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Machine learning-enhanced acoustic emission technique for impact source identification and classification in steel pipes.

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Machine Learning-Enhanced Acoustic Emission Technique for Impact Source Identification and Differentiation in Steel Pipes

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Introduction

- Carbon steel pipes are used for oil and gas transportation.
- External impacts of various magnitudes are sources of defects in steel pipes.
- Pipe defects start as micro-cracks and may progress to cause failure of pipelines.
- Failures of pipelines are associated with disasters.

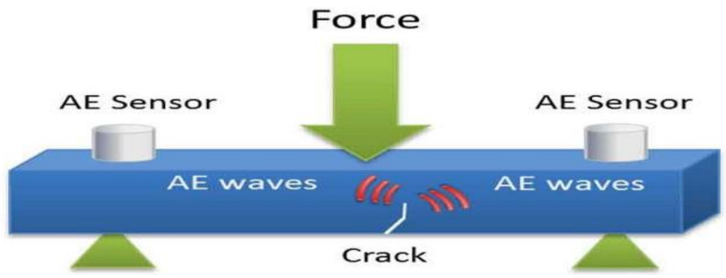
- 2023 Pipelines' significant incident consequences is $216,784,416.
- External Impacts caused about 47% of subsea pipeline failure-IAGA (Zhang et al., 2023).
- There is need for SHM of pipes to ensure sustainable reliability and integrity.

Aim

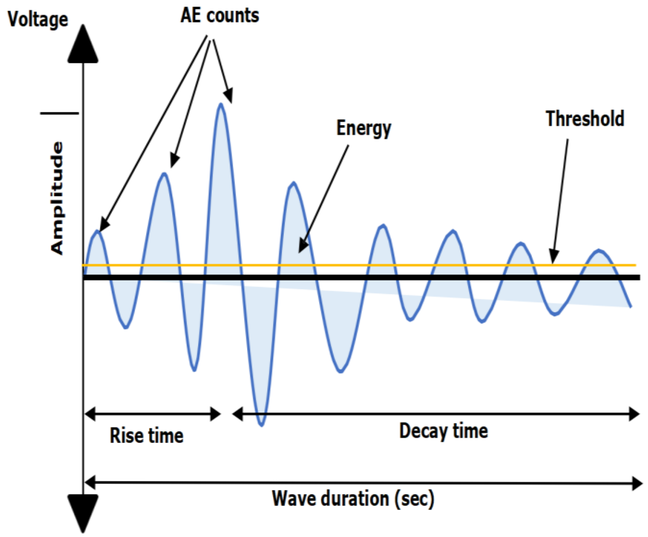
- To develop a machine learning-enhanced acoustic emission technique for impact source identification and differentiation in steel pipes.

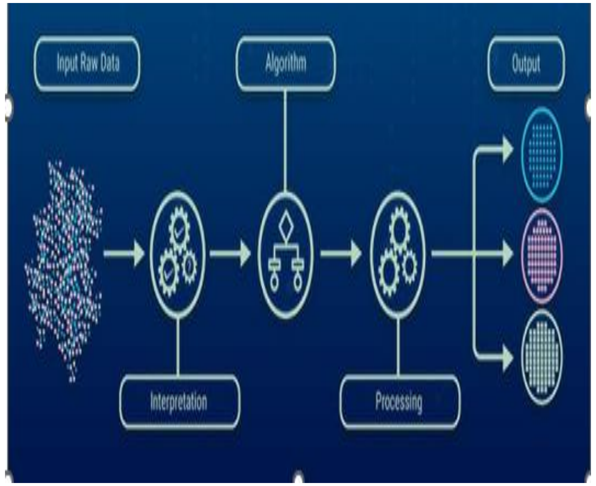
Background

- Acoustic Emission Testing (AET) is a Passive NDT.
- Materials crack initiation and growth degradation release the elastic stress waves.
- Conventional AE analysis often struggle to differentiate between closely related damage mechanisms.
- The integration of ML models will enhance the accuracy of AET's differentiation of external impacts sources in steel pipe.



AET at a glance

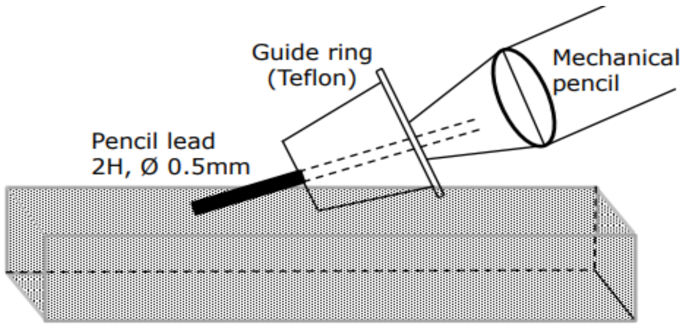




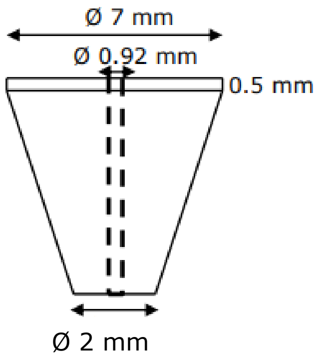
Supervised Machine Learning

Pencil Lead Break (PLB) Experiment

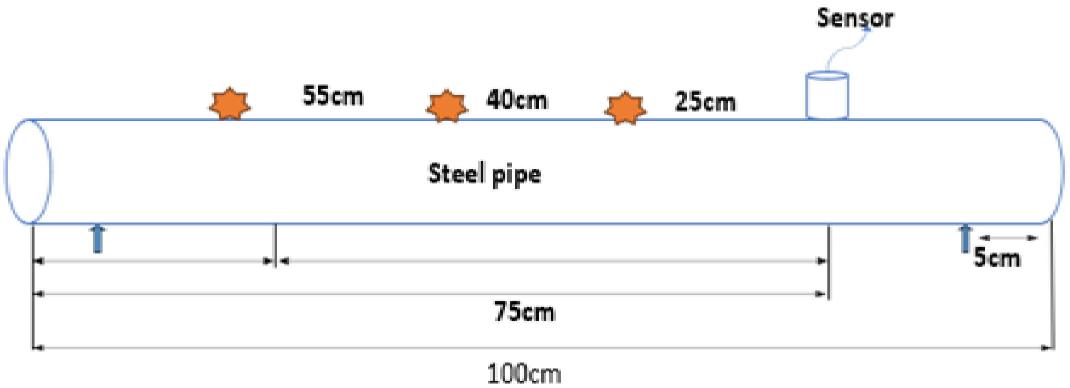
- The PLB experiment aims to calibrate AE set-up.
- The test object is 100cm carbon steel pipe, 15cm internal diameter, 1cm thickness.
- 20 PLBs were broken at 25cm, 40cm & 55cm distance to the sensor.
- The experiment was repeated on damped pipe.
- Data sampled at 2.5M/s.



PLB test illustration (ASTM E 976 – 99)



Guide Ring Dimension

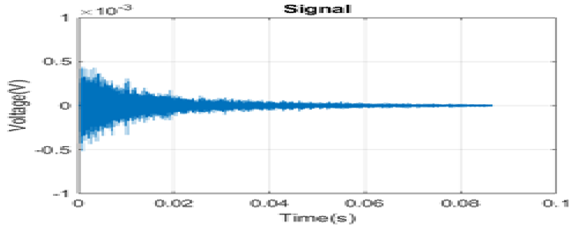


Pencil lead break experiment set-up

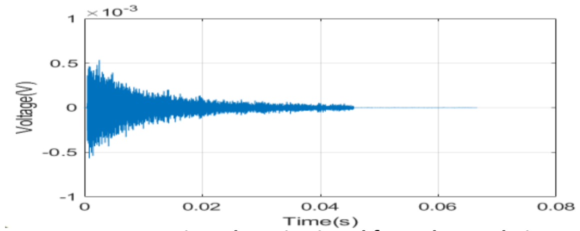
Pencil Lead Break Results

Time Domain Analysis

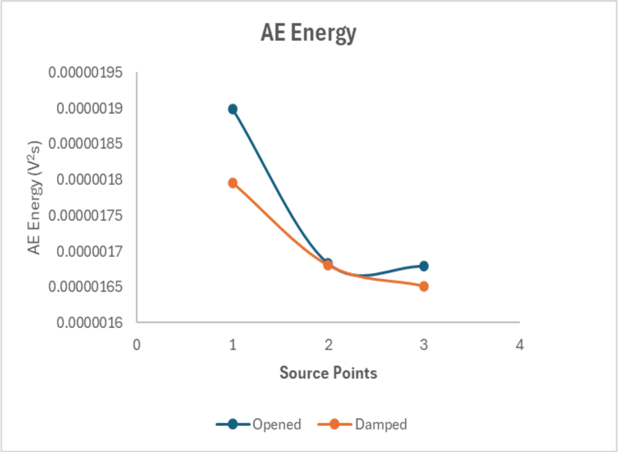
- Open-ended pipe exhibited higher Energy and peak amplitude across 3 source points.
- Open pipe exhibited highest AE Energy **(0.0000019V^2s).**
- Open pipe recorded highest peak amplitude **(0.0007Volts)**.
- AE energy and amplitude decrease with longer distances due to wave attenuation.
- The number of rise decreases as the PLB source is farther away from sensor.

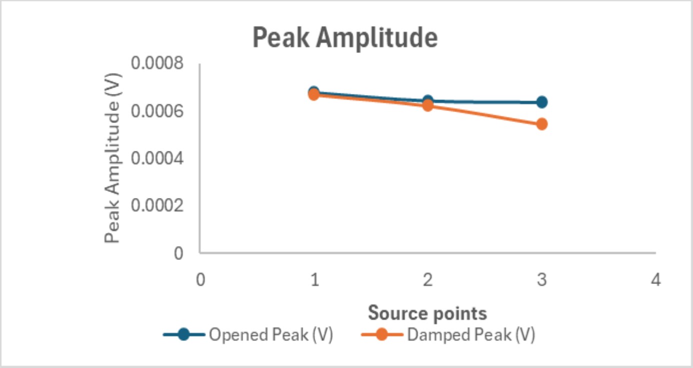


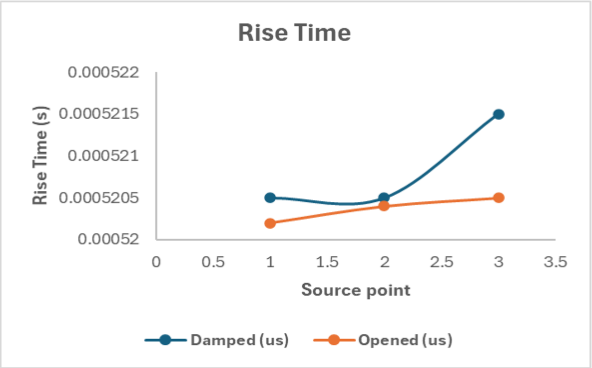
Raw time domain signal from open pipe



Raw time domain signal from damped pipe



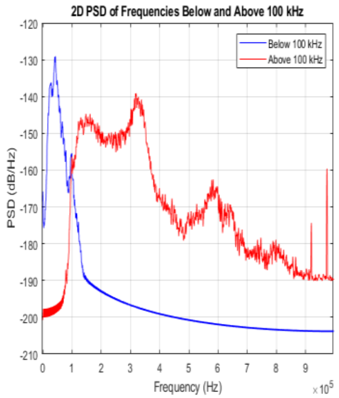


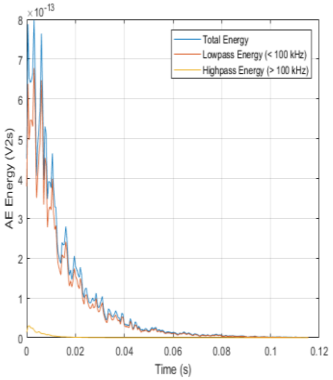


Time -frequency Analysis

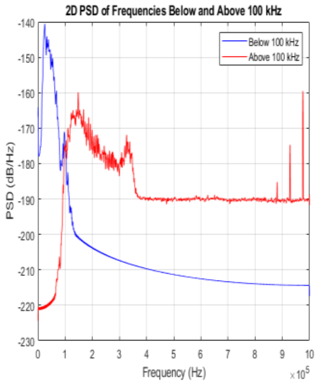
- Digital filtering is applied to frequencies below and above 100KHz.
- Both pipe set-ups recorded higher AE energy in Low pass Cut-off frequency (< 100KHz).
- Both set-ups recorded the highest AE energy at the 25cm source point.
- Open pipe exhibited peak energy at 49 kHz and 2.46µs time at low pass band.
- Damped pipe recorded highest AE energy at 48KHz frequency and time 1.6µs.

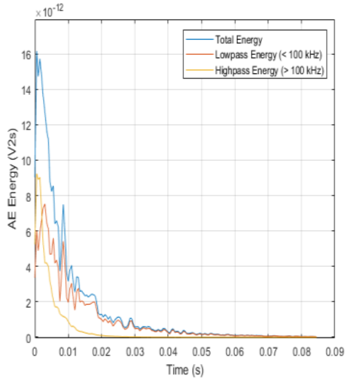
Open Pipe

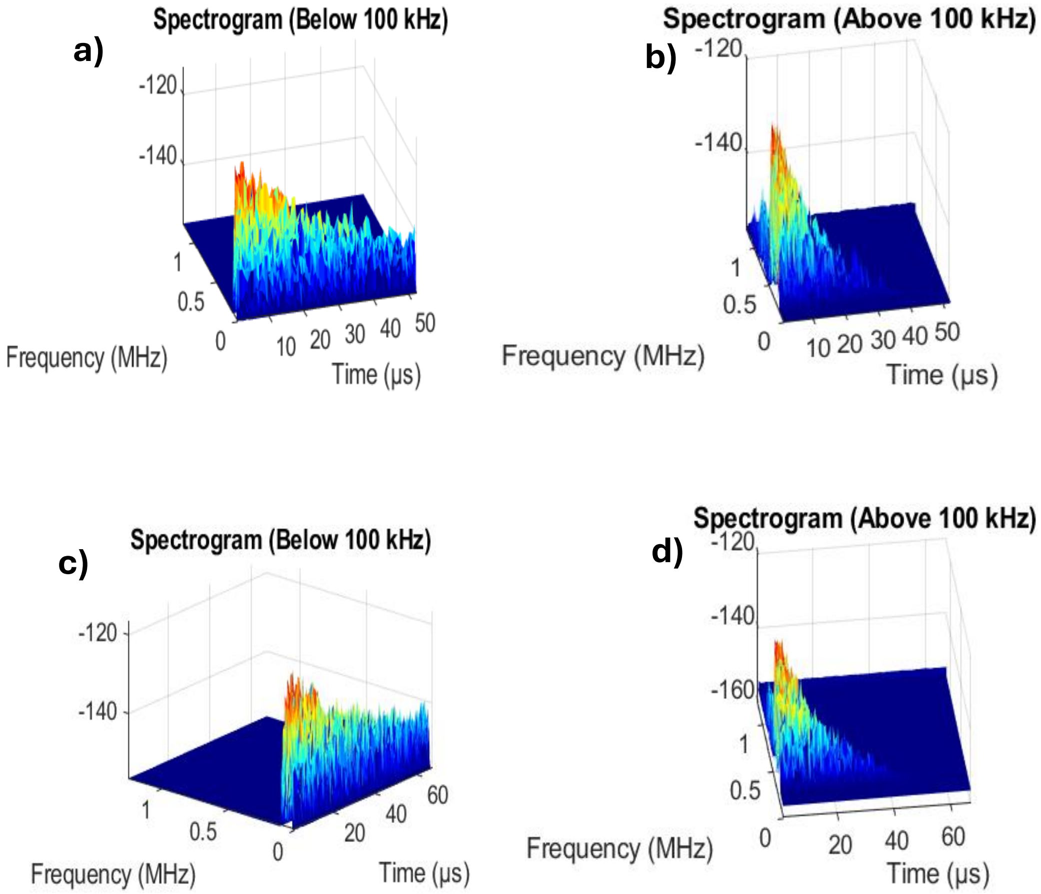




Damped Pipe



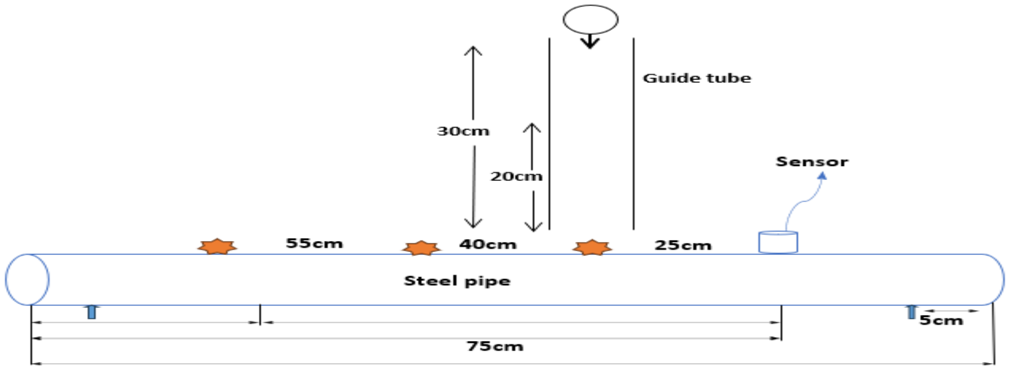




3D spectrograms for:
(a) low pass (b) high pass for open pipe
(c) low pass and (d) high pass for damped pipe

Drop ball Experiment

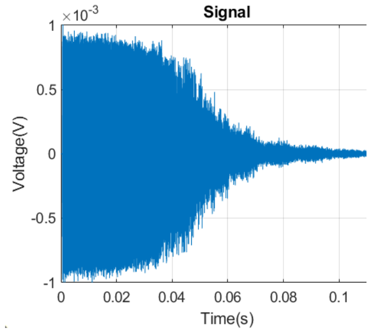
- 9g and 17g steel balls dropped from 20cm and 30cm heights.
- AE source points are located at 25cm, 40cm, and 55cm source to sensor distances.
- The experiment consists of 12 variables of 100 tests each (1200 tests)
- FFT, STFT were performed on the AE wave signals.
- The extracted time series features (AE energy, peak amplitude, and rise time) were used to train supervised ML models.

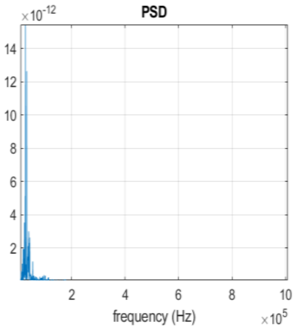


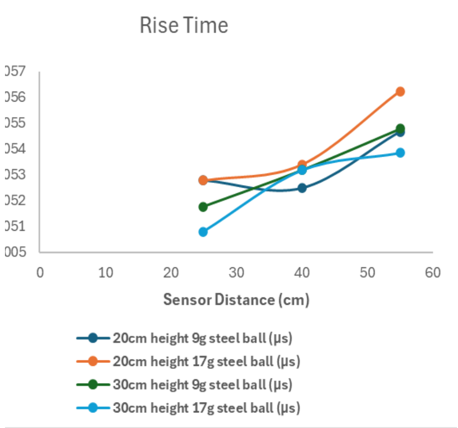
Schematic representation of Drop ball impact experimental set-up.

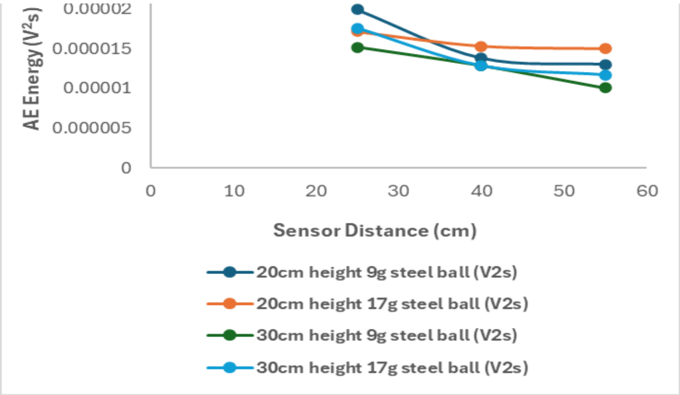
Drop Ball Results

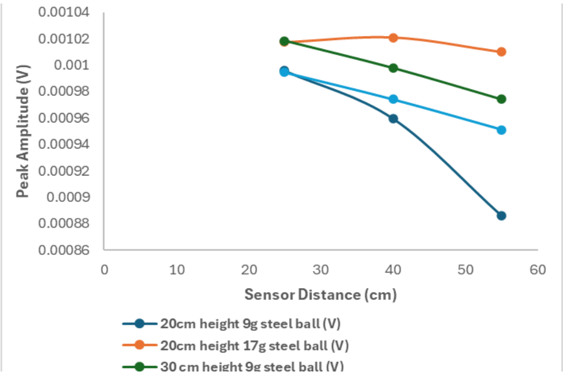
- Steel ball impacts produced distinct burst-type AE signatures.
- The highest AE energy and peak amplitude are recorded at 25cm source points.
- AE energy and peak amplitude decreases with further distance.
- Rise time exhibits linear increase with propagation distance







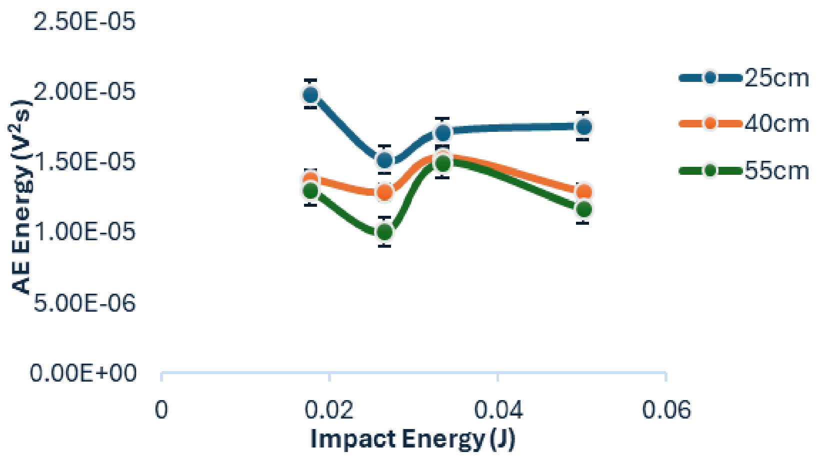




Effect of Ball mass and drop heights

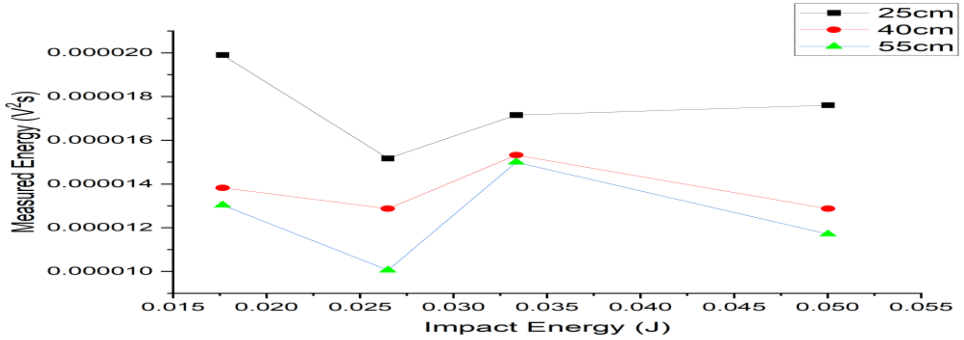
- The highest AE energy (**1.98986 x 10^{-5} V^2s)** was recorded from the impact energy **(0.017658J)** of 9g ball from 20cm height at 25cm source point.
- All the impact scenario recorded highest AE energy at the closest distance (25cm) to the sensor.
- Impact energy exhibits direct proportionality to both mass variation (9g to 17g).
- Similar trend was recorded with increase in drop heights at all sensor distances.

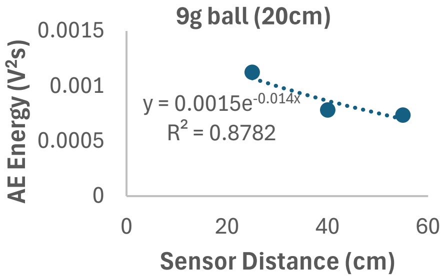
Ball Mass (g)	Drop height (cm)	Impact Energy (Joules)	Measured Energy (V2s) 25cm	Measured Energy (V2s) 40cm	Measured Energy (V2s) 55cm
9	20	0.017658	1.98986E-05	1.38265E-05	1.30295E-05
9	30	0.026487	1.51707E-05	1.28698E-05	1.00552E-05
17	20	0.033354	1.71538E-05	1.53241E-05	1.49961E-05
17	30	0.050031	1.76061E-05	1.28698E-05	1.17108E-05

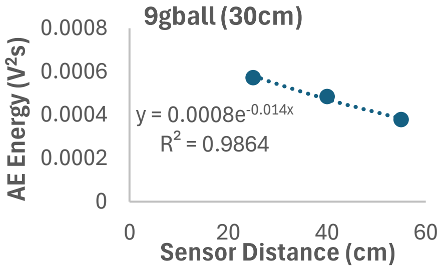


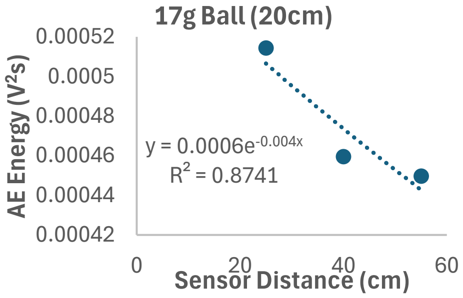
Effect of Sensor Distance

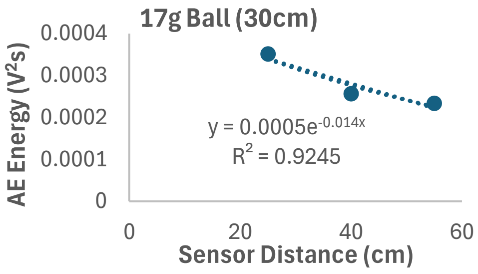
- AE energy decrease as the distance from the impact point increases in all variables.
- All variables produced highest energy at 25cm source points.
- Attenuation coefficient ‘α’ of 0.014 observed when 9g and 17g steel ball was dropped from 20cm & 30cm heights.
- Slightly lower attenuation coefficient ‘α’ of 0.004 recorded from 17g balls dropped from 20cm height.
- This represent a unique behaviour at higher mass/lower height combination.







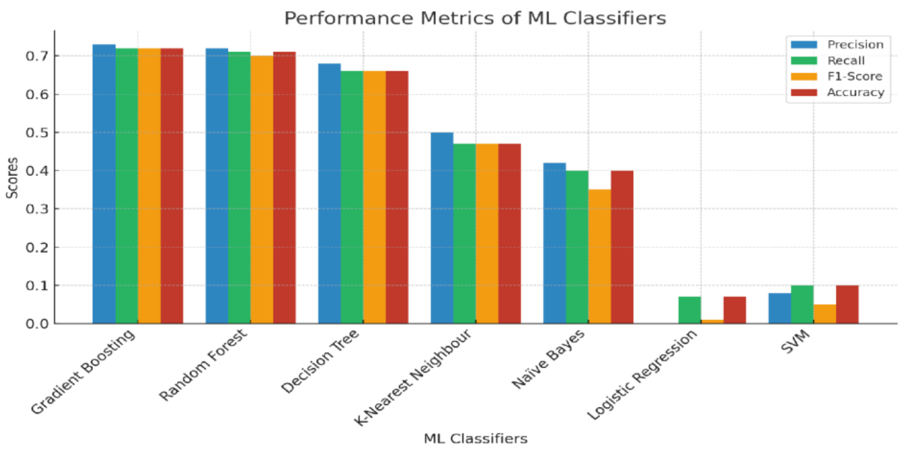




Machine learning classification

- 3600 data sets were loaded in jupyter notebook using Panda.
- X and Y values are defined.
- Categorical Y values were encoded (0 -11).
- 80% of the data was used for training, and 20% was used for validation.
- Random state was used for reproducibility.
- 7 Classification ML models defined.
- Gradient boosting produced the highest accuracy 0.72 based on a weighted average.

	ML Classifiers	Precision	Recall	F1- Score	Accuracy
1	Gradient Boosting	0.73	0.72	0.72	0.72
2	Random Forest	0.72	0.71	0.70	0.71
3	Decision Tree	0.68	0.66	0.66	0.66
4	K- Nearest Neighbour	0.50	0.47	0.47	0.47
5	Naïve Bayes	0.42	0.40	0.35	0.40
6	Logistic Regression	0.00	0.07	0.01	0.07
7	SVM	0.08	0.10	0.05	0.10



Conclusion

- The impact sources were accurately identified and classified by the ML model developed.
- Increasing impact energy will increase acoustic energy and wave amplitudes.
- The elastic stress caused by dropping steel balls of different masses from heights was effectively characterized and differentiated in steel pipe.
- AE features (amplitude, energy, rise time, frequency content) showed clear differences between impact scenarios.
- A robust methodology for impact source classification in pipeline monitoring was developed.

Acknowledgements / Thank You / Questions

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