## How inelastic Constitutive Artificial Neural Networks (iCANN) help us to automatically discover materials

Hagen Holthusen\*, Lukas Lamm, Tim Brepols, Stefanie Reese, and Ellen Kuhl

Institute of Applied Mechanics Faculty of civil engineering RWTH Aachen University, Aachen, Germany \* E-mail: hagen.holthusen@ifam.rwth-aachen.de

## **Extended Abstract**

Following the principles of thermodynamics, constitutive material models have been derived that obey these laws. We usually pre-select a particular model and try to find the best material parameters to fit our data; instead, it is our strong belief that we should find the best model explaining our data. To achieve this paradigm shift, machine learning algorithms may help us. Since these algorithms lack from knowledge of thermodynamics, it is not surprising that they may learn the data used for training very well, but fail to predict material behavior outside the training regime. This is already the case for elasticity and is even worse for inelastic material behavior. To overcome this issue, a family of Constitutive Artificial Neural Networks [1] has been developed that teaches the neural network thermodynamics. These networks are designed for elastic material behavior and satisfy thermodynamics a priori. A critical missing link is to expand the general concept to inelastic materials. One way to do so is to introduce a pseudo potential depending on stress-like quantities associated with the inelastic rate [2]. We extend CANNs to inelastic materials (iCANN) [3]. Our network discovers both the Helmholtz free energy and the pseudo potential explaining the experimental data the best. As the design is not limited to specific inelastic phenomena, thermodynamics are satisfied regardless of the inelastic behavior. Our vision for iCANNs is that they help us to reveal the various inelastic phenomena hidden in the data, such as plasticity, viscosity, phase transformation, degradation, growth and remodeling. For illustrative purposes, we specialize our iCANN to visco-elasticity and demonstrate that it is capable of discovering a model for polymers and skeletal muscle data.

## References

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