Fatigue Damage Detection and Risk Assessment via Wavelet Transform and Neural Network Analysis of Ultrasonic Signals

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Abstract

This paper develops a data-driven autonomous method for detection of fatigue damage and classification of the associated damage risk in mechanical structures, based on ultrasonic signal energy. The underlying concept is built upon attenuation of the signal and stability of the attenuation process. The attenuation provides pertinent information for damage quantification, whereas the stability represents resistance towards the fatigue damage growth. The proposed neural network (NN) model has been trained using the scaled conjugate-gradient back-propagation method. The NN model is capable of damage detection and damage classification into five classes of increasing risk. The Daubechies wavelet transform has been used to reduce the noisy pattern of the ultrasonic signal energy by using the associated approximation coefficients. The results show that the proposed method of approximation signal energy can detect and classify the damage with an accuracy of up to 98.5%.

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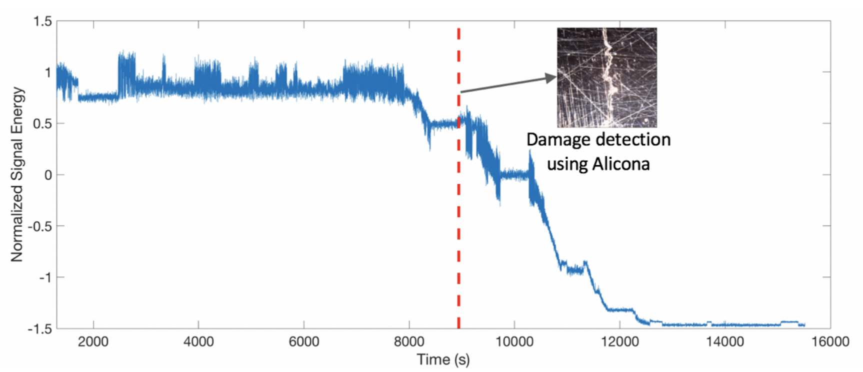
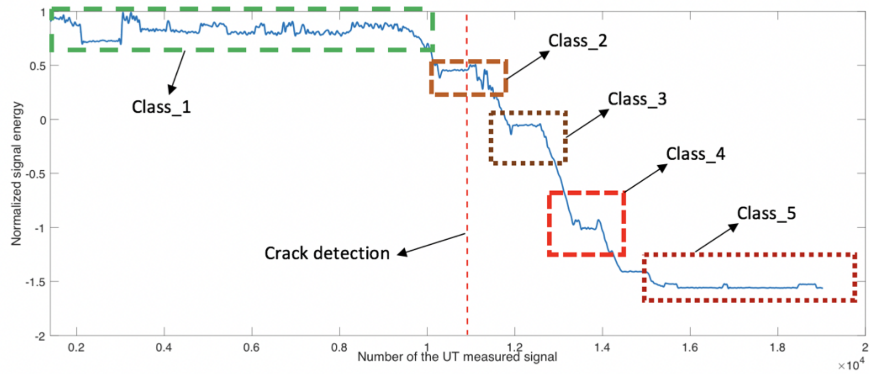
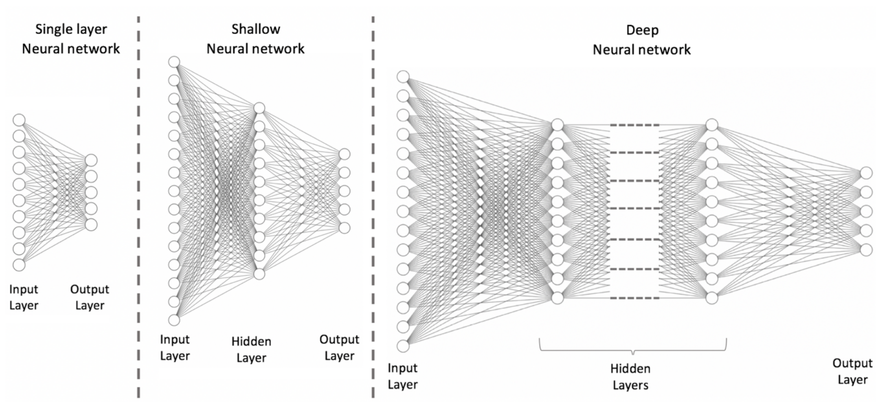
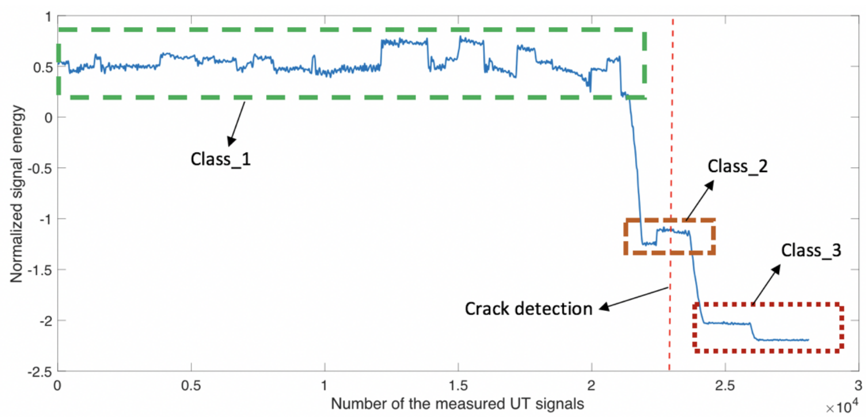
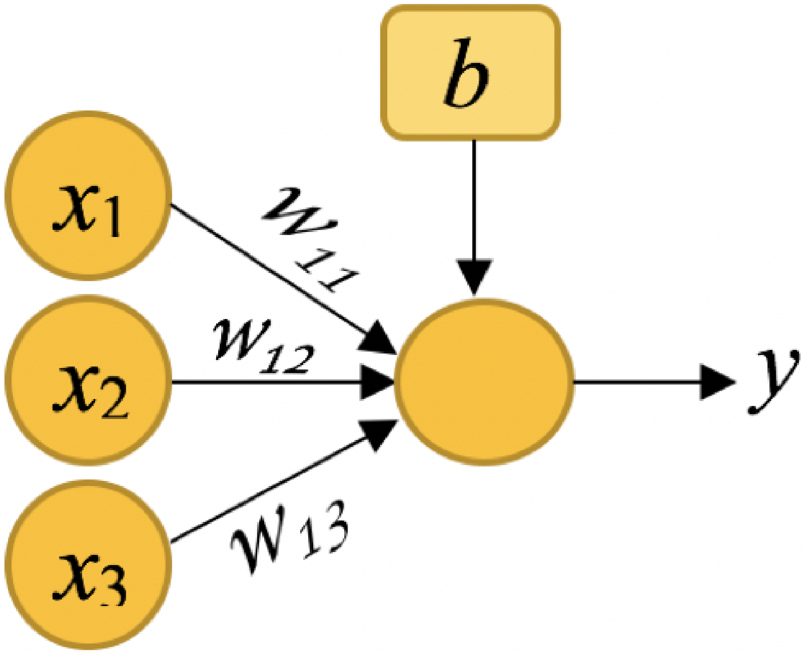
`Fatigue Damage Detection and Risk  Assessment via Wavelet Transform and Neural Network Analysis of Ultra` available at https://authorea.com/users/438987/articles/540029-fatigue-damage-detection-and-risk-assessment-via-wavelet-transform-and-neural-network-analysis-of-ultrasonic-signals

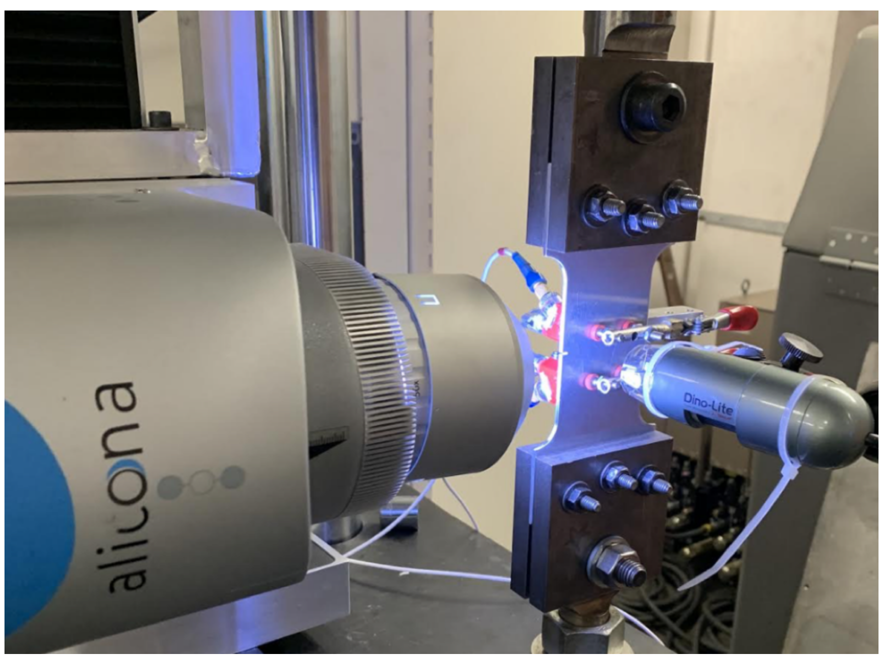


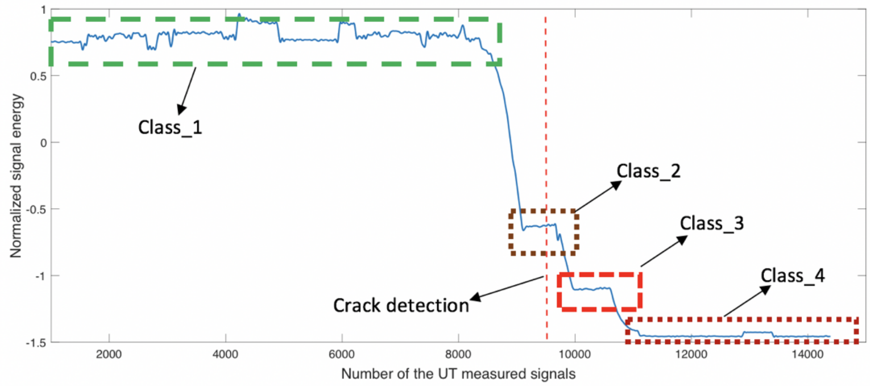

Class_1
Class_2
Class_3
Class_4
Class_5
Crack detection
Normalized signal energy
Number of the UT measured signal
×10^4

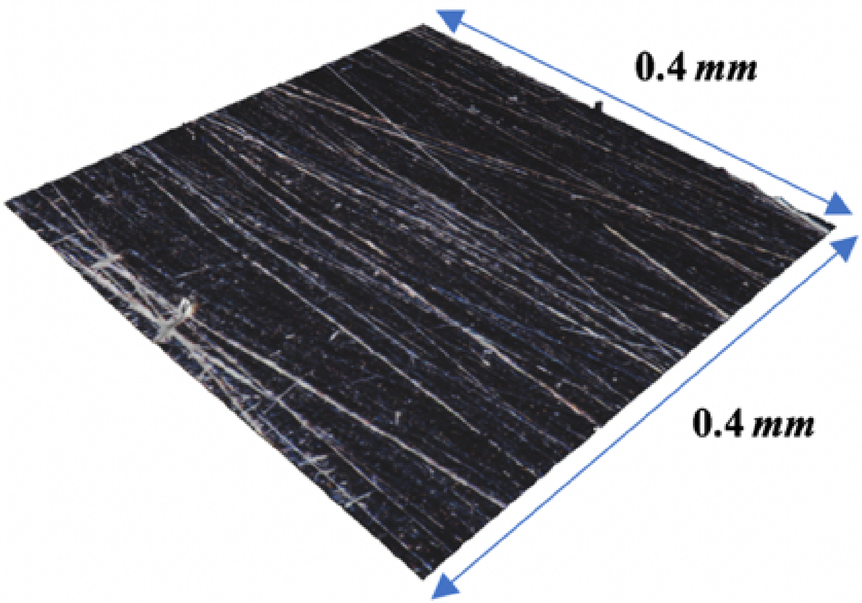

Single layer
Neural network
Input Layer
Output Layer
Shallow
Neural network
Input Layer
Hidden Layer
Output Layer
Deep
Neural network
Input Layer
Hidden Layers
Output Layer

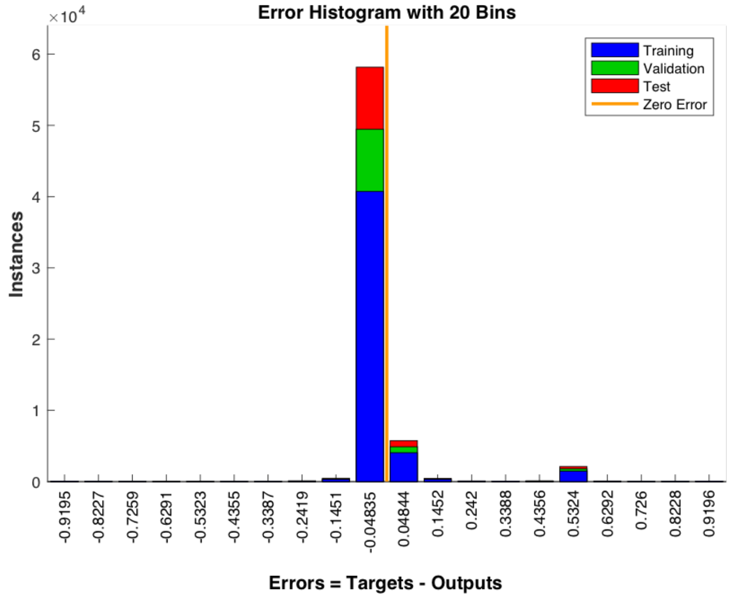

Class_1
Class_2
Class_3
Crack detection
Normalized signal energy
Number of the measured UT signals
×10^4

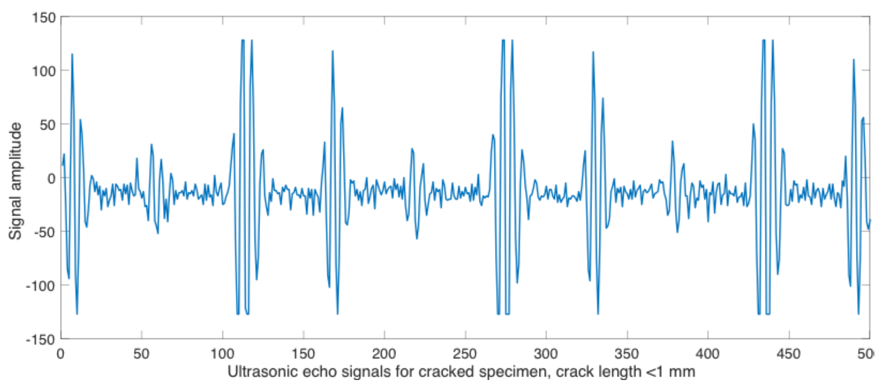

b
x1
x2
x3
w11
w12
w13
y

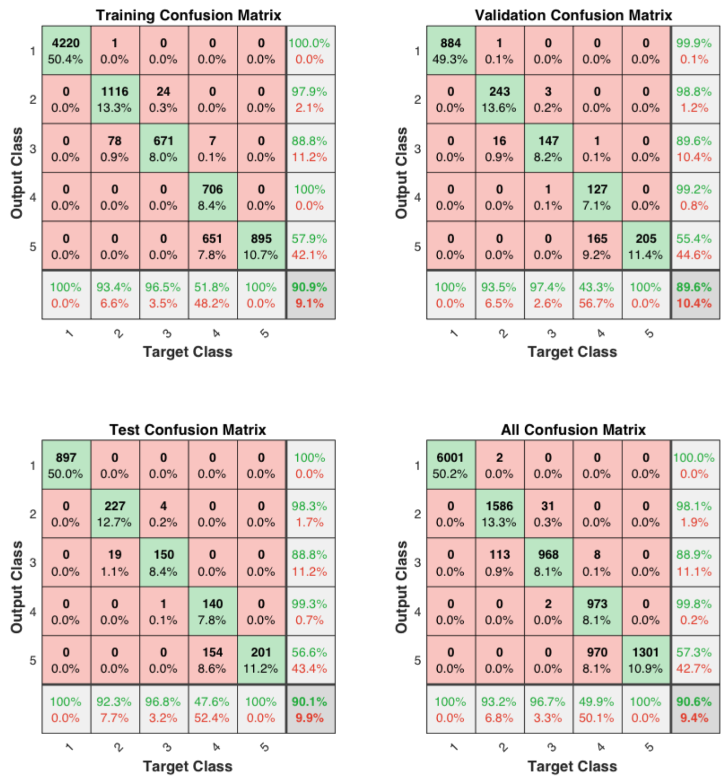

alicona
Dino-Lite

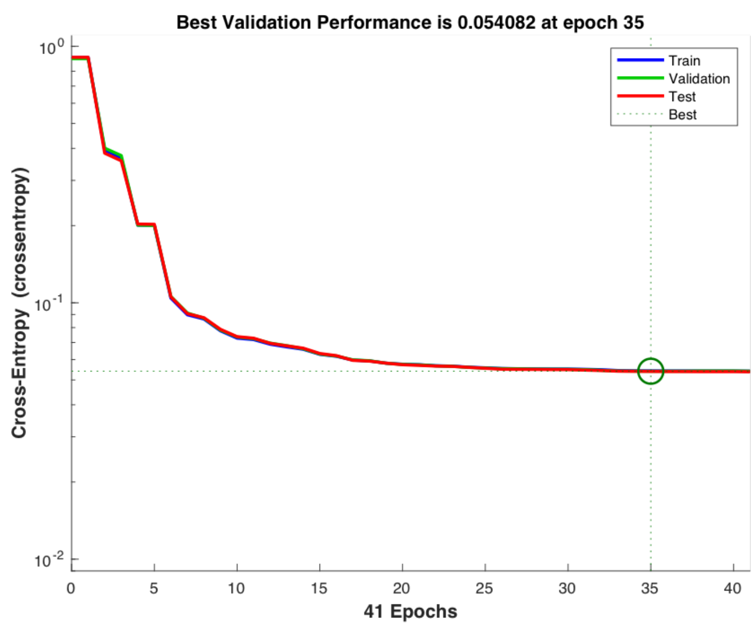

Normalized signal energy
Number of the UT measured signals
Class_1
Class_2
Class_3
Class_4
Crack detection
1
0.5
0
-0.5
-1
-1.5
2000
4000
6000
8000
10000
12000
14000

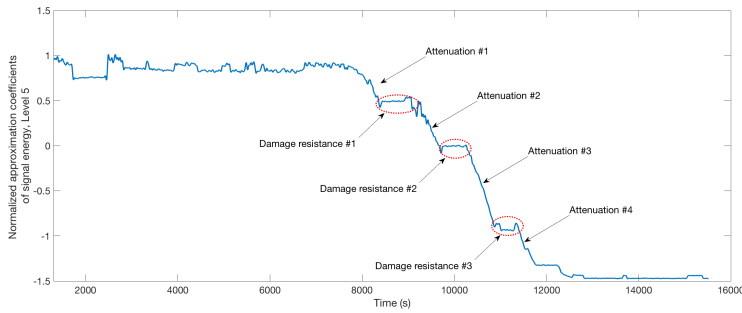

0.4 mm
0.4 mm

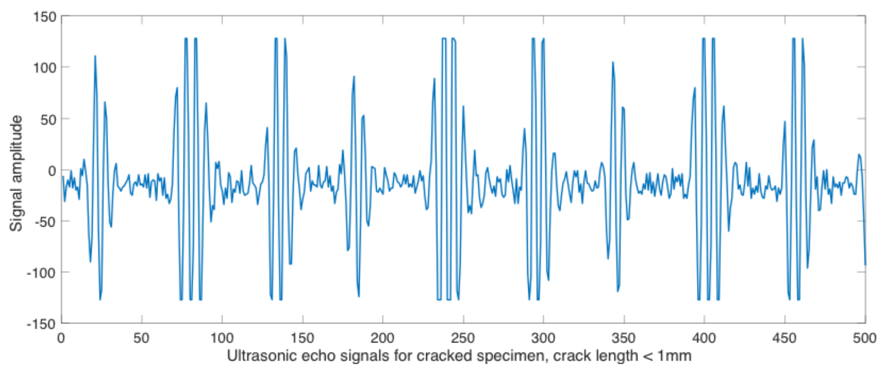

Error Histogram with 20 Bins
×10^4
Instances
Training
Validation
Test
Zero Error
-0.9195
-0.8227
-0.7259
-0.6291
-0.5323
-0.4355
-0.3387
-0.2419
-0.1451
-0.04835
0.04844
0.1452
0.242
0.3388
0.4356
0.5324
0.6292
0.726
0.8228
0.9196
Errors = Targets - Outputs

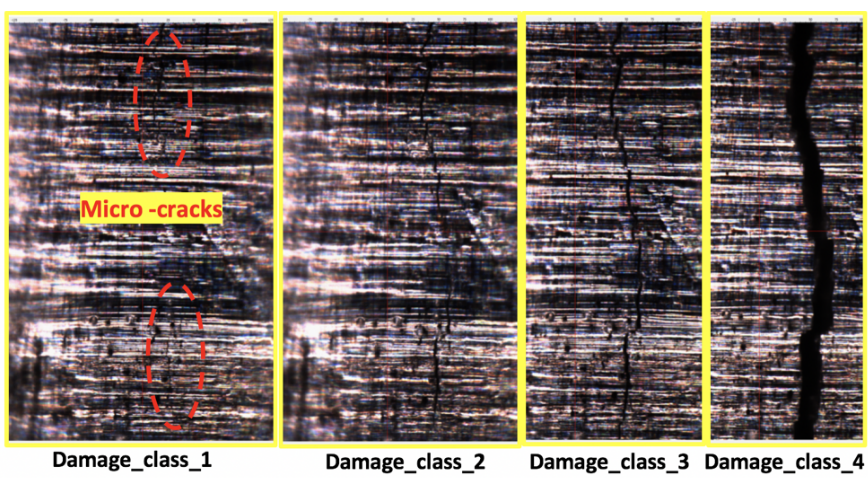

Signal amplitude
Ultrasonic echo signals for cracked specimen, crack length <1 mm

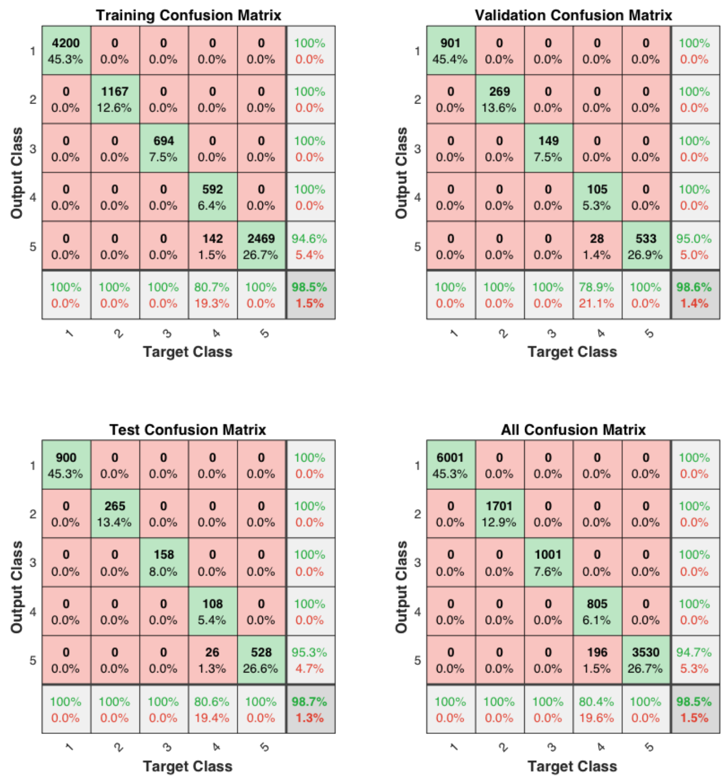

Training Confusion Matrix
4220 50.4% | 1 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 100.0% 0.0%
0 0.0% | 1116 13.3% | 24 0.3% | 0 0.0% | 0 0.0% | 97.9% 2.1%
0 0.0% | 78 0.9% | 671 8.0% | 7 0.1% | 0 0.0% | 88.8% 11.2%
0 0.0% | 0 0.0% | 0 0.0% | 706 8.4% | 0 0.0% | 100% 0.0%
0 0.0% | 0 0.0% | 0 0.0% | 651 7.8% | 895 10.7% | 57.9% 42.1%
100% 0.0% | 93.4% 6.6% | 96.5% 3.5% | 51.8% 48.2% | 100% 0.0% | 90.9% 9.1%
Validation Confusion Matrix
884 49.3% | 1 0.1% | 0 0.0% | 0 0.0% | 0 0.0% | 99.9% 0.1%
0 0.0% | 243 13.6% | 3 0.2% | 0 0.0% | 0 0.0% | 98.8% 1.2%
0 0.0% | 16 0.9% | 147 8.2% | 1 0.1% | 0 0.0% | 89.6% 10.4%
0 0.0% | 0 0.0% | 1 0.1% | 127 7.1% | 0 0.0% | 99.2% 0.8%
0 0.0% | 0 0.0% | 0 0.0% | 165 9.2% | 205 11.4% | 55.4% 44.6%
100% 0.0% | 93.5% 6.5% | 97.4% 2.6% | 43.3% 56.7% | 100% 0.0% | 89.6% 10.4%
Test Confusion Matrix
897 50.0% | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 100% 0.0%
0 0.0% | 227 12.7% | 4 0.2% | 0 0.0% | 0 0.0% | 98.3% 1.7%
0 0.0% | 19 1.1% | 150 8.4% | 0 0.0% | 0 0.0% | 88.8% 11.2%
0 0.0% | 0 0.0% | 1 0.1% | 140 7.8% | 0 0.0% | 99.3% 0.7%
0 0.0% | 0 0.0% | 0 0.0% | 154 8.6% | 201 11.2% | 56.6% 43.4%
100% 0.0% | 92.3% 7.7% | 96.8% 3.2% | 47.6% 52.4% | 100% 0.0% | 90.1% 9.9%
All Confusion Matrix
6001 50.2% | 2 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 100.0% 0.0%
0 0.0% | 1586 13.3% | 31 0.3% | 0 0.0% | 0 0.0% | 98.1% 1.9%
0 0.0% | 113 0.9% | 968 8.1% | 8 0.1% | 0 0.0% | 88.9% 11.1%
0 0.0% | 0 0.0% | 2 0.0% | 973 8.1% | 0 0.0% | 99.8% 0.2%
0 0.0% | 0 0.0% | 0 0.0% | 970 8.1% | 1301 10.9% | 57.3% 42.7%
100% 0.0% | 93.2% 6.8% | 96.7% 3.3% | 49.9% 50.1% | 100% 0.0% | 90.6% 9.4%
Output Class
Target Class
1 2 3 4 5

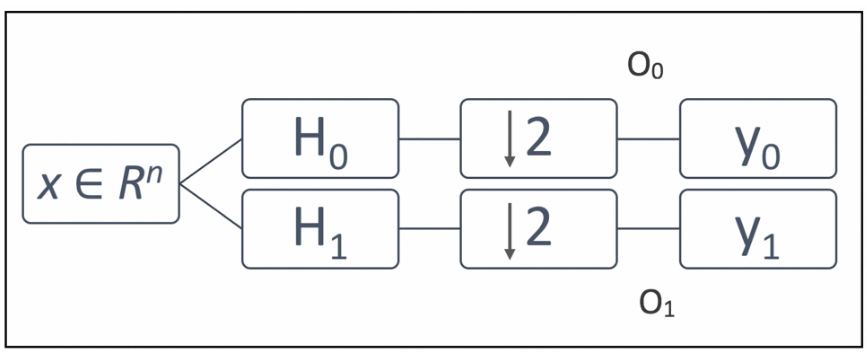

Best Validation Performance is 0.054082 at epoch 35
Cross-Entropy (crossentropy)
41 Epochs
Train
Validation
Test
Best
10^0
10^-1
10^-2
0 5 10 15 20 25 30 35 40

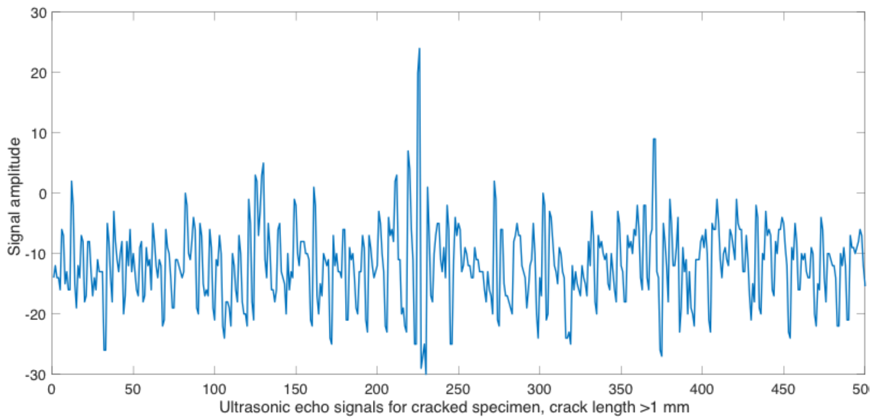

Attenuation #1
Attenuation #2
Attenuation #3
Attenuation #4
Damage resistance #1
Damage resistance #2
Damage resistance #3
Normalized approximation coefficients of signal energy, Level 5
Time (s)

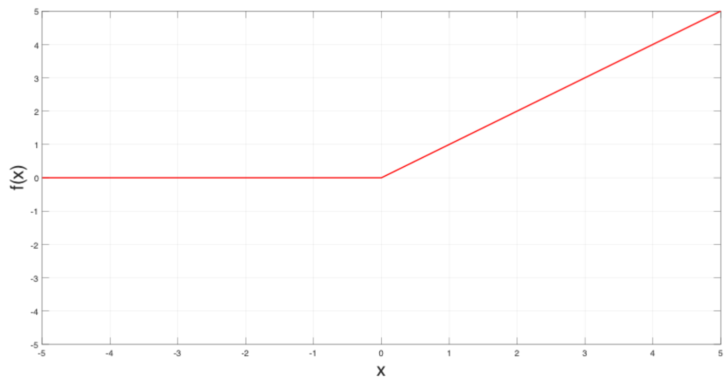

Signal amplitude
Ultrasonic echo signals for cracked specimen, crack length < 1mm

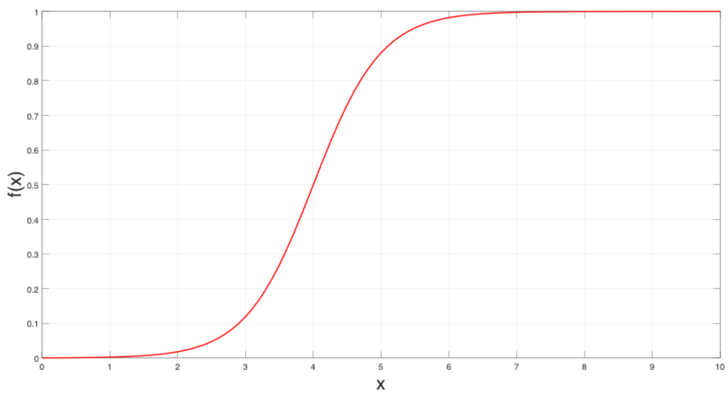

Micro -cracks
Damage_class_1
Damage_class_2
Damage_class_3
Damage_class_4

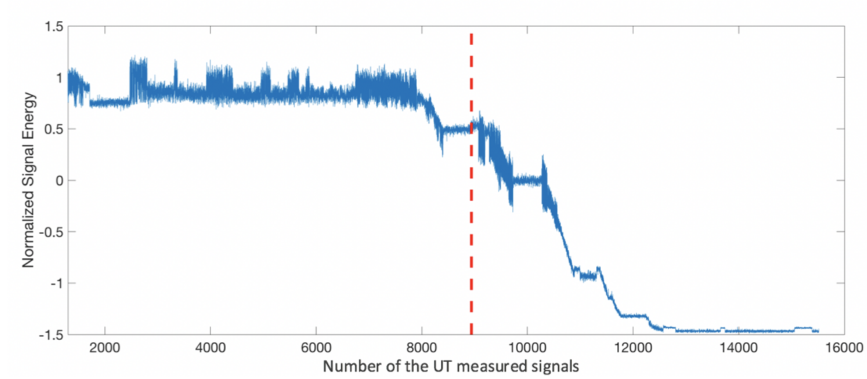

Training Confusion Matrix
Validation Confusion Matrix
Test Confusion Matrix
All Confusion Matrix
Output Class
Target Class

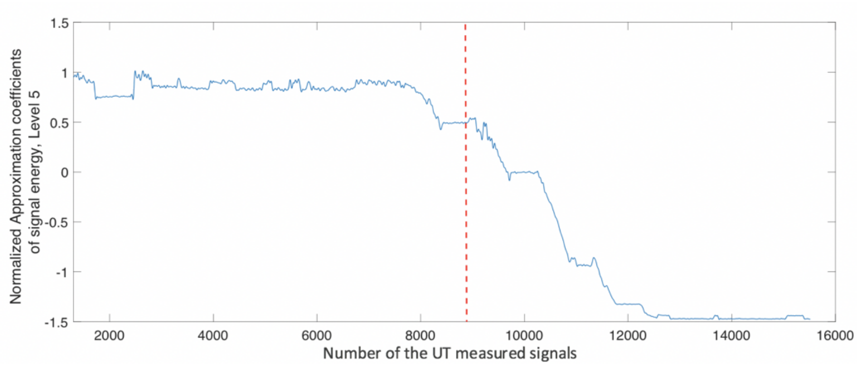

$x \in R^n$
H_0
H_1
$\downarrow 2$
$\downarrow 2$
y_0
y_1
O_0
O_1

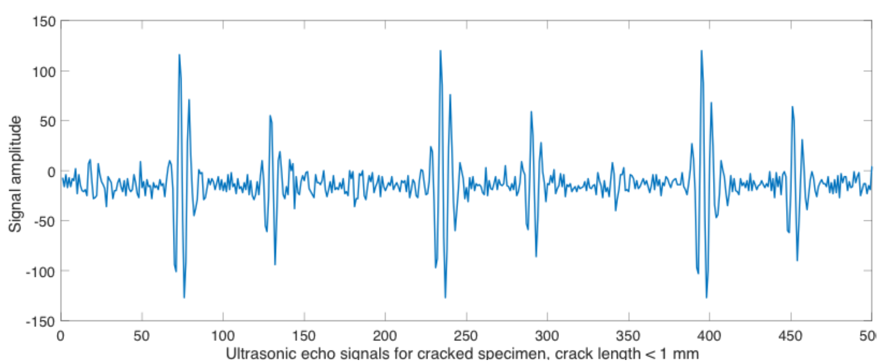

Signal amplitude
Ultrasonic echo signals for cracked specimen, crack length >1 mm

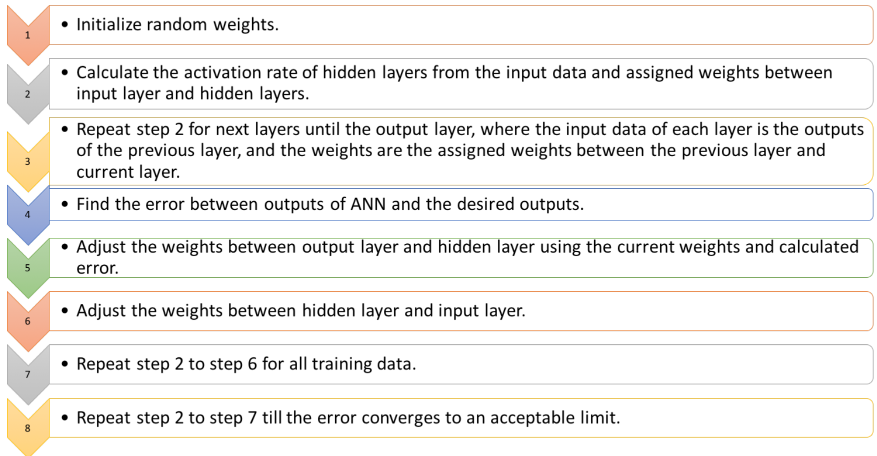

f(x)
x

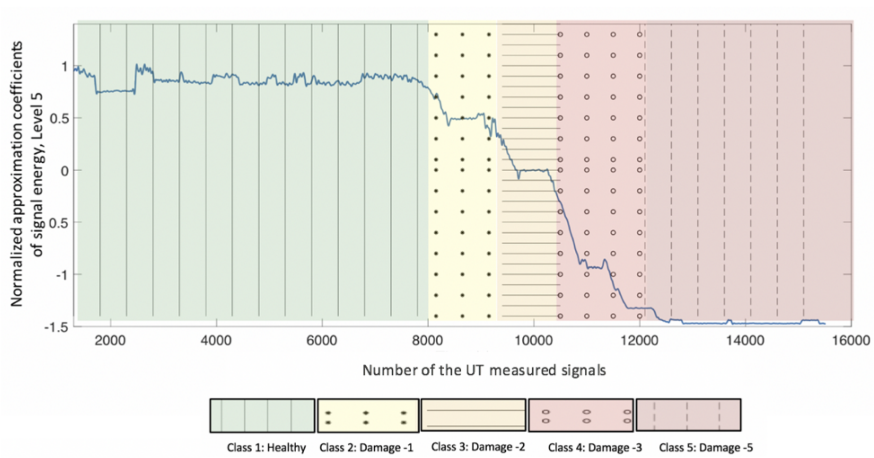

f(x)
x

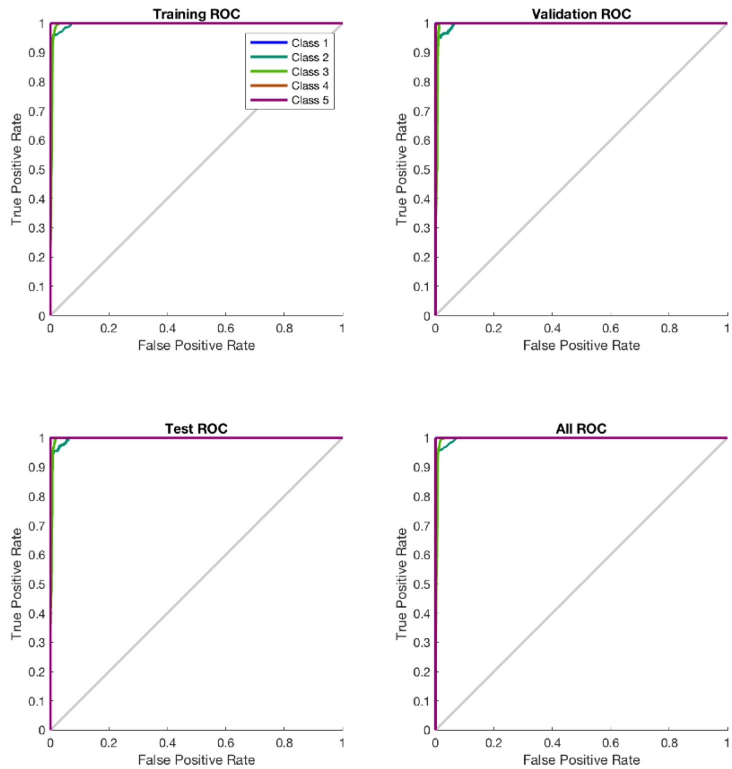

Normalized Signal Energy
1.5
1
0.5
0
-0.5
-1
-1.5
2000
4000
6000
8000
10000
12000
14000
16000
Number of the UT measured signals

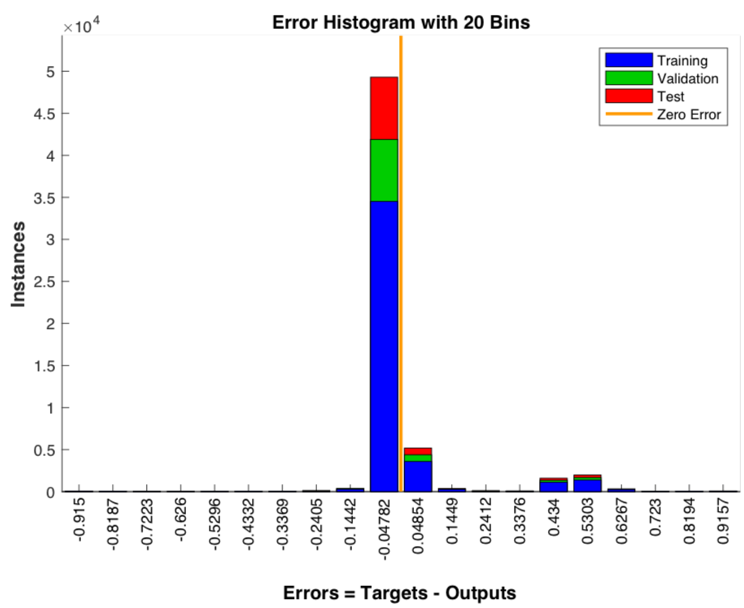

Normalized Approximation coefficients
of signal energy, Level 5
1.5
1
0.5
0
-0.5
-1
-1.5
2000
4000
6000
8000
10000
12000
14000
16000
Number of the UT measured signals

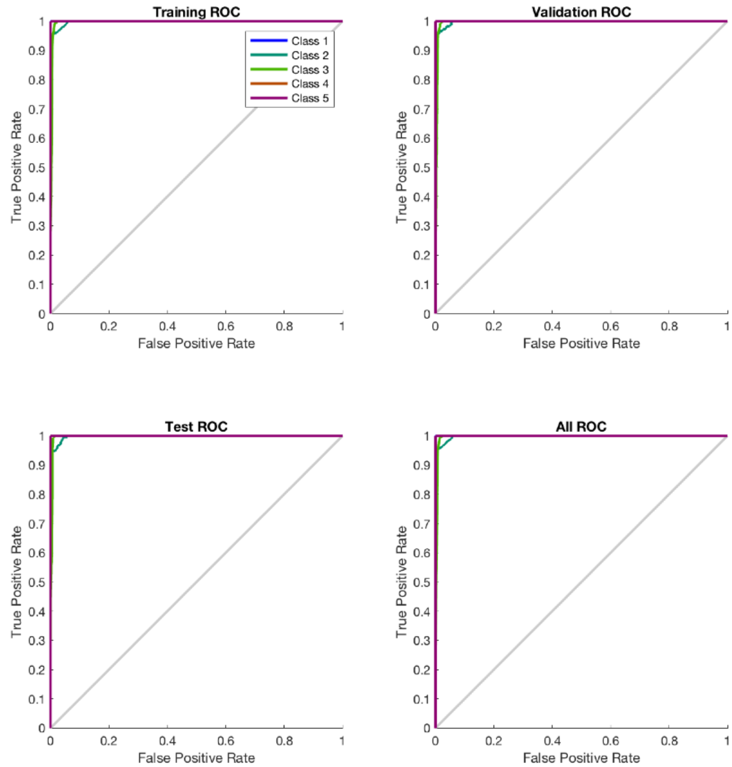

Signal amplitude
150
100
50
0
-50
-100
-150
0
50
100
150
200
250
300
350
400
450
50
Ultrasonic echo signals for cracked specimen, crack length < 1 mm

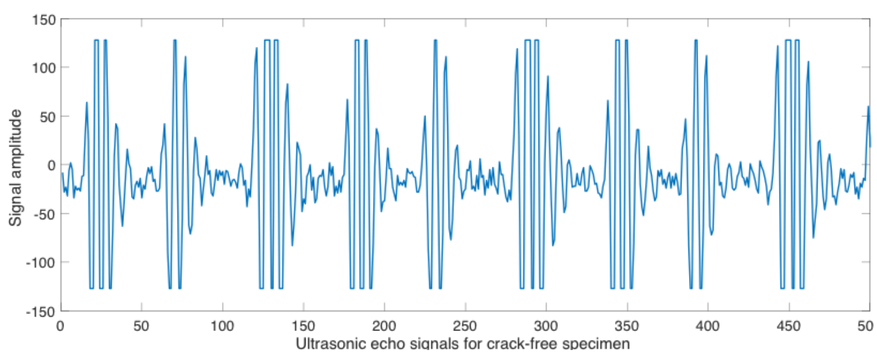

1
• Initialize random weights.
2
• Calculate the activation rate of hidden layers from the input data and assigned weights between input layer and hidden layers.
3
• Repeat step 2 for next layers until the output layer, where the input data of each layer is the outputs of the previous layer, and the weights are the assigned weights between the previous layer and current layer.
4
• Find the error between outputs of ANN and the desired outputs.
5
• Adjust the weights between output layer and hidden layer using the current weights and calculated error.
6
• Adjust the weights between hidden layer and input layer.
7
• Repeat step 2 to step 6 for all training data.
8
• Repeat step 2 to step 7 till the error converges to an acceptable limit.

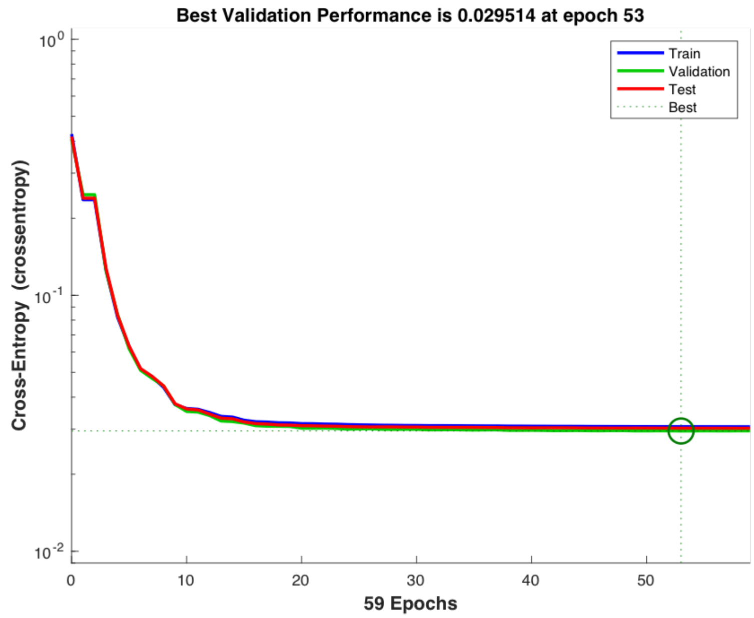

Normalized approximation coefficients of signal energy, Level 5
1
0.5
0
0.5
-1
-1.5
2000
4000
6000
8000
10000
12000
14000
16000
Number of the UT measured signals
Class 1: Healthy
Class 2: Damage -1
Class 3: Damage -2
Class 4: Damage -3
Class 5: Damage -5


Training ROC
Validation ROC
Test ROC
All ROC
Class 1
Class 2
Class 3
Class 4
Class 5
True Positive Rate
False Positive Rate


Error Histogram with 20 Bins
×10^4
Instances
Training
Validation
Test
Zero Error
-0.915
-0.8187
-0.7223
-0.626
-0.5296
-0.4332
-0.3369
-0.2405
-0.1442
-0.04782
0.04854
0.1449
0.2412
0.3376
0.434
0.5303
0.6267
0.723
0.8194
0.9157
Errors = Targets - Outputs


Training ROC
Validation ROC
Test ROC
All ROC
True Positive Rate
False Positive Rate
Class 1
Class 2
Class 3
Class 4
Class 5


Signal amplitude
Ultrasonic echo signals for crack-free specimen


Best Validation Performance is 0.029514 at epoch 53
Train
Validation
Test
Best
Cross-Entropy (crossentropy)
10^0
10^{-1}
10^{-2}
0
10
20
30
40
50
59 Epochs