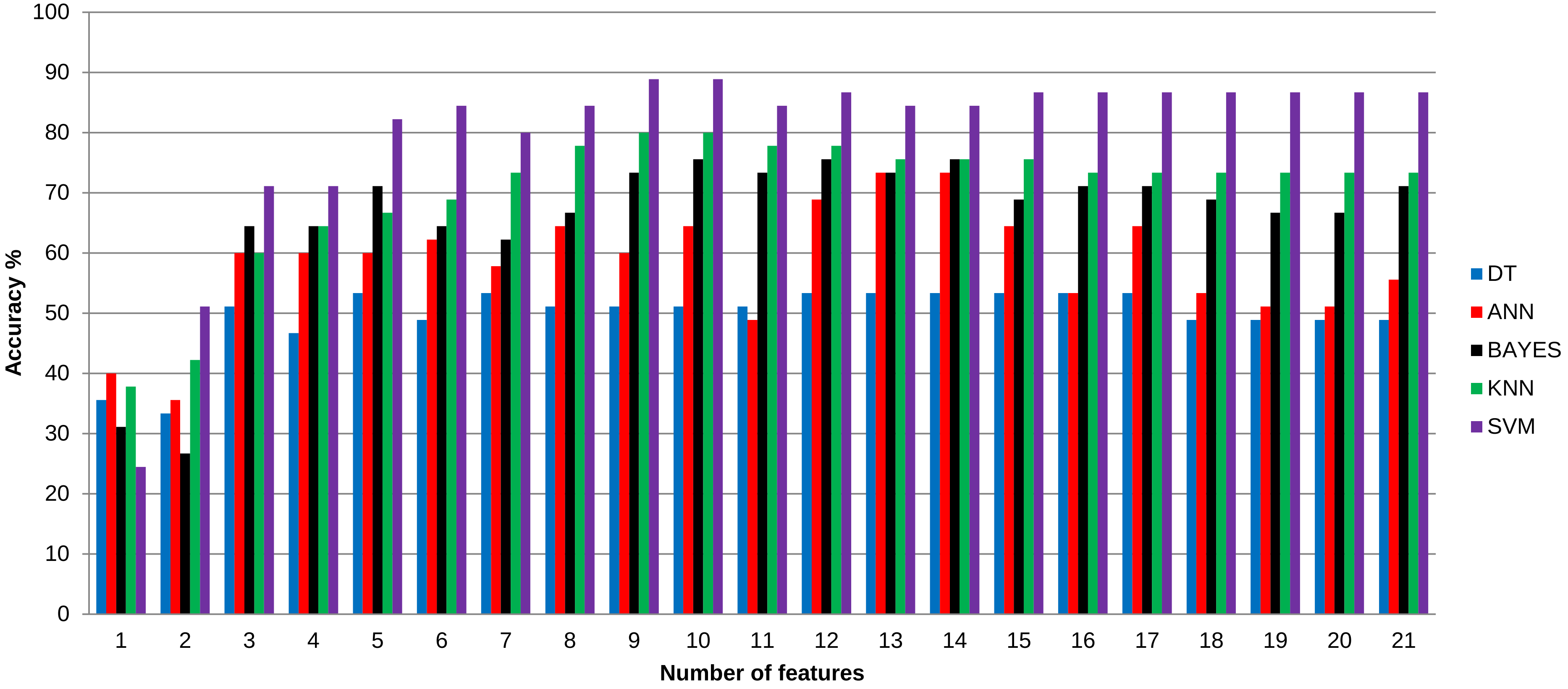

Fault classification (steady-state)

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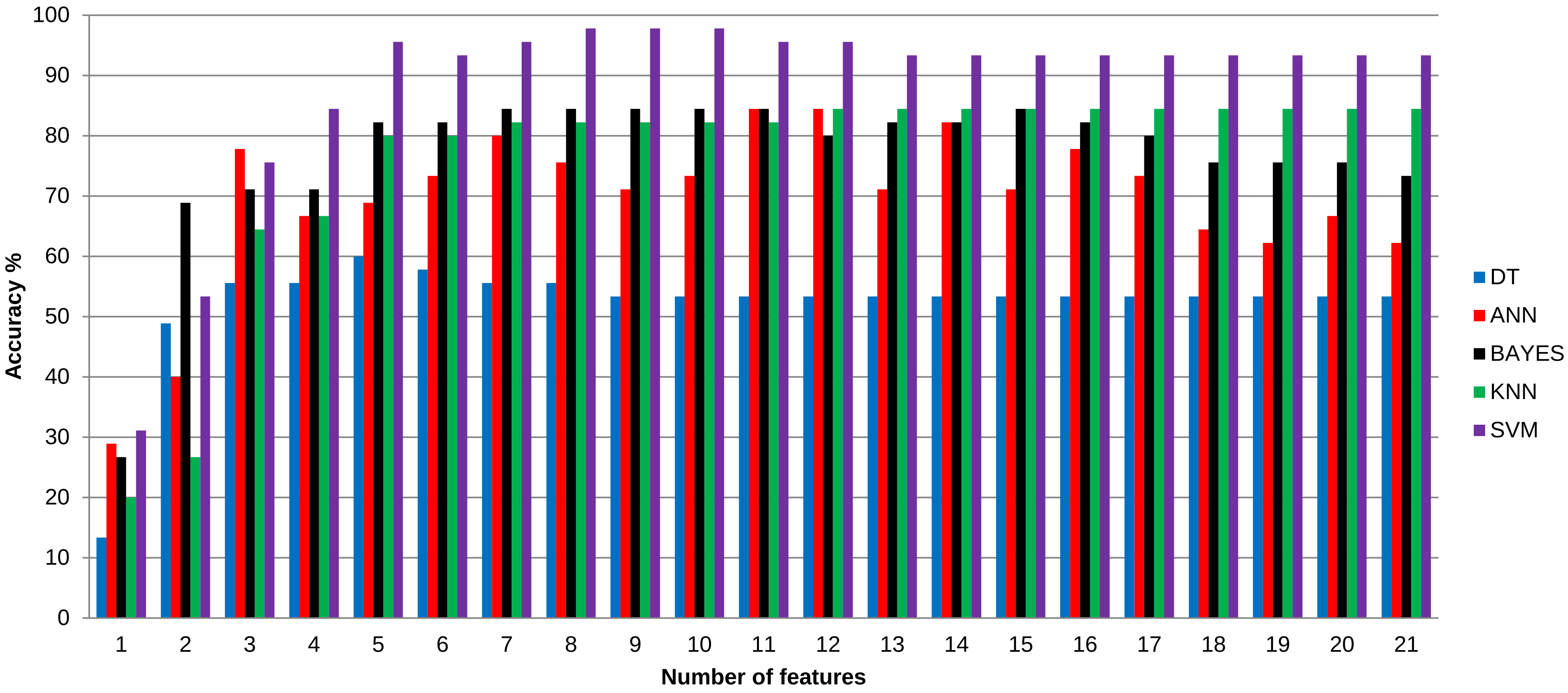
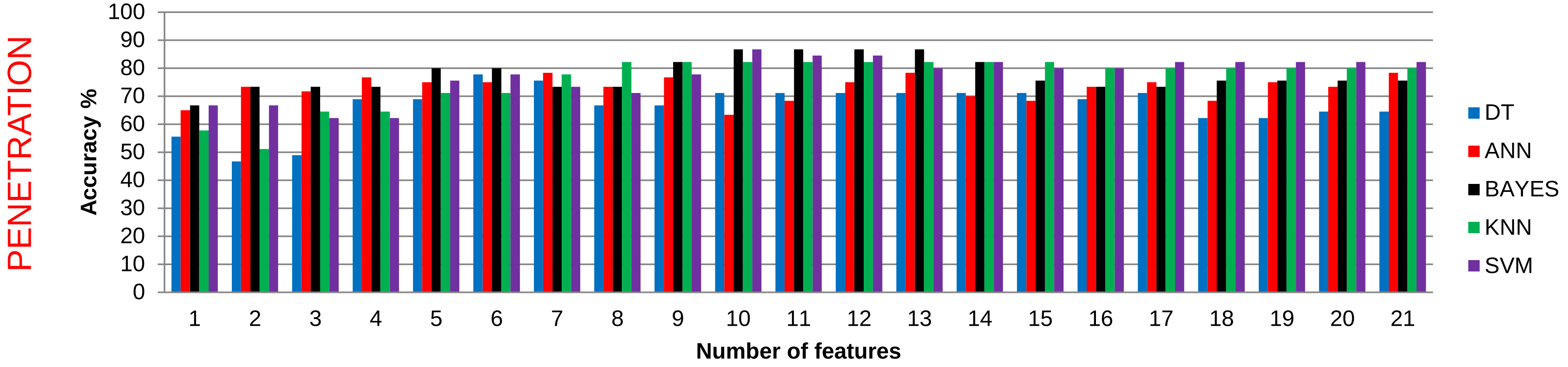
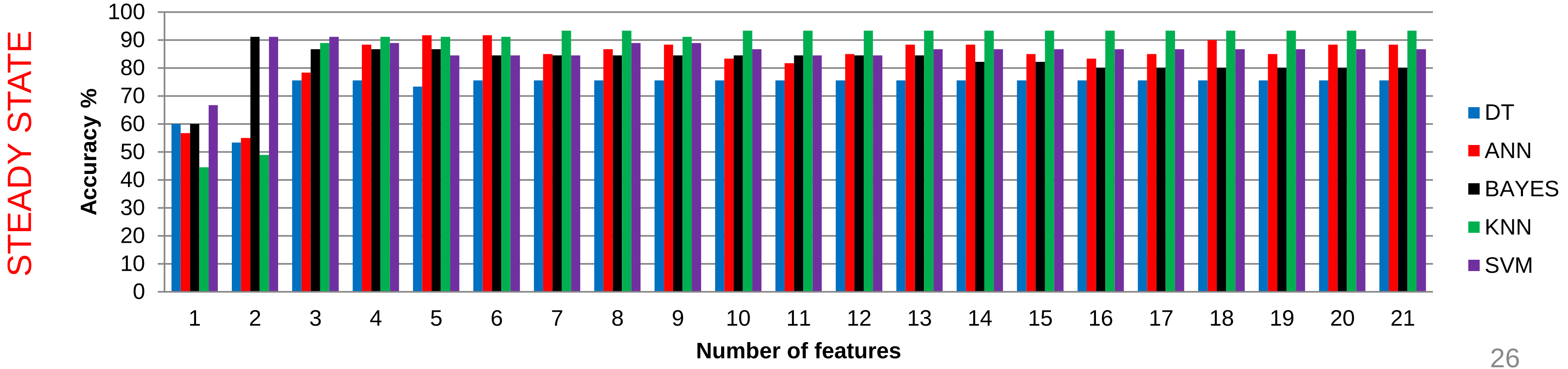


Individual wear type detection results

Flank wear detection





Chisel wear detection

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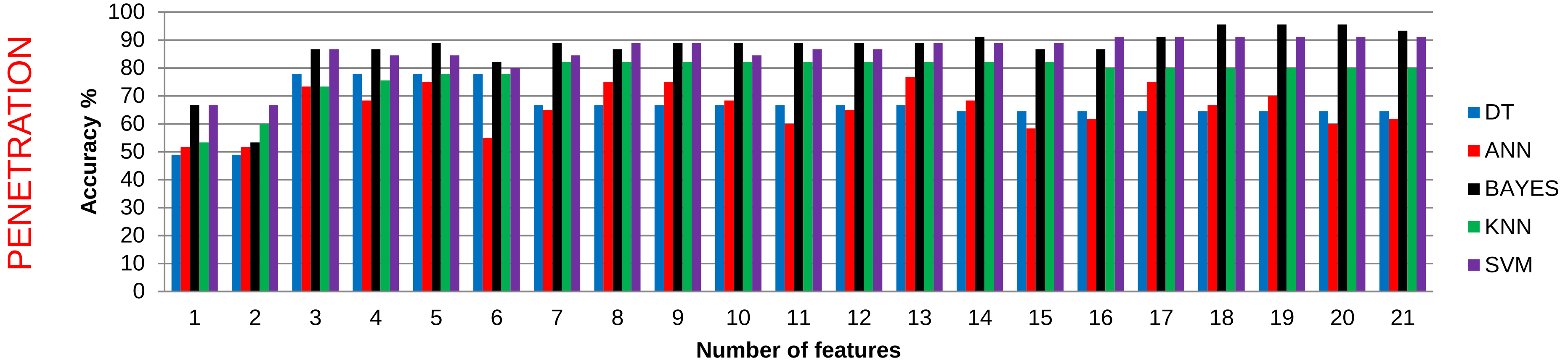

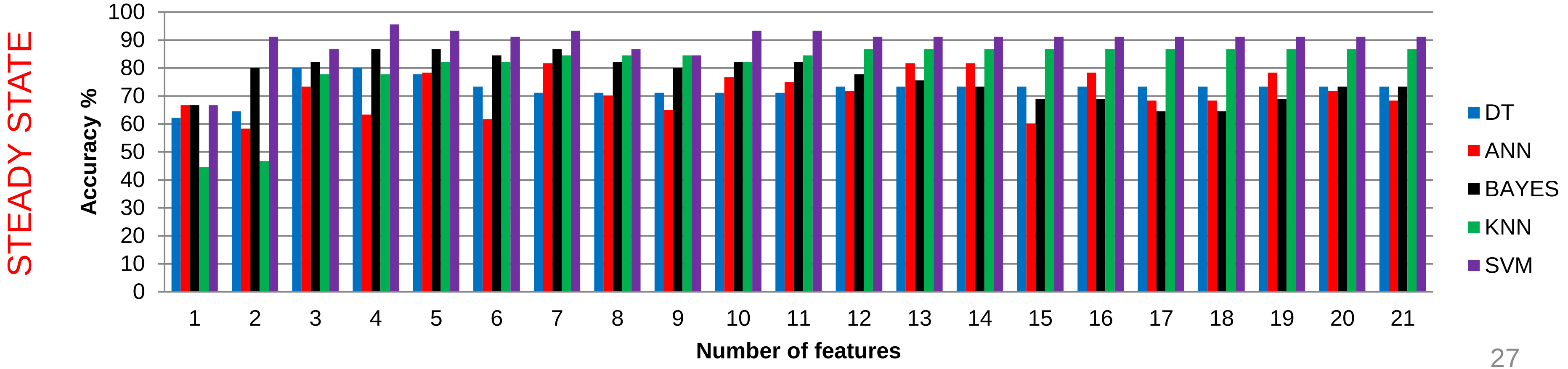

Outer corner wear detection

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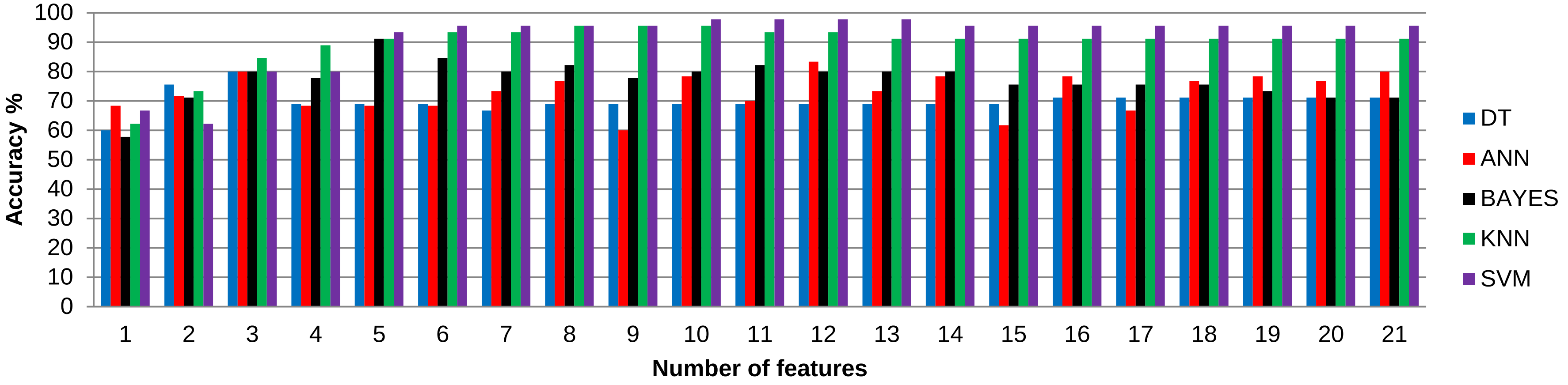
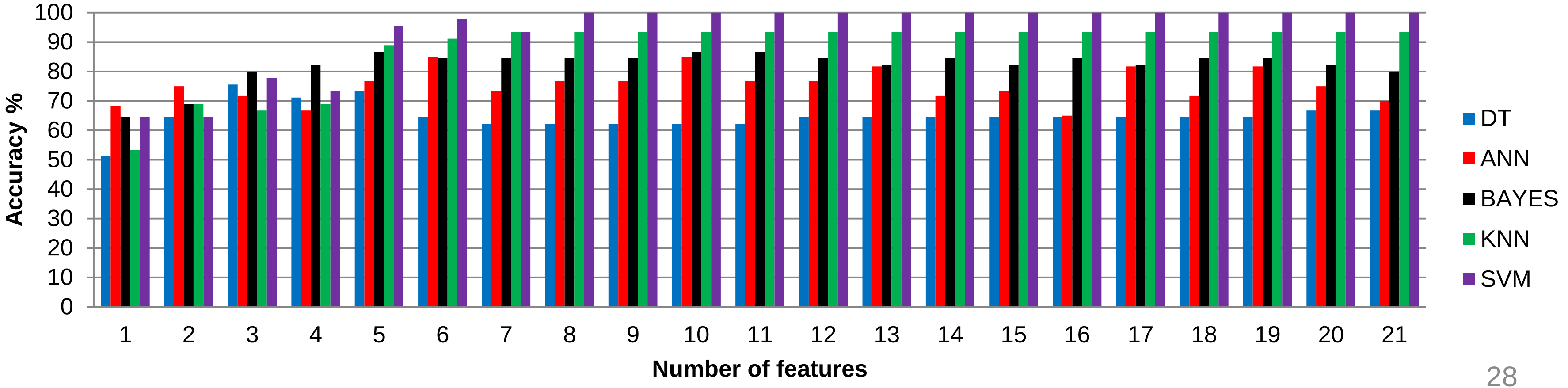
PENETRATION



STEADY STATE



Classification with fault correlation

kNN

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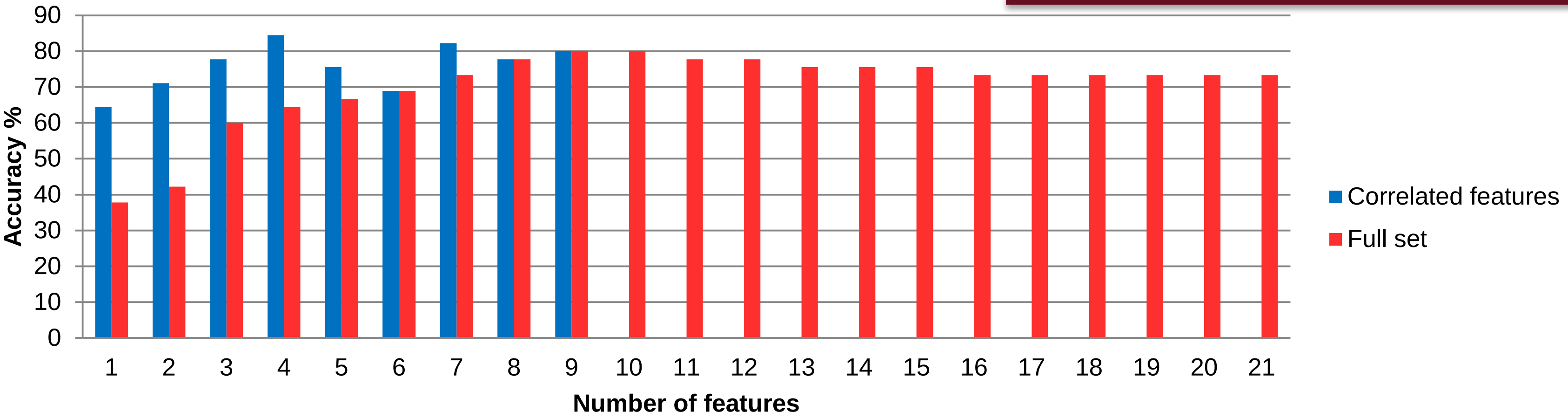
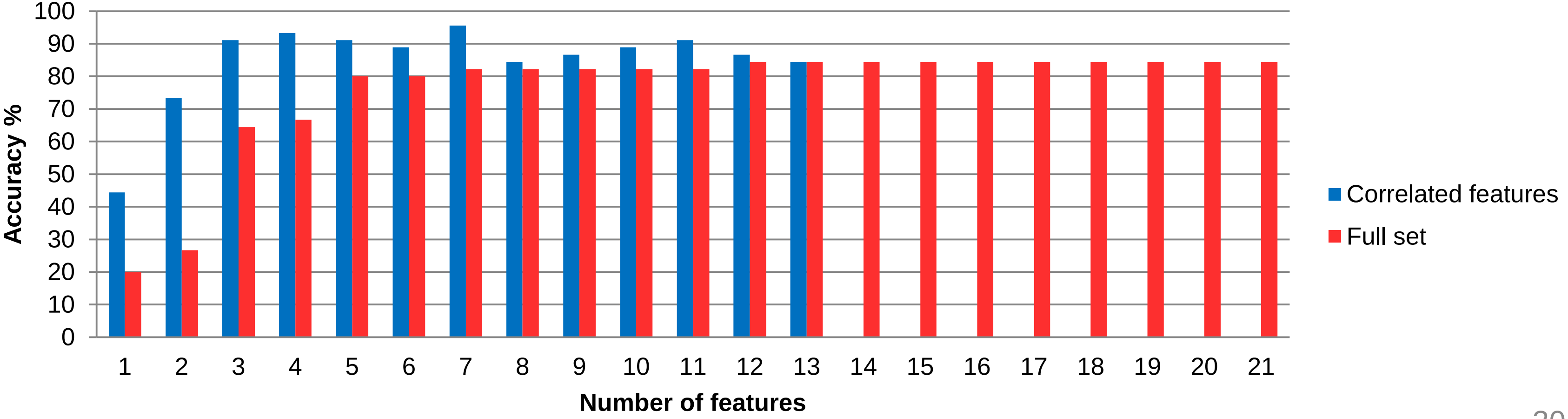
PENETRATION

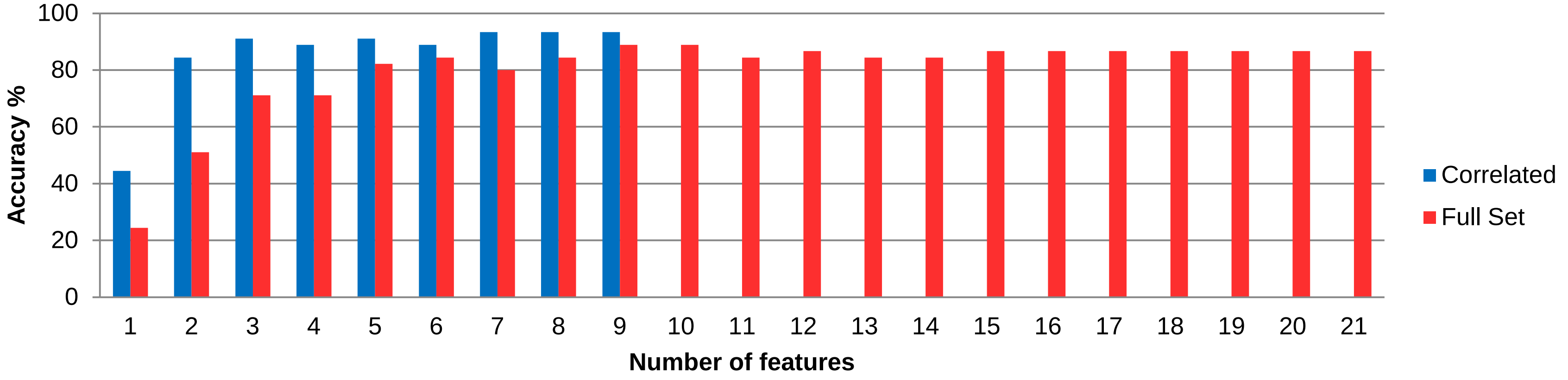


STEADY STATE

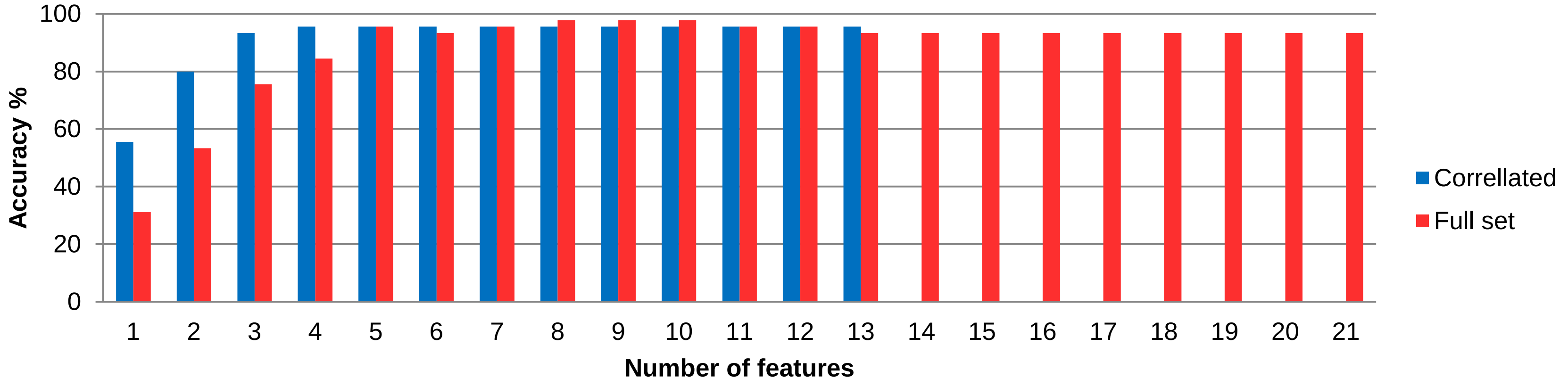


SVM

PENETRATION



STEADY STATE



Conclusions and future work

Conclusions

- SVM & kNN performed best overall out of the five classifiers.
  - **SVM**: 75% for detection, 93% for classification
  - **kNN**: 78% for detection, 84% for classification
- Impact of penetration vs. steady-state data
  - Minimal impact on fault detection accuracy.
  - Higher classification accuracies were derived from steady-state data.
  - Higher individual wear type detection accuracies were derived from steady-state data.

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Conclusions

- Decision tree performed poorly
  - Excessive pruning = overly generalized
  - Simple classifier excessively sensitive to changes in training data.
- ANN performed poorly
  - Overfitting (able to classify training data without error, but not testing data)
    - Increase the number of training samples by splitting 8-second samples into increments.

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Future work

- Re-train ANN with more training data.
- Implement ensemble learning techniques for improved accuracy.
- Requiring additional data: detect and classify <u>multiple</u> types of wear affecting the same drill bit.
- Optimization of parameters using ROC curves
- Optimization of the model using detailed analysis of the frequency spectrum

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