Mechanics with Machine Learning: Applications in Flaw and Tumor Detection

BROWN

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Objective

The purpose of this study is to apply machine learning to reflected ultrasound time signals (**A-scans**) for accurately characterizing and quantifying anomalies present in inorganic and biological structures.

- Length and position of **penny-shaped embedded cracks** in semicrystalline polymers
- Material properties of stiff tissue in softer matrices for **early tumor detection**

Background

High-density polyethylene (HDPE) is a semi-crystalline polymer used in several critical applications [1].

- Cooling water pipelines in nuclear power plants, distribution pipelines for natural gas and hydrogen, biomedical implants, and *more*

Failure Mechanism of HDPE

HDPE is susceptible to **slow crack growth** even under low stresses.

- Crack length determines the failure stress

Non-destructive evaluation (NDE) of Structures

Ultrasounds can image and detect embedded features in HDPE structures and biological materials such as breast tissue [2, 3, 4, 5].

- **A-scan** = Simple time–amplitude ultrasound signal (Figure 1)
- Rapidly scan large structures without approximation errors

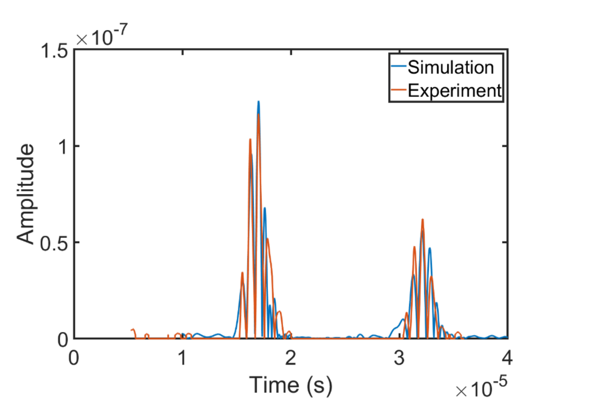

Figure 1. Experimental and simulation ultrasound signals for a 12.7 mm thick smooth sheet of HDPE.

Applying Machine Learning to Ultrasound Signals

Machine learning can **eliminate** ultrasound signal interpretation errors by technicians (Figure 2), lowering costs and improving speed and accuracy.

- Typical convolutional neural networks (CNN) consist of the convolutional layer, the pooling layer, and the fully connected (FC) layer

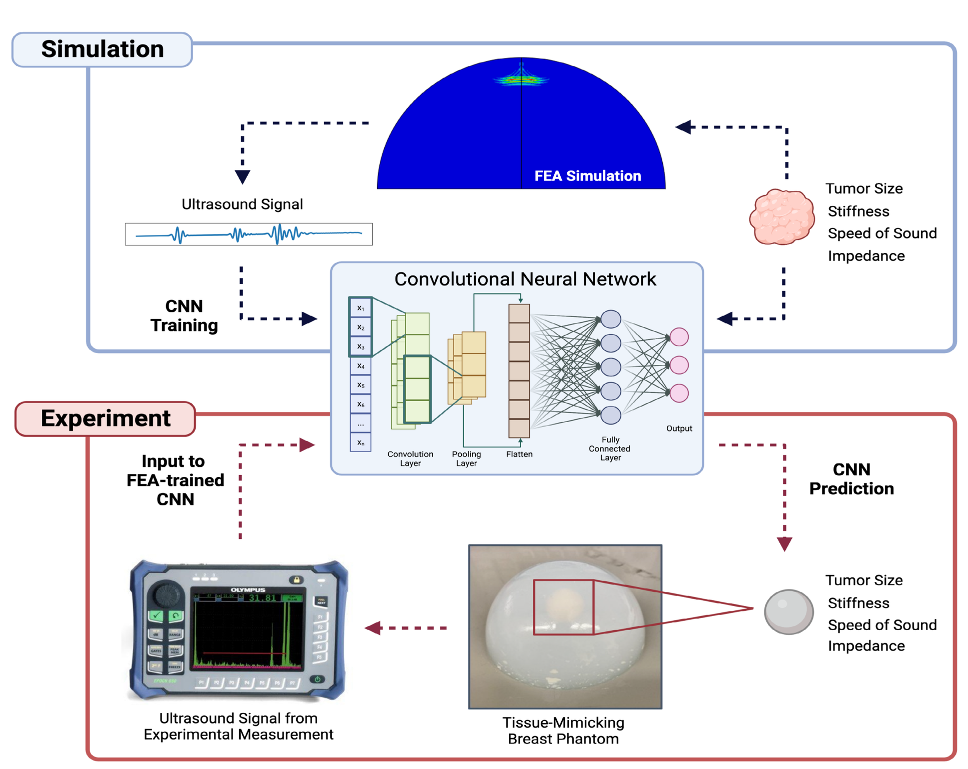

Figure 2. Simulation-trained CNN using A-scan ultrasound to detect and characterize breast tumors [5].

Computational Experiments

Finite element simulations for ultrasonic NDT

Finite element simulations were conducted using **Abaqus**.

- Evaluate acoustic attenuation and dispersion of the transmitted A-scan ultrasound signals within HDPE specimens
- Create a simulation-based training dataset for the CNN

Table 1. Geometry ranges of penny-shaped, elliptical embedded cracks in HDPE considered in this study.

Parameter	Length	Position
Min	1 mm	3 mm
Max	6 mm	11 mm

Minor axis length fixed at **0.5 mm**.

Effects of viscoelasticity can be **disregarded** in this study because of negligible signal attenuation.

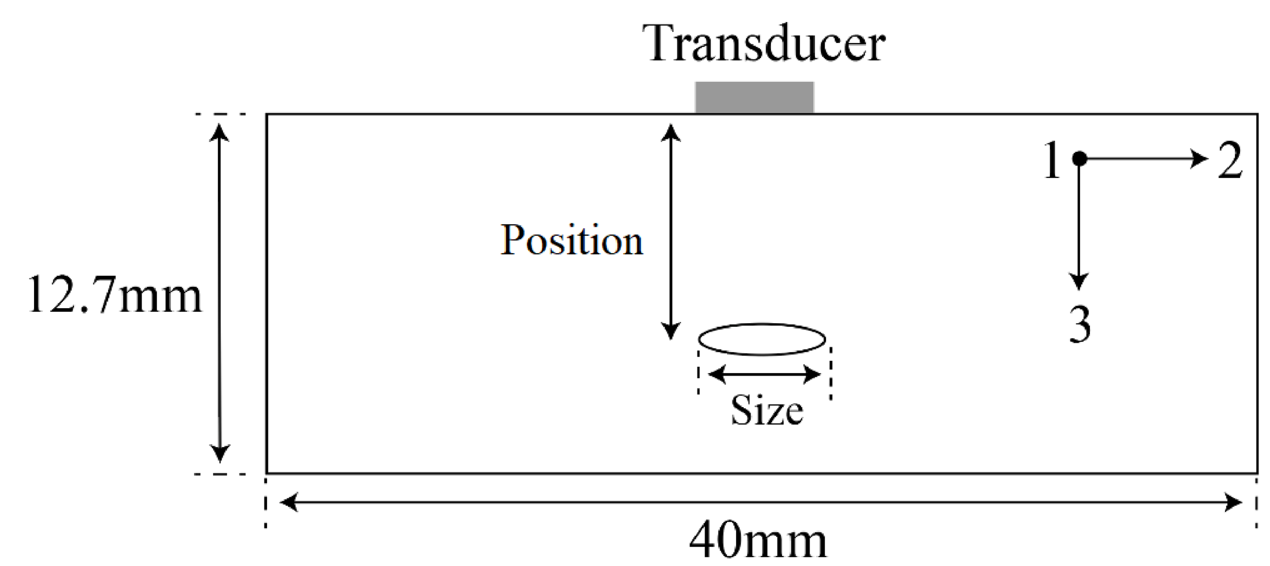

Figure 3. Cross-sectional view illustrating two key crack properties of the HDPE block on its symmetry plane. These properties are the crack length *a* and the crack position *d*.

Simulation trained convolutional neural network

The CNN architecture used in this study (Figure 4) consists of **two** convolutional layers, **one** pooling layer, and **two** fully connected (FC) layers, including the output layer.

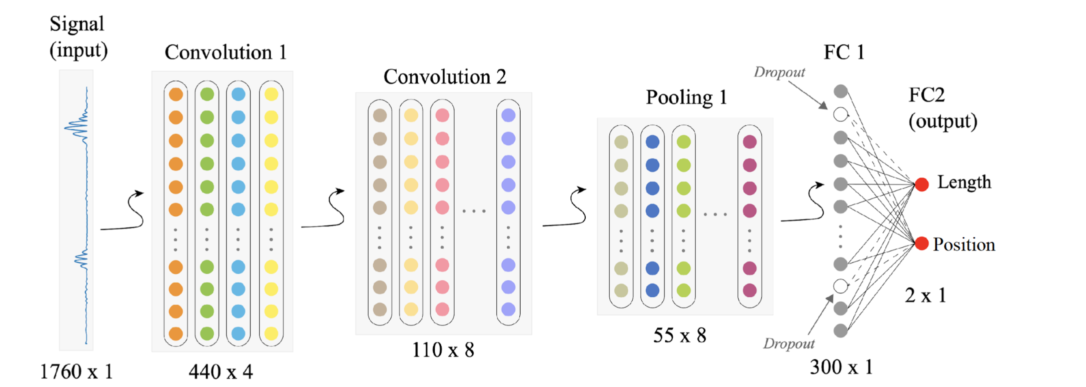

Figure 4. CNN architecture for quantification of embedded crack length and position in HDPE from ultrasound A-scan signals.

Computational Results

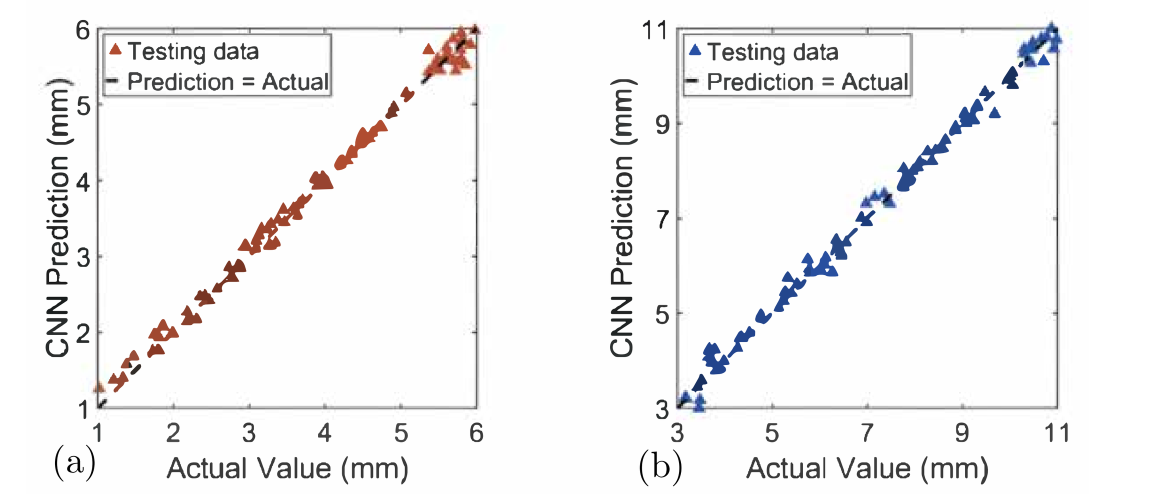

Figure 5. Performance of CNN on simulations generated testing data. Performance on crack length (left) and crack position (right). Points closer to the 45° line indicate higher accuracy predictions.

Validation Ultrasound Non-Destructive Experiments

Experimental Setup

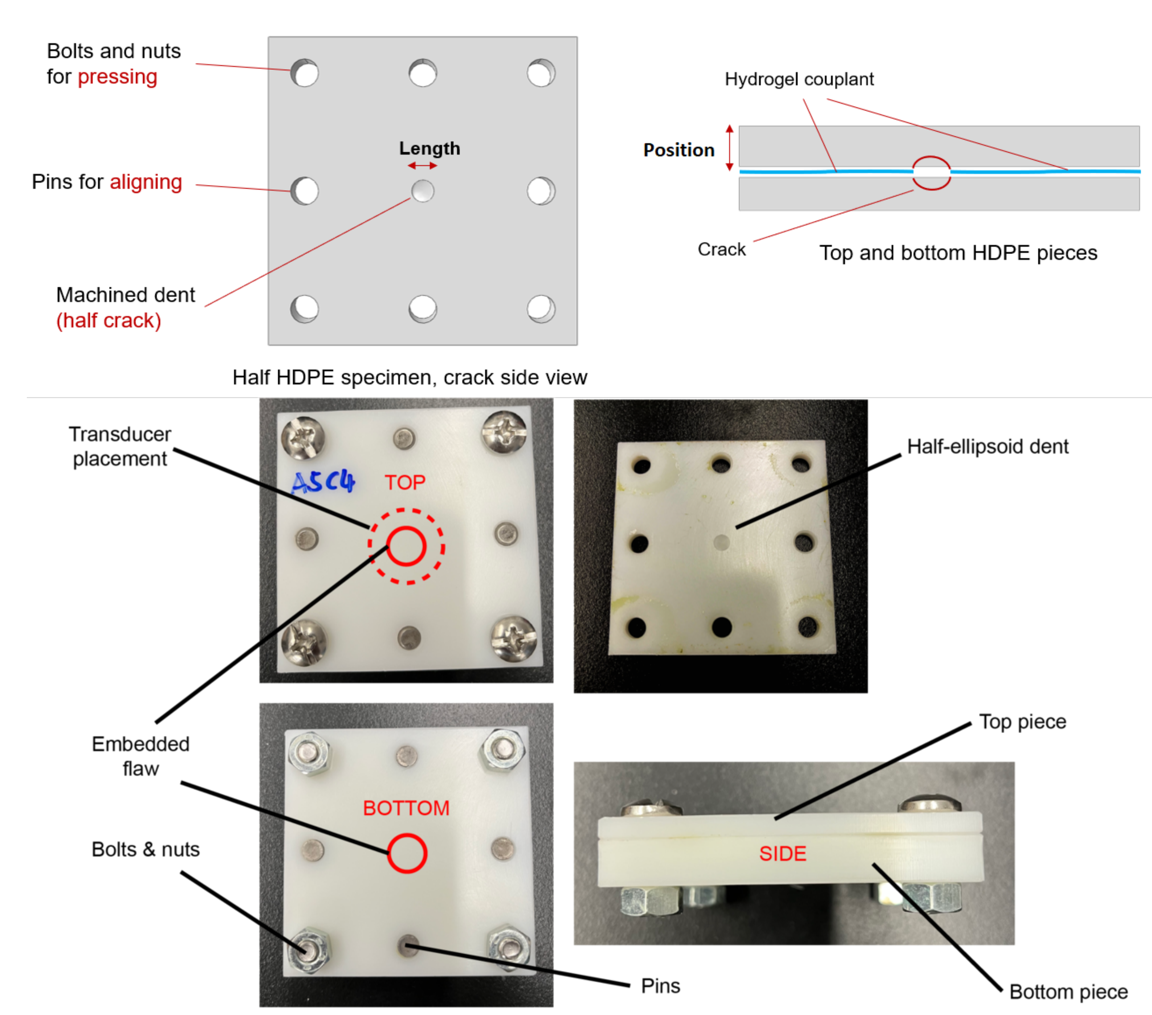

Figure 6. The experimental design for HDPE specimen with an embedded crack (top), and one of the fabricated HDPE specimens for ultrasound testing following the design procedure (below).

Every test specimen was constructed using **two** flat sheets of HDPE. The crack size and position were varied across fifteen fabricated HDPE specimens.

- Crack *lengths* of 2, 3, 4, 5, and 6 mm
- Crack *positions* of 4, 7, and 10 mm from the surface of the specimen
- Each specimen can be tested from both sides, resulting in thirty possible experiments (25 when excluding shallow crack positions of 2.7 mm)
- **Olympus Epoch 650 Ultrasound NDT Flaw Detector** with straight-beam and single element transducer with frequency of 1 MHz and sensor surface diameter of 12.7 mm

Experimental Results

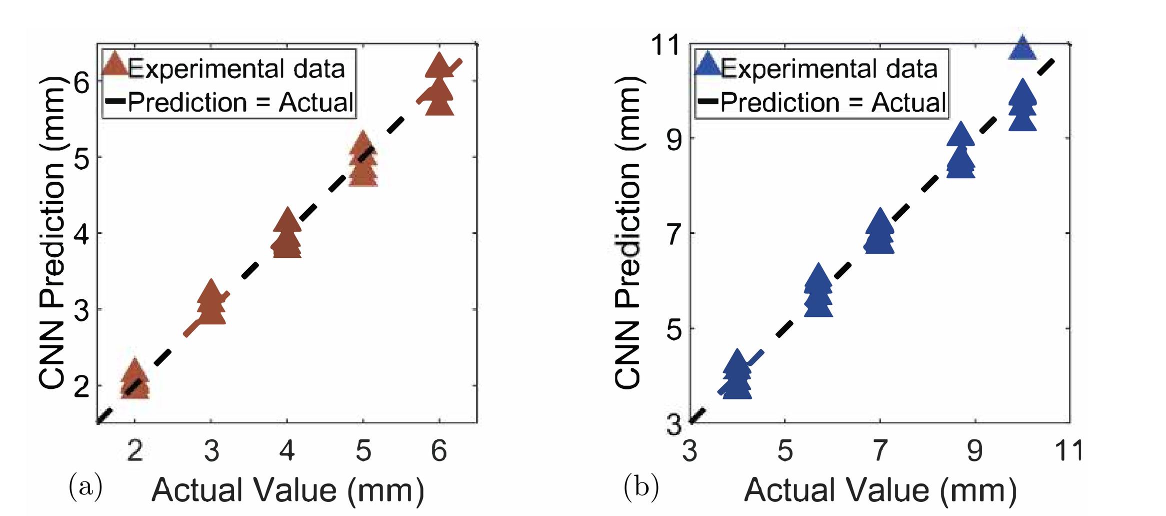

Figure 7. CNN performance on ultrasound NDT experimental data. CNN predictive performance for (a) crack length and (b) crack position. Points closer to the 45° line indicate higher accuracy predictions.

Conclusions

Our finite element trained CNN method for HDPE is based on ultrasound time amplitude signal and **not** based on image analysis.

- The ultrasound time signal data is fast to measure in the field for large structures
- **Acoustic attenuation and dispersion** due to viscoelasticity in HDPE can be **reasonably neglected** for 1 MHz frequency and relatively shorter signal travel distances (∼50 mm)
- 3D finite element simulation-generated ultrasound signals can **train signal-based CNN well**

A **simulation-trained CNN** can predict the crack length and position of penny-shaped embedded cracks in real HDPE samples with very good accuracy.

- *Average error* in crack length and position predictions less than **3.8%**

Future Directions

As the **demand** for polymers and other materials increases, so does the **need** for rapid and accurate characterization of crack length and position to avoid *sudden catastrophic failures*.

- *Extend* method to other solid materials (i.e. more polymers, biological tissue) to detect and characterize embedded flaws (Figures 8 and 9)

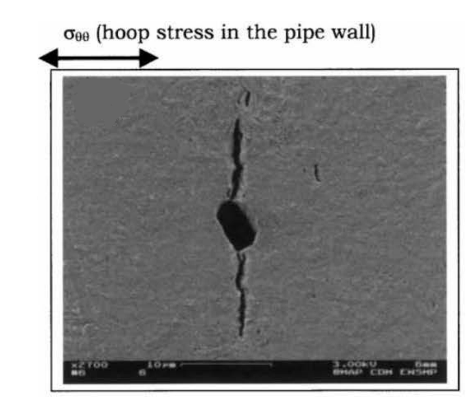

Figure 8. Internal pressure driven brittle-type crack failure in HDPE tubing [6].


Figure 9. Breast Phantoms with Different Tumor Sizes and Elastic Moduli [5].

References

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