Identification of steel grade and predicting mechanical properties using machine learning for laser ultrasonic data

Krister Ekström[1], Filip Tuvenvall[1], Mikael Malmström[1], Anton Jansson[1]

krister.ekstrom@swerim.se

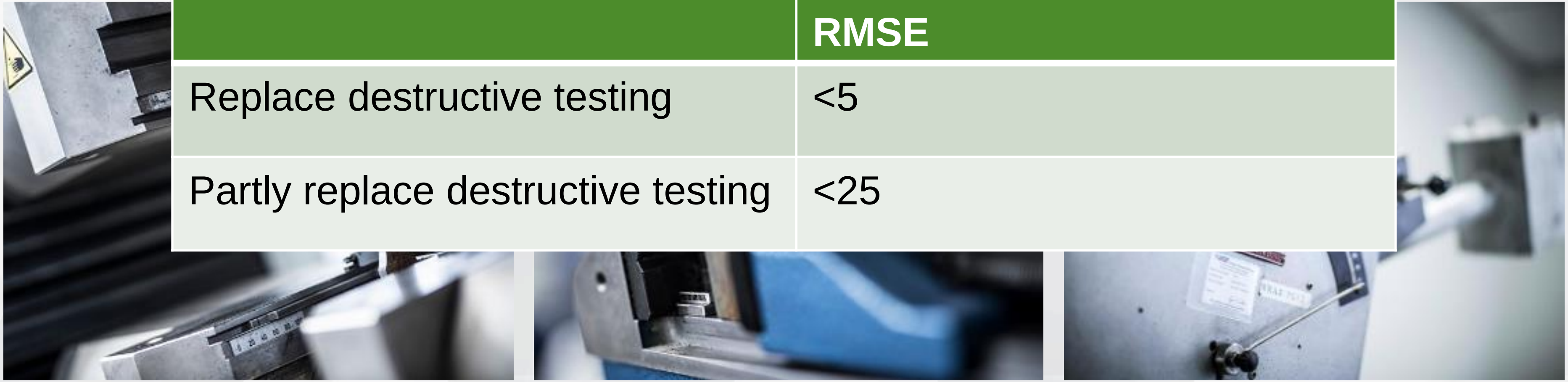
[1]Swerim AB, Stockholm, Sweden.

Overview

- Introduction
- Setup and samples
- Method
- Results
- Conclusion

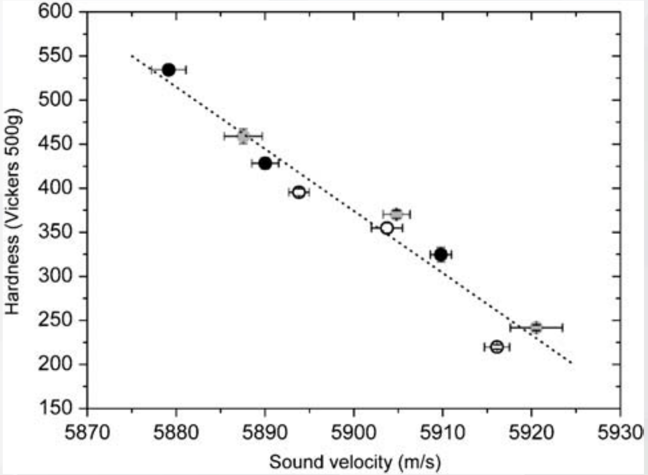
Introduction

	Brinell hardness estimation RMSE
Replace destructive testing	<5
Partly replace destructive testing	<25

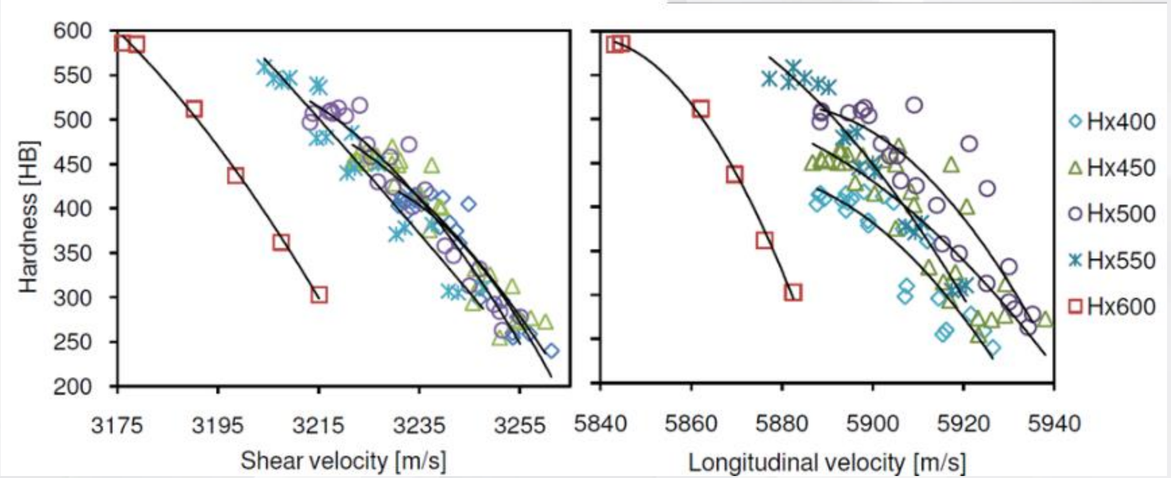


Example, off-line destructive mechanical testing of test coupons (tensile, hardness, charpy)

Background



Hardness vs P-wave velocity measured with LUS [1]



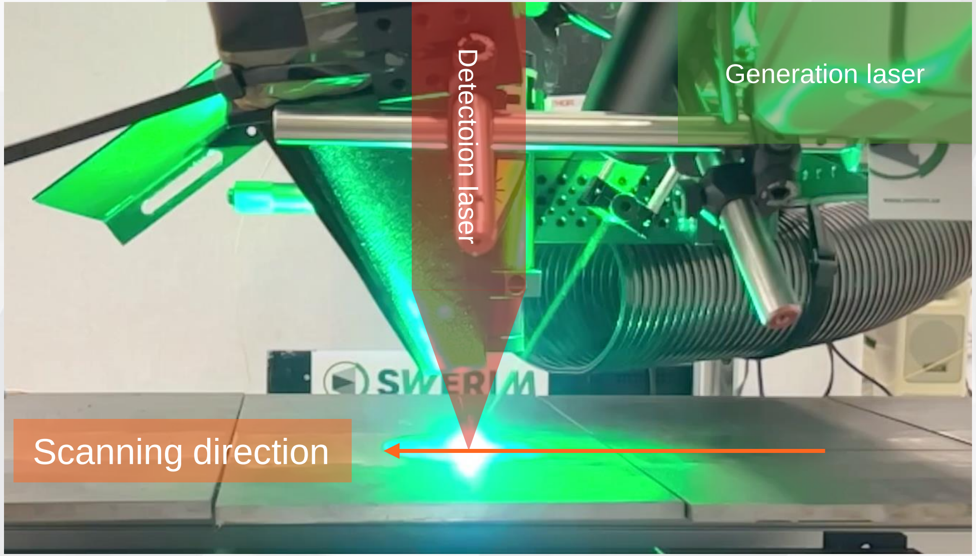
Hardness vs S-wave velocity measured with EMAT, and P-wave velocity measured with conventional immersion tank ultrasound.

[1] M. Engman and M. Falkenström, “Yield strength correlated to directional dependent wave velocities in hot rolled steel using laser ultrasonics,” *AIP Conference Proceedings*, vol. 1211, no. 1, pp. 303–309, Feb. 2010, doi: 10.1063/1.3362409

[2] T. Lukomski and T. Stepinski, “Steel hardness evaluation based on ultrasound velocity measurements,” *Insight - Non-Destructive Testing and Condition Monitoring*, vol. 52, no. 11, pp. 592–596, Nov. 2010, doi: 10.1784/insi.2010.52.11.592

Swerim laser ultrasound laboratory

Setup and samples



Sample information

- 244 samples
- 16 elemental fractions
- Carbon equivalent
- Tempering temperature
- Brinell hardness [HB]
- 8 mm thickness

- Sample temperature

Setup and samples

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- 244 samples
- 16 elemental fractions
- Carbon equivalent
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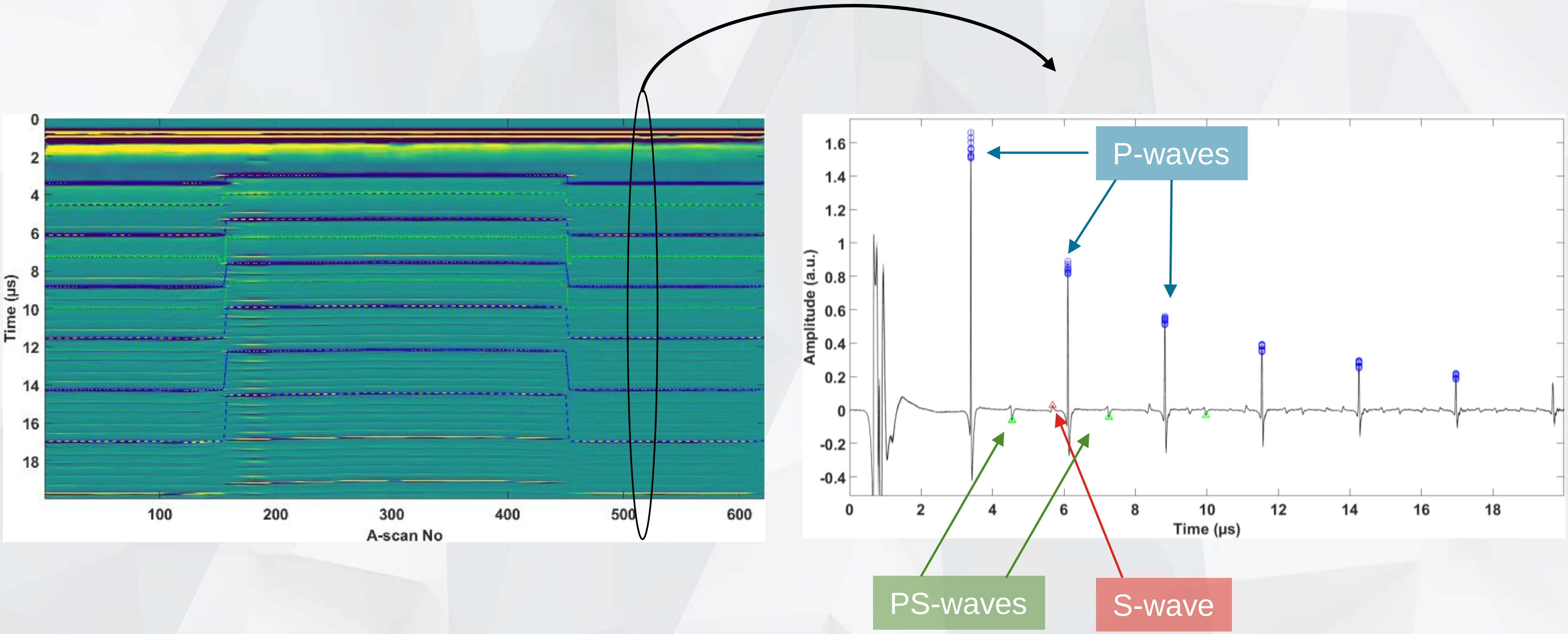
- Sample temperature
- 8 mm thickness
- Brinell hardness [HB]

Typical B- and A-scans



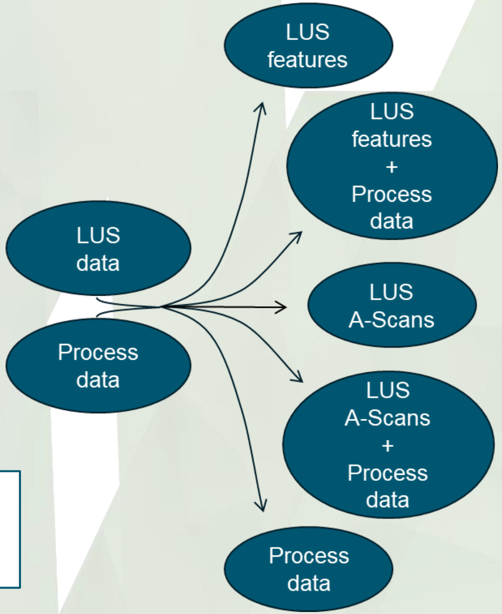
Machine learning method overview

- Three machine learning algorithms
- Combinations of LUS and process data
- 7 algorithm-dataset combinations
- Hyperparameter optimization
- Dataset split into 4 parts:
  train (70%),
  validation (10%),
  model comparison (test 1, 10%),
  final evaluation (test 2, 10%)

XGBoost
Extreme gradient boosting

MLP
Multilayer perceptron

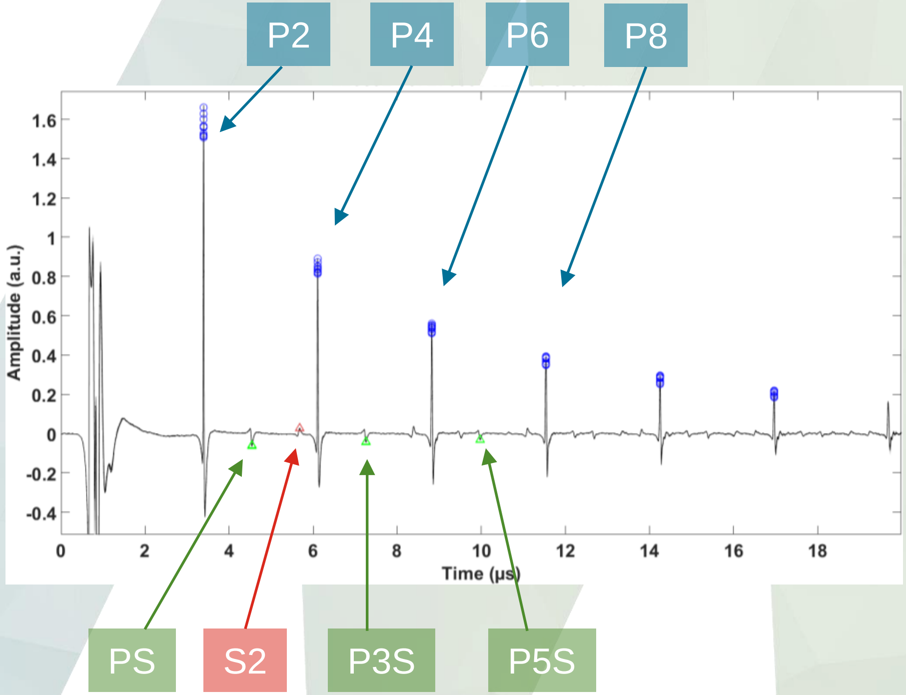
CNN
Convolutional neural network



LUS features

Time-of-flight for:

- P2-P12
- S2
- PS, P3S and P5S



Extreme gradient boosting (XGBoost)

- Specific implementation of gradient boosting

Parameter	Description
eta	Learning rate. [0,1]
gamma (γ)	Minimum loss reduction factor. [0,∞]
max_depth	The max depth of a tree. [0,∞]
subsample	Creates a subset for training by sampling the given ratio of available training data each iteration. [0,1]
colsample_bytree	Creates a subset of features for building each tree. [0,1]
lambda (λ)	L2 regularization term. [0,∞]

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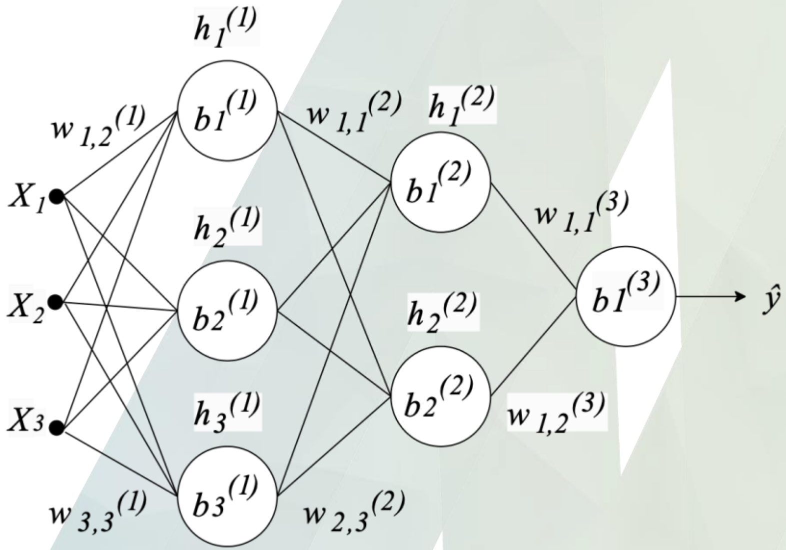
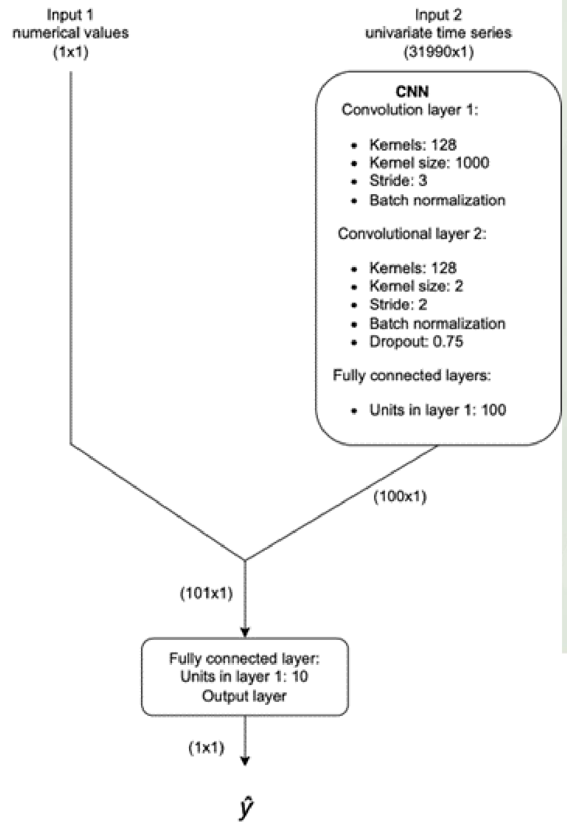
Multilayered perceptron (MLP)

- Fully connected neural network.
- Hyperparameters:
    - Hidden layers
    - Units in hidden layers
    - Dropout
    - Minibatch size



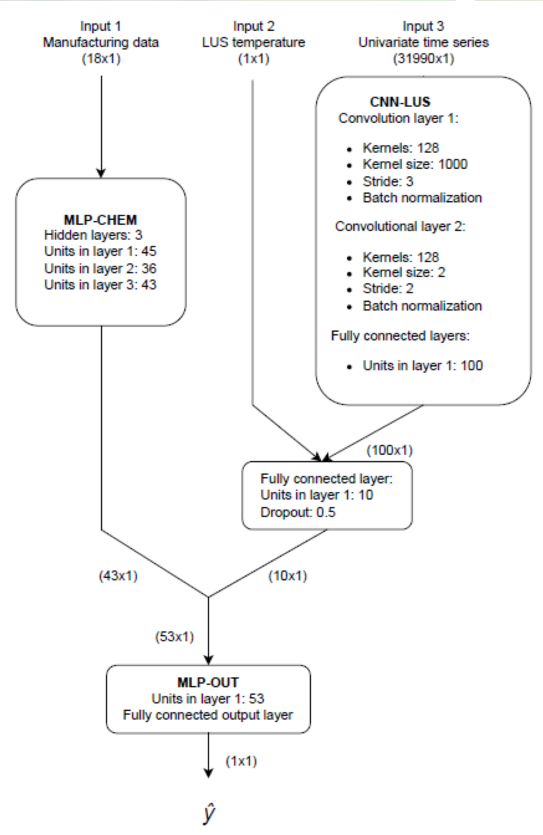
Convolutional neural network (CNN-LUS)

Inputs: A-scans and sample temperatures



Convolutional neural network (CNN-ALL)

Inputs: A-scans, sample temperatures and production data



Results

Model	Validation RSME [HB]	Test 1 RSME [HB]	Test 2 RMSE [HB]
XGBoost-LUS	58.0	102.1	-
XGBoost-ALL	3.3	**4.6**	-
MLP-LUS	52.4	63.5	-
MLP-ALL	13.0	12.8	-
CNN-LUS	45.3	63.1	69.6
CNN-ALL	7.9	9.0	-
MLP-CHEM	19.6	14.5	-

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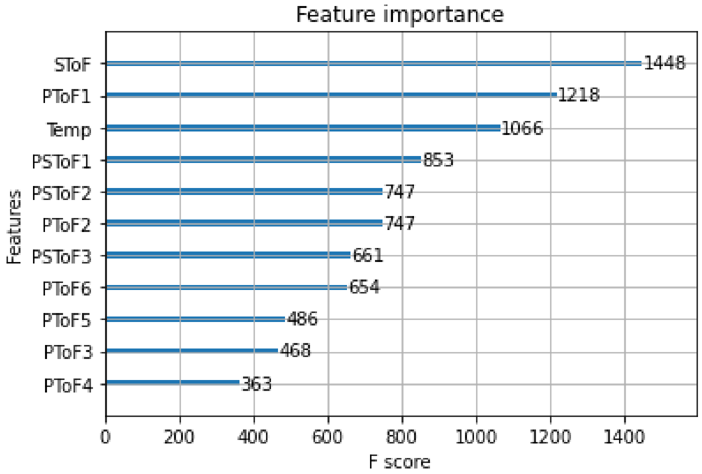
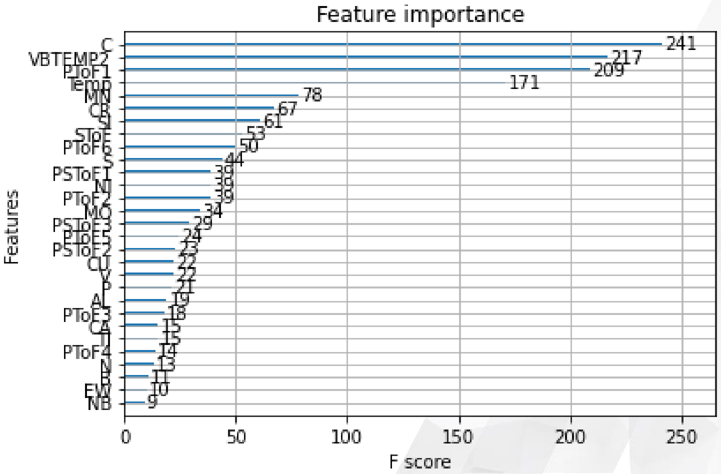
Results

- Best model: XGBoost-ALL
- Worst model: XGBoost-LUS



XGBoost-LUS



XGBoost-ALL

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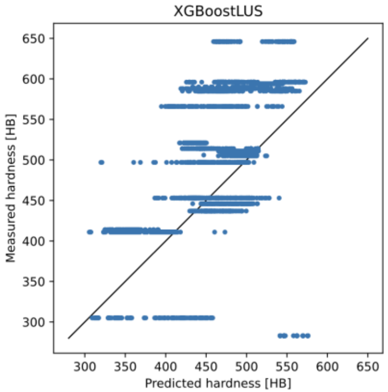
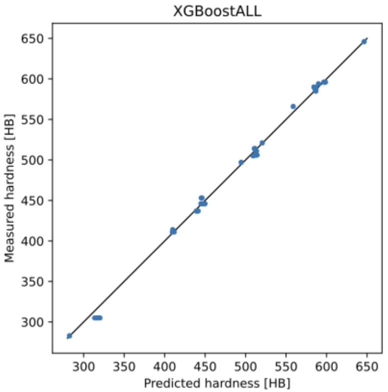
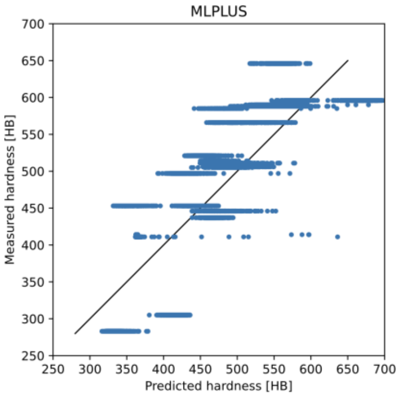
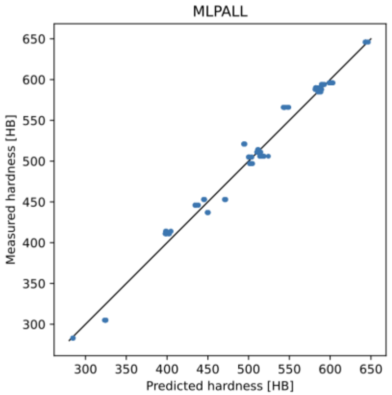
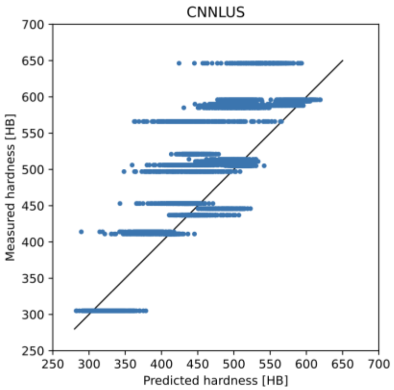
Results

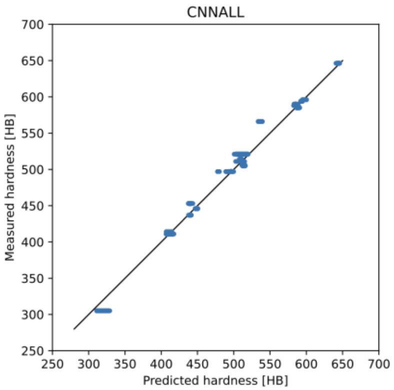












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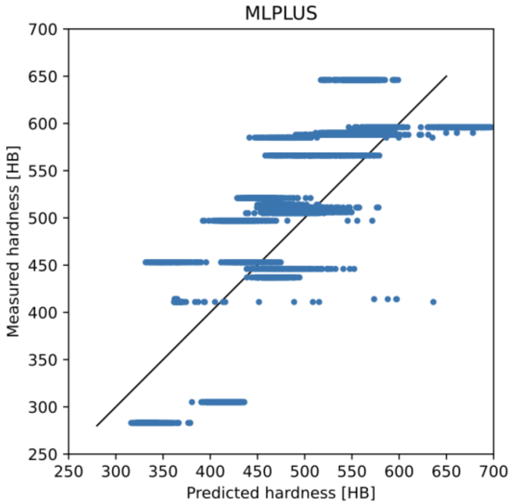

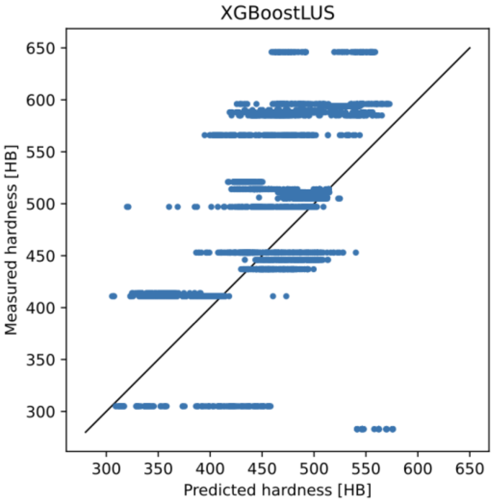

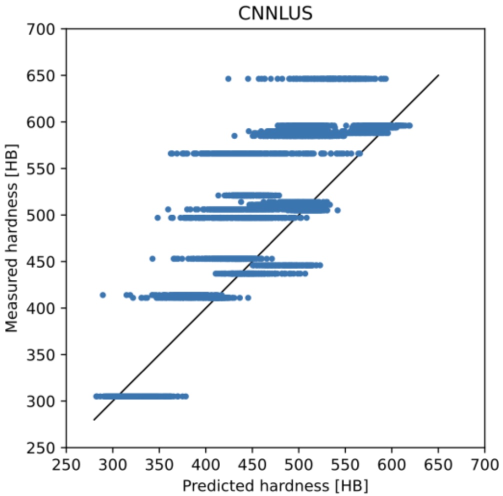

Conclusions (1/3)

- The LUS measurements on their own was not able to infer the brinell hardness accurately enough

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Conclusions (2/3)

- Using the A-scans directly to train a CNN performed just as well as the MLP model with time-of-flight as input

- Eliminate the need for pre-processing at the cost of slower computation

- Advancements in neural network architectures for image analysis could serve as an inspiration for future research

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Conclusions (3/3)

- The Brinell hardness of these samples can be accurately estimated using LUS and material data

- LUS adds additional information that improves the model

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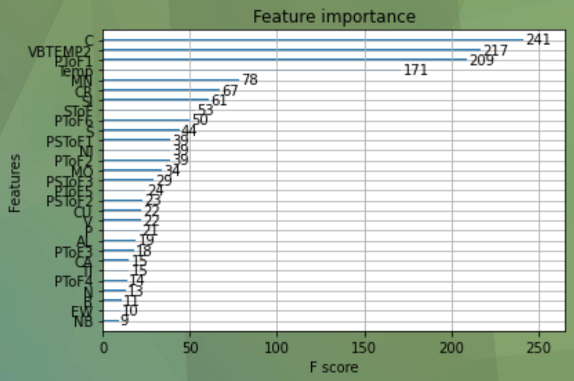

Krister Ekström
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