PROBLEM DEFINITION

- Shape memory materials are smart materials that stand out due to a variety of remarkable properties, particularly their shape memory effect and pseud- elasticity. Shape memory alloys (SMAs) are widely used in various fields, such as sensors, actuators, and robotics.

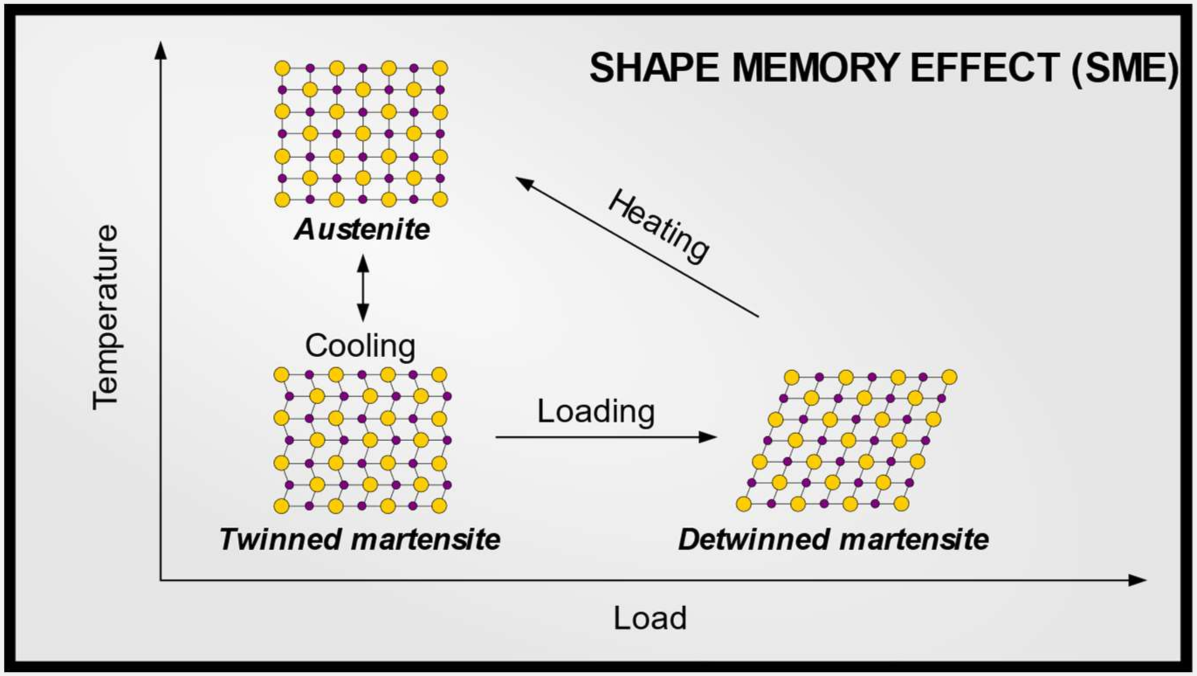
- However, their application is limited due to the fatigue mode of failure. Unlike traditional materials, fatigue prediction is not well defined for shape memory alloys in the literature.

- In addition, these materials exhibit a nonlinear behaviour that complicates the use of conventional methods, such as the finite element method, because it increases the computing time required to model their humungous variations in possible shapes and the variety of applications adequately.

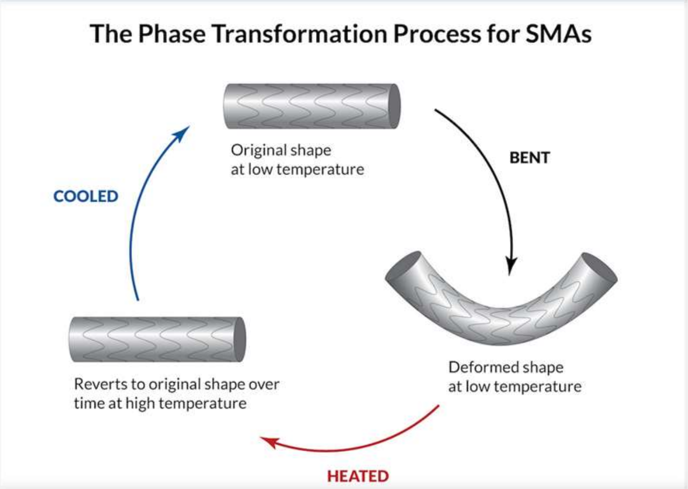
MOTIVATION TO AI

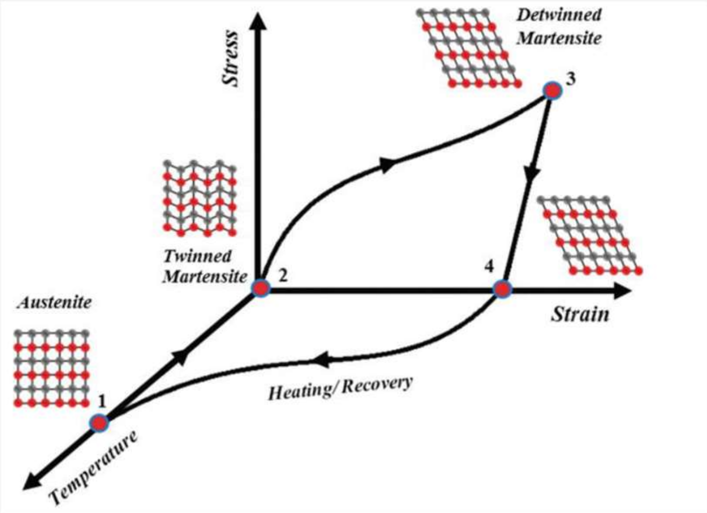
- A few ML algorithms have been used in the literature for traditional materials, but these will not work for shape memory alloys due to nonlinearity.
- As a result, developing new methodological approaches based on artificial intelligence (AI) that aim for efficient computation time and accurate results is a promising solution.
- AI has recently demonstrated some success in modelling SMA features efficiently using machine- and deep-learning methods. Notably, SMAs have been characterized using artificial neural networks (ANNs), a subset of deep learning.
- Our research focuses on predicting the fatigue life of Shape Memory Alloys using Deep Neural Networks. We are training the fatigue data using a series of Deep Neural Network layers and have observed significant differences compared to training with Machine Learning Algorithms.

INTRODUCTION TO SMA

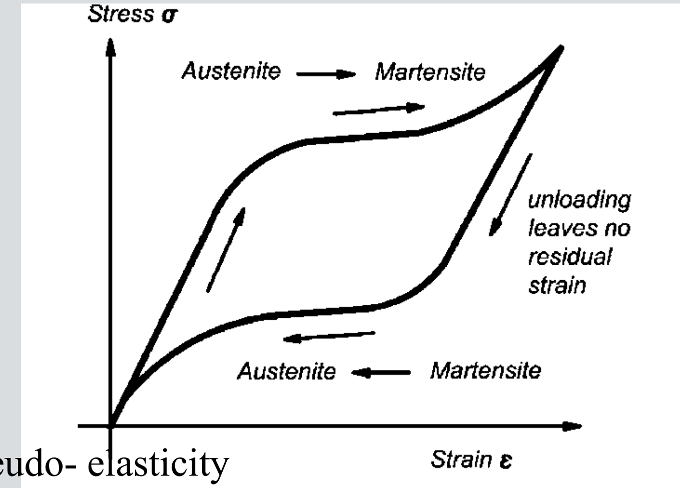


Shape Memory Effect

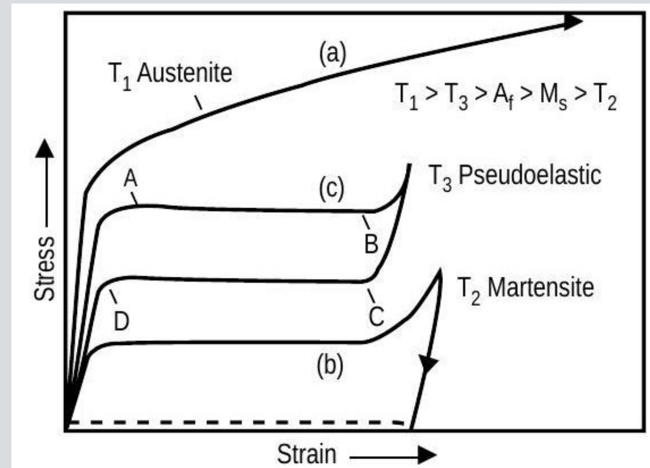




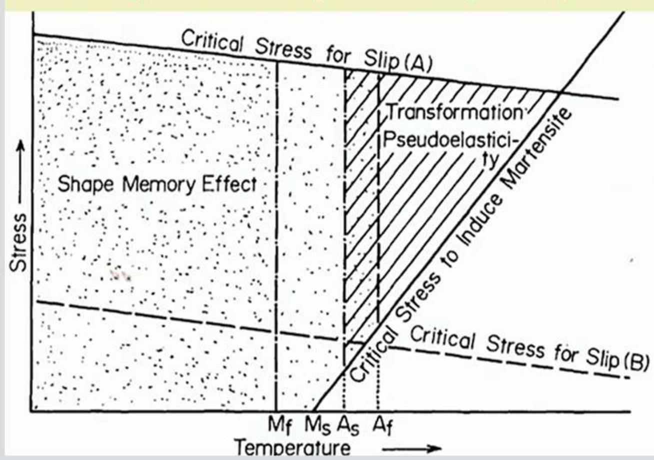
Pseudo- elasticity(PE) of SMA



pseudo- elasticity



Shape Memory Effect (SME) and Pseudo-elasticity (PE)



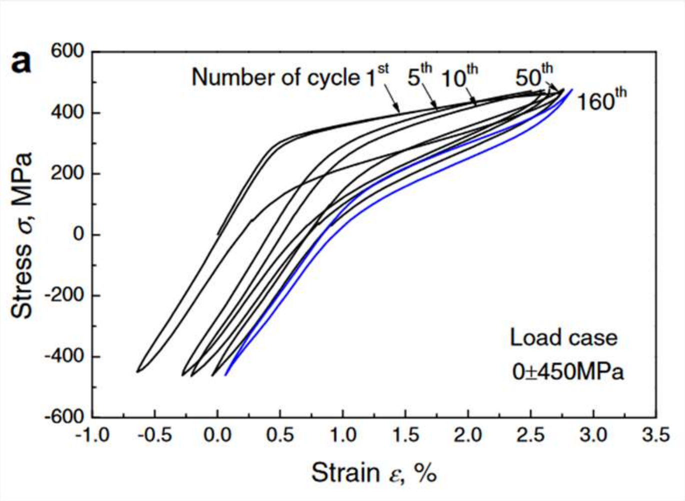
Clausius - Clapeyron relation

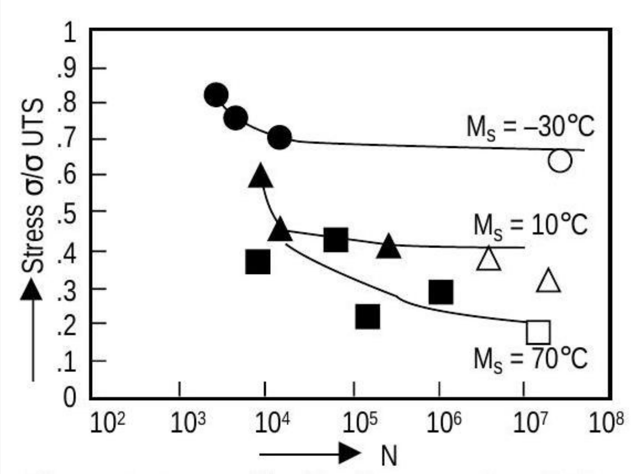
$$\frac{d\sigma}{dT} = -\frac{\Delta S}{\varepsilon} = -\frac{\Delta H^*}{\varepsilon T},$$

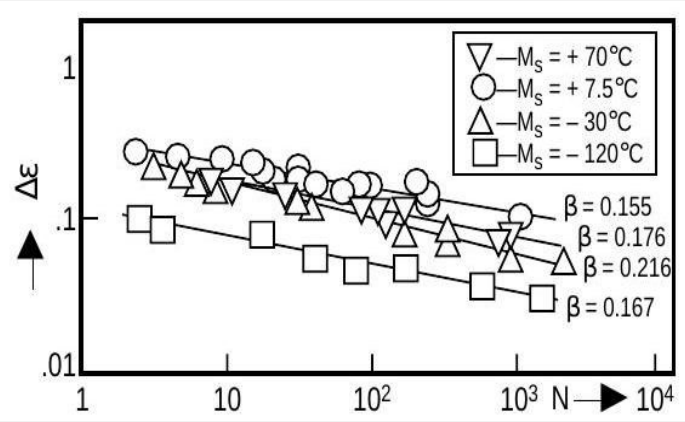
$$\frac{d\sigma}{dT} = -\frac{\Delta S^{P\to M}}{\varepsilon^{P\to M}} =$$

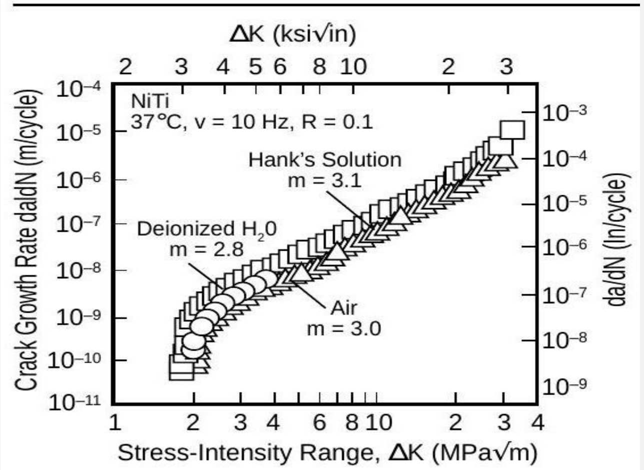
$$-\frac{\Delta H^{*P\to M}}{T_0(\sigma)\varepsilon^{P\to M}} = -\frac{\Delta Q(\sigma)}{T_0(\sigma)\varepsilon^{P\to M}}$$

Fatigue Behavior of the Shape Memory Alloys









ARTIFICIAL INTELLIGENCE-DEEP LEARNING

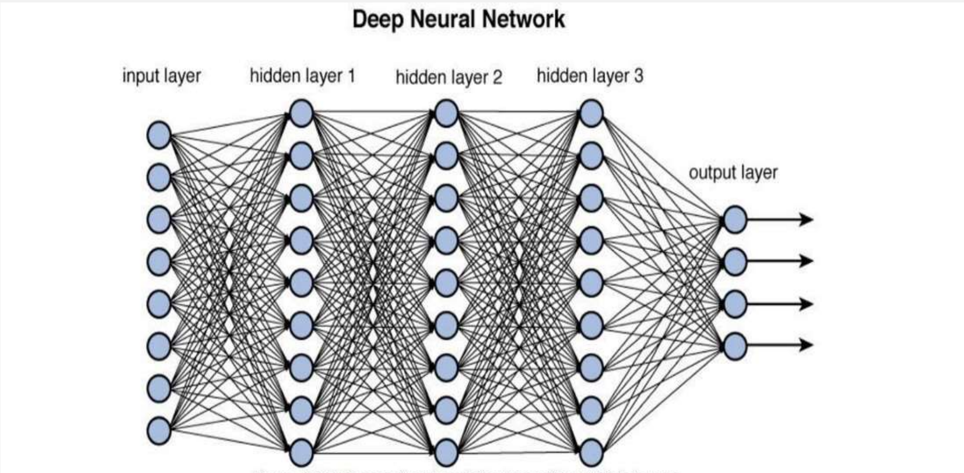
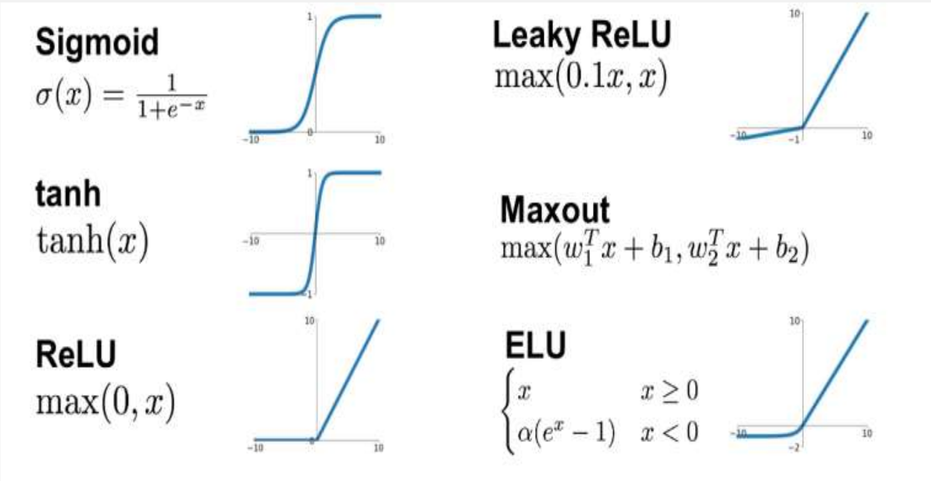
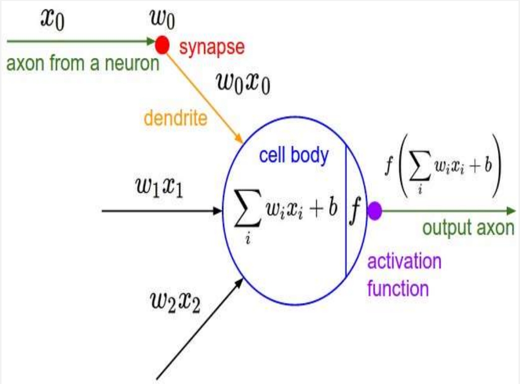
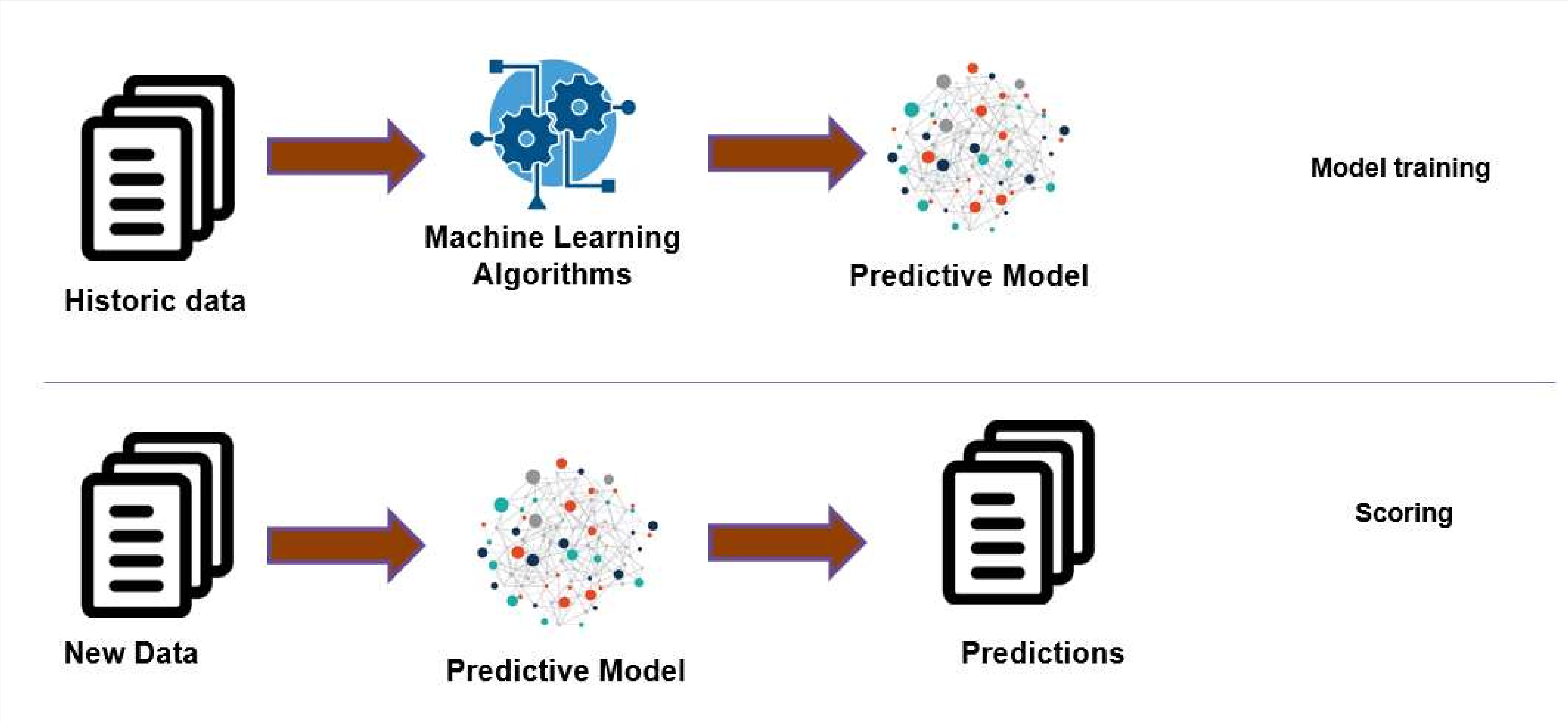


Figure 12.2 Deep network architecture with multiple layers.

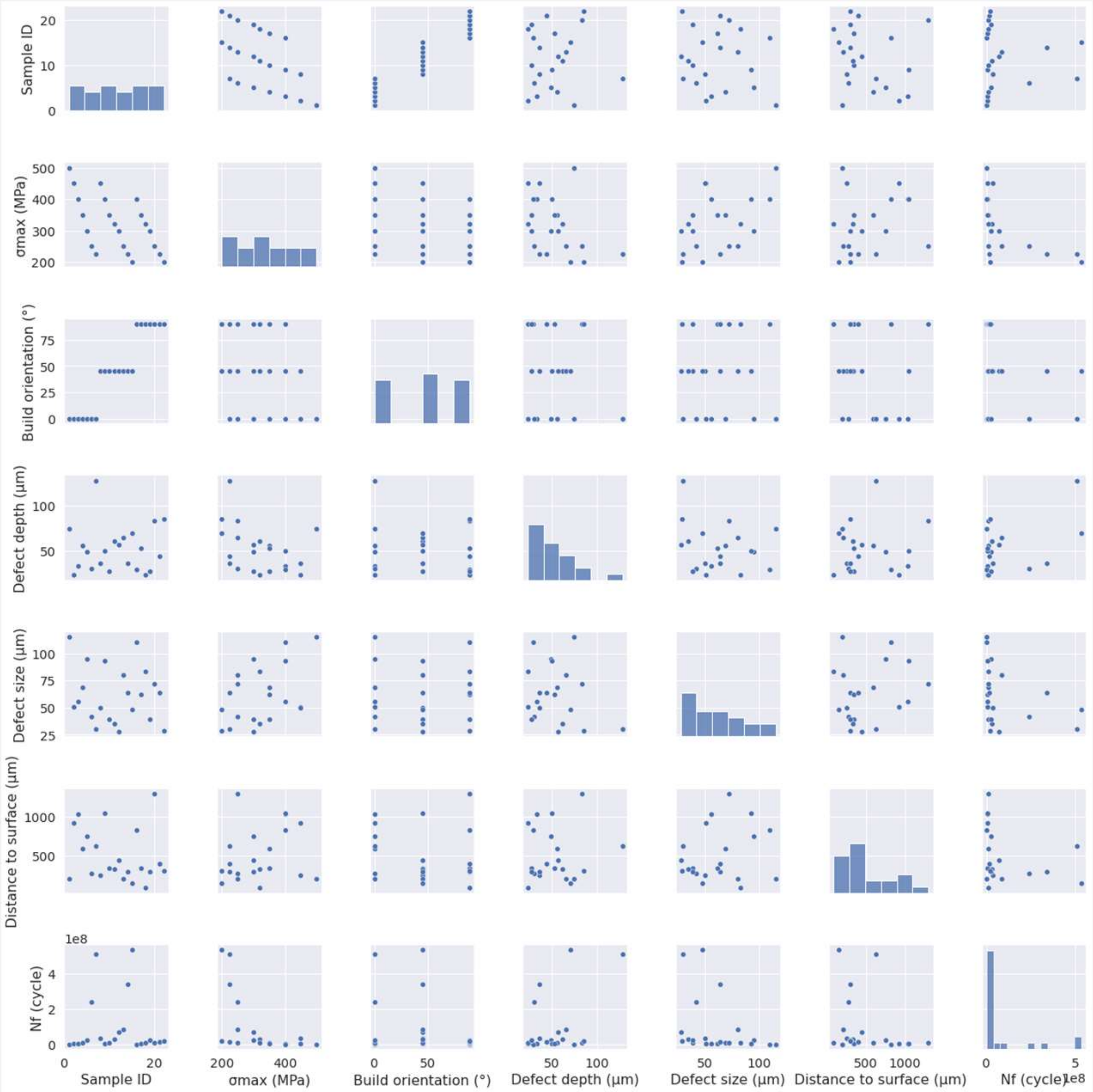




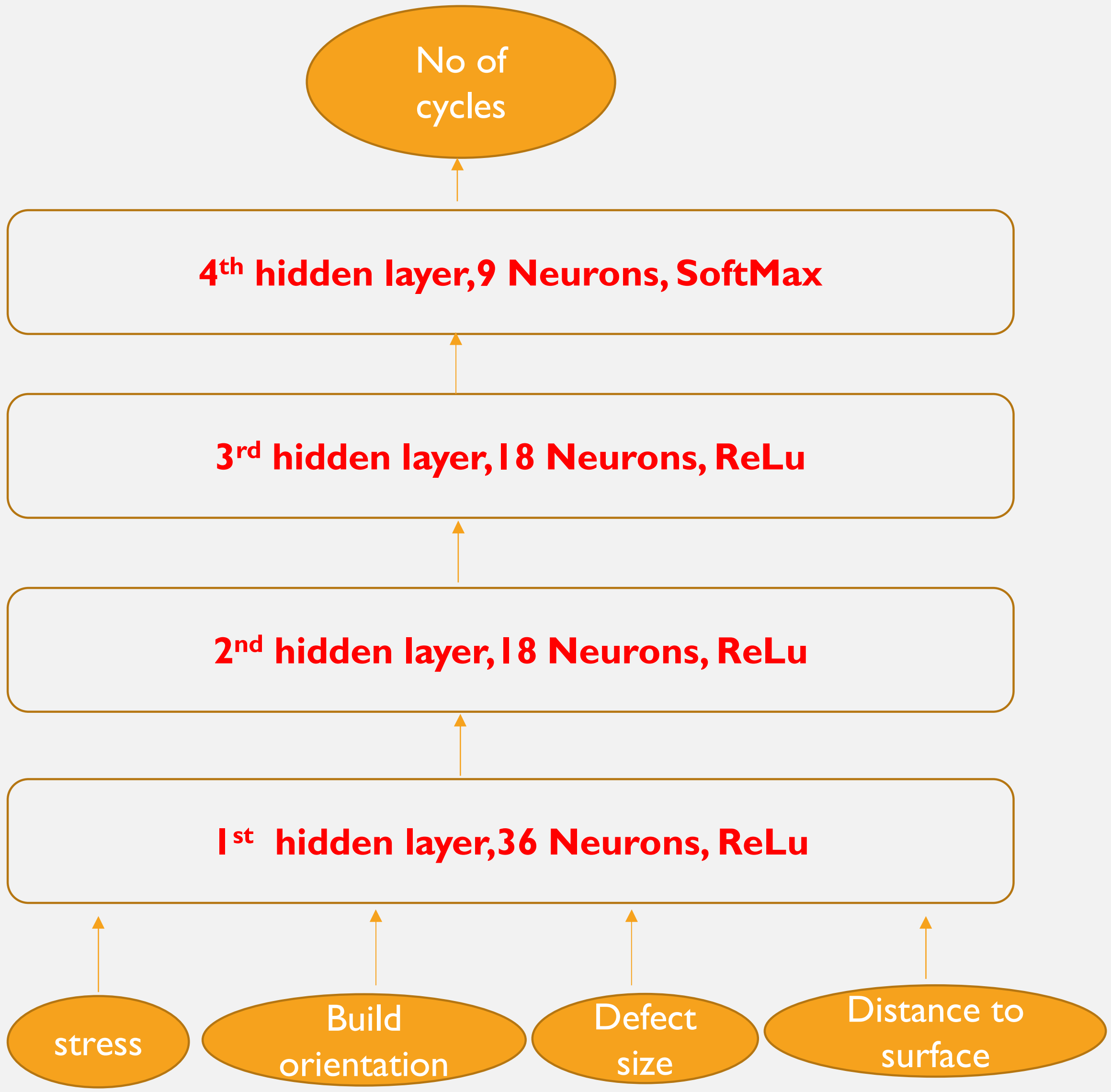
TRAINING PROCEDURE THROUGH NEURAL NETWORKS



Results:


Sample ID
σmax (MPa)
Build orientation (°)
Defect depth (μm)
Defect size (μm)
Distance to surface (μm)
Nf (cycle)
1e8

Results:


No of cycles
4th hidden layer,9 Neurons, SoftMax
3rd hidden layer,18 Neurons, ReLu
2nd hidden layer,18 Neurons, ReLu
1st hidden layer,36 Neurons, ReLu
stress
Build orientation
Defect size
Distance to surface

Results:

NN Parameters
Activation Functions: ReLu, SoftMax
Loss Function : Mean Square Error
Learning Rate : 0.185

Algorithms	Accuracy [R-score(%)]
Linear Regression	58
Logistic Regression	67
SVM	71
ANN(Deep Neural Network)	74

DISCUSSION & PLAN

Due to the scarcity of data for Shape Memory alloys, we first gathered Steels data from various text books, data handbooks, and the Internet. And, because there were less data points, the results of ML algorithms and DNN differed less here. According to the literature, having large and clean data sets allows DNN to be a powerful tool for dealing with problems and producing highly accurate results.

Month	Work
Jan	Data Collection(DC) from Reference papers + Training the DNN
Feb	DC from (References Simulation software)+Training
March	Hyper Parametric Tuning
April	Model Evaluation
May	Attempt to reach the goal of accuracy above 92%

Thank you