Digital Twins in Metrology

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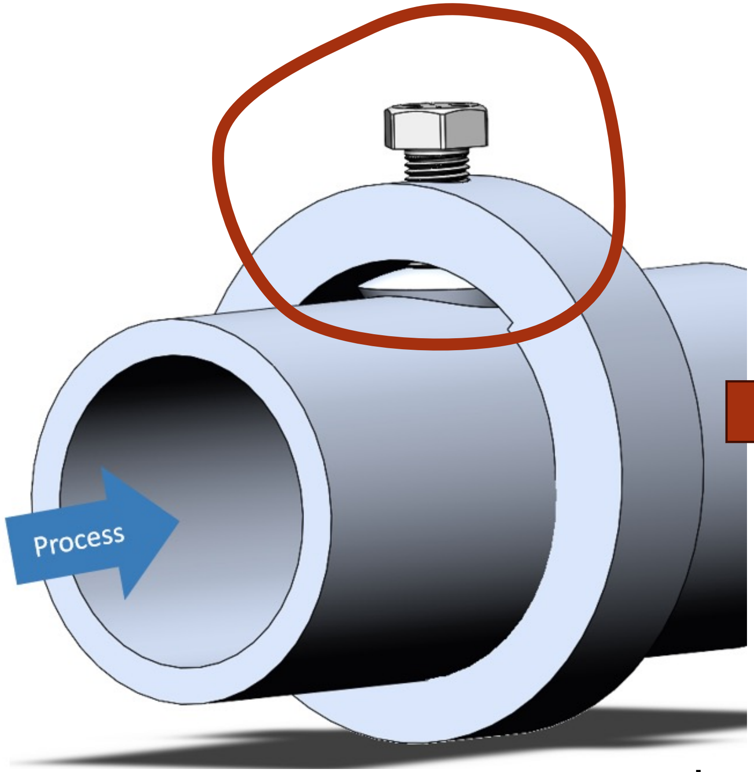
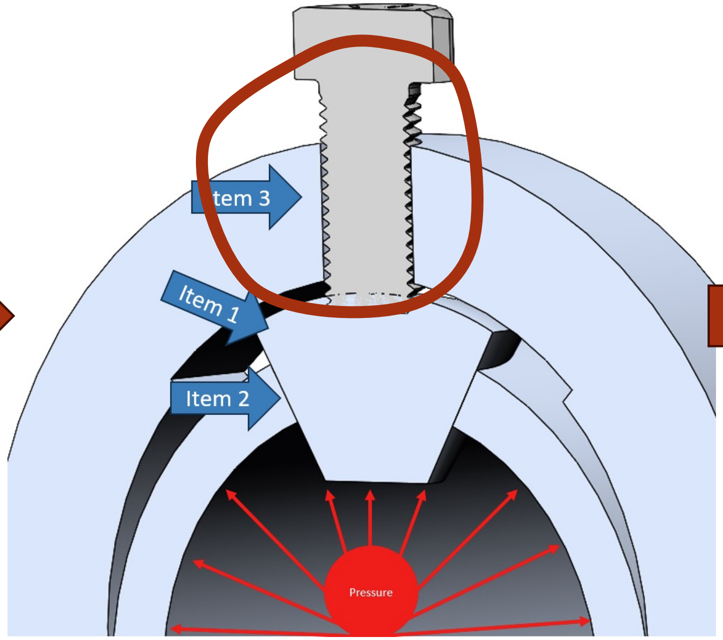
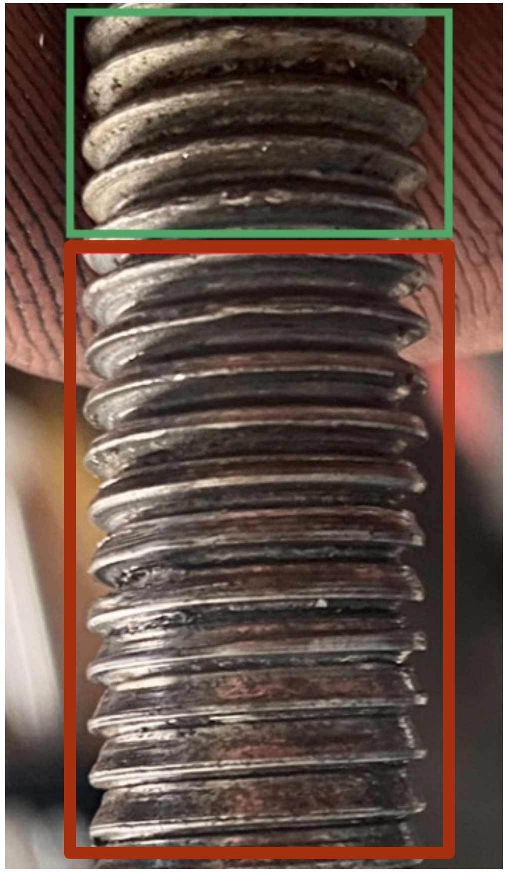
DSA 5900 Spring 2024

Motivation

Would a Machine Learning Model have predicted this failure?







Injection Pressure:
1,400 bar (22k psi)

Project Definition

The purpose of this project is to:

- Develop an applicable approach to implementing a Digital Twin of a Mechanical System.
- Develop Machine Learning Model using data ingested by the Digital Twin.
- Utilize the Machine Learning Model to predict the life expectancy of a Physical Twin.

The stakeholders include:

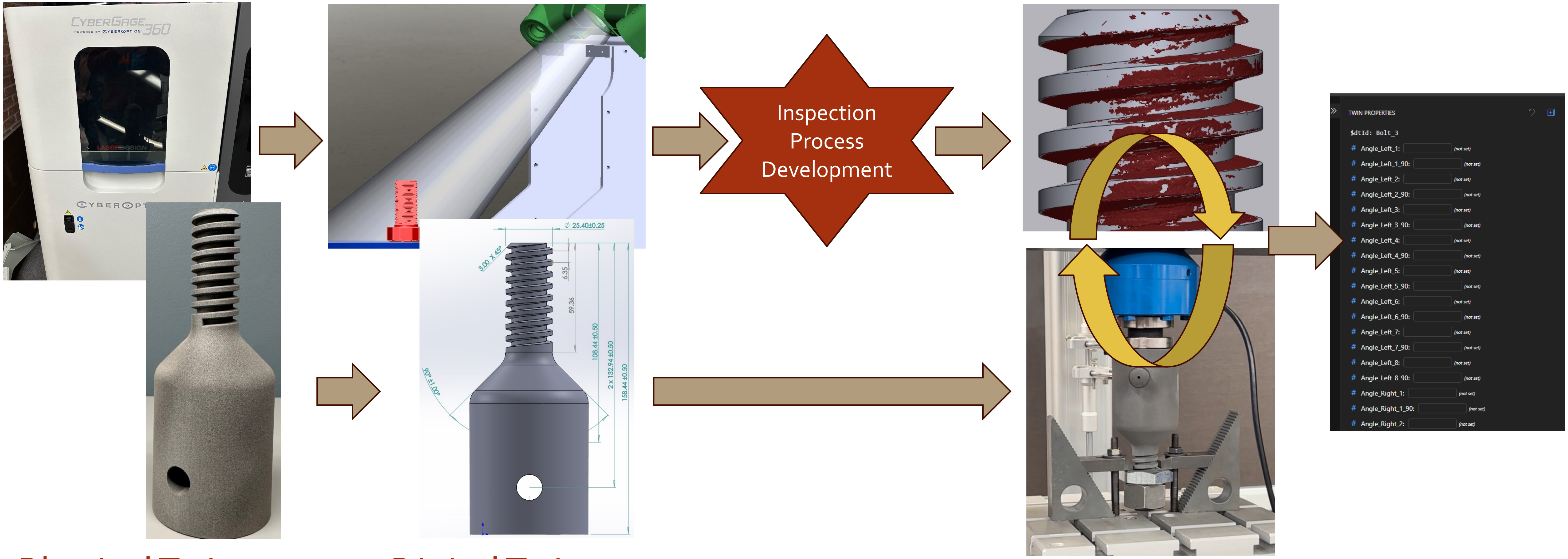
- My employer, OtterBox
- University of Oklahoma, Department of Industrial & Systems Engineering

Advisor:

- Dr. Shiva Raman
  - Department of Industrial & Systems Engineering

What is a Digital Twin?

A Digital Twin is a Digital Representation of a Physical Entity, with data streams connecting them, to drive optimization, predictability, data driven decisions, etc.

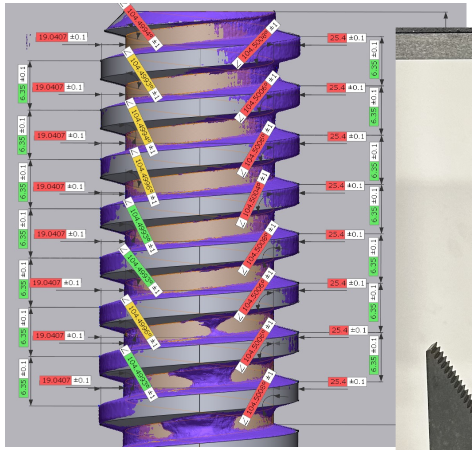


Physical Twin | Digital Twin | Production | Digital Twin

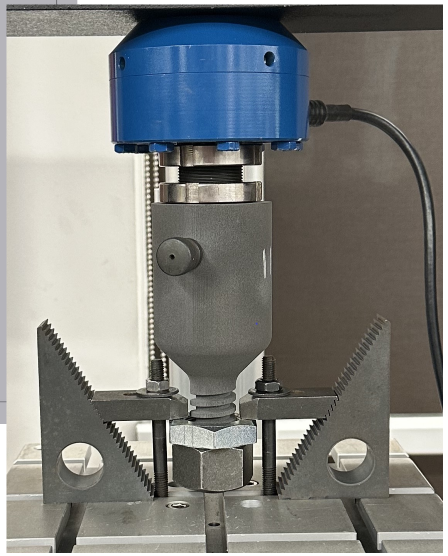
Data Ingestion

Data Sources

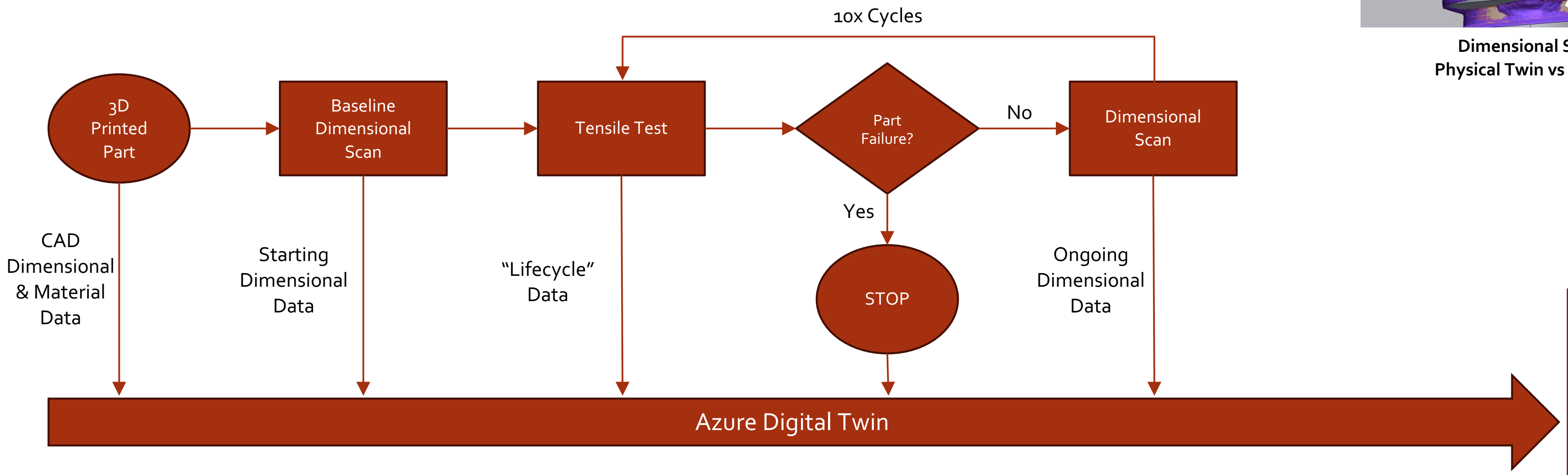
- **3D CAD Model Data:** 1”-4 ACME Threaded Rod
- **3D Scan of Physical Twins:** 96 Measurements per scan, per part
- **Tensile Testing:** Pulling Force (lbs) and Elongation (inch) per part
  - Cyclical Tensile Testing performed until failure or 10x repetitions.

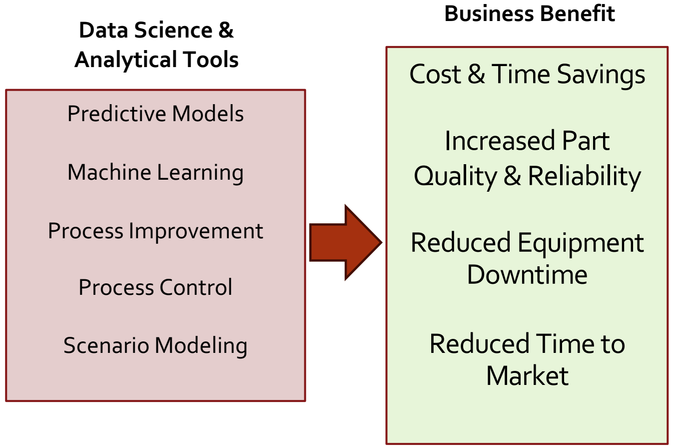


Dimensional Scan of Physical Twin vs 3D Model



Tensile Test of Physical Twin

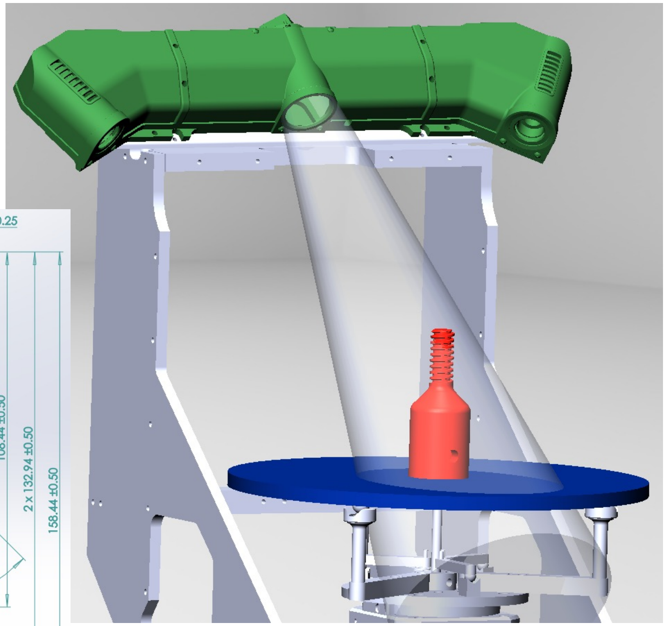




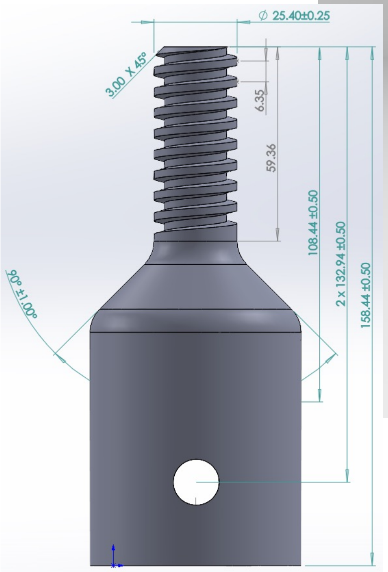
Data Preparation: 3D Model of Physical Twin

A 3D model representing the Physical Twin gives baseline engineering data of what the theoretical optimal part, assembly, or system will look like and how it will function.

- Fully Defined Computer Aided Designed (CAD) Model in Solidworks prior to production
  - **Critical Dimensions adhere to Form, Fit, and Function requirements**
    - How should the part look?
  - **Material Properties**
    - How should the part perform?
  - **Manufacturing & Quality Inspection Methods**
    - How will the part be produced and inspected?



Test Inspection Process
Prior to Production



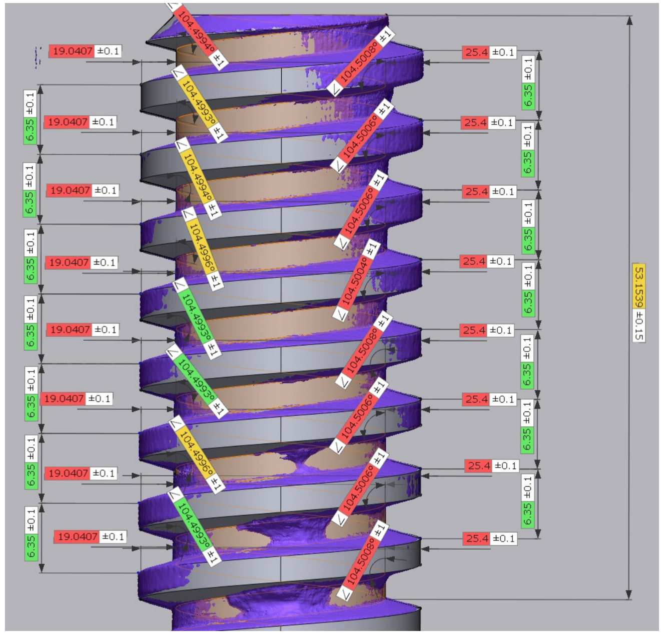
Fully Defined CAD Model

<u>DATA OUTPUT:</u> **Theoretical Dimensional Data**

Data Preparation: Physical Part Quality Inspection

The Production and resultant Quality Inspection processes of the Physical Twin are critical to ensure all parts were produced to the Engineering Intent.

- Utilize CyberGage 360 Laser Scanning System to generate 3D Model of Physical Twin Dimensions
  - What are the actual initial dimensional measurements of the physical parts?
  - Are there any initial quality defects that would impact form, fit, or function expectations?
  - How does the part dimensionally change over time?
- Utilize Tensile Tester to apply a cyclical tensile load to the part.
  - How will the part react to usage?
  - What load (lbs) is required to deform the part?



Theoretical vs Actual Inspection

<u>DATA OUTPUT:</u> Actual Dimensional, Testing, and Failure Data

Data Preparation: Digital Twin

The Digital Twin is based in the Microsoft Azure Digital Twin Environment, with 1 Twin for each of 10 Physical Twins.

- Model Structure imported using JSON files
  - Dimensional, Usage, and Failure Attributes
- SQL Data Stream built using concatenation of data, per Physical Twin
  - Historical View of what each part looks like and what its usage has been
- Data Cleanliness
  - Feature Engineering: Stress, Strain, Elongation %
  - Missing Values: Average, for like dimensions from the same twin.
  - Outliers: Data imputation based on average usage in previous tests.
  - Bootstrapping: Increase size of dataset (n = 100)

Model Information


```
{
  "@id": "dtmi:demo:Bolt_1;1",
  "@type": "Interface",
  "@context": "dtmi:dtdl:context;2",
  "displayName": "Bolt_1",
  "contents": [
   {
    "name": "Angle_Left_1",
    "@type": "Property",
    "schema": "float"
   },
   {
    "name": "Angle_Left_2",
    "@type": "Property",
    "schema": "float"
   },
```

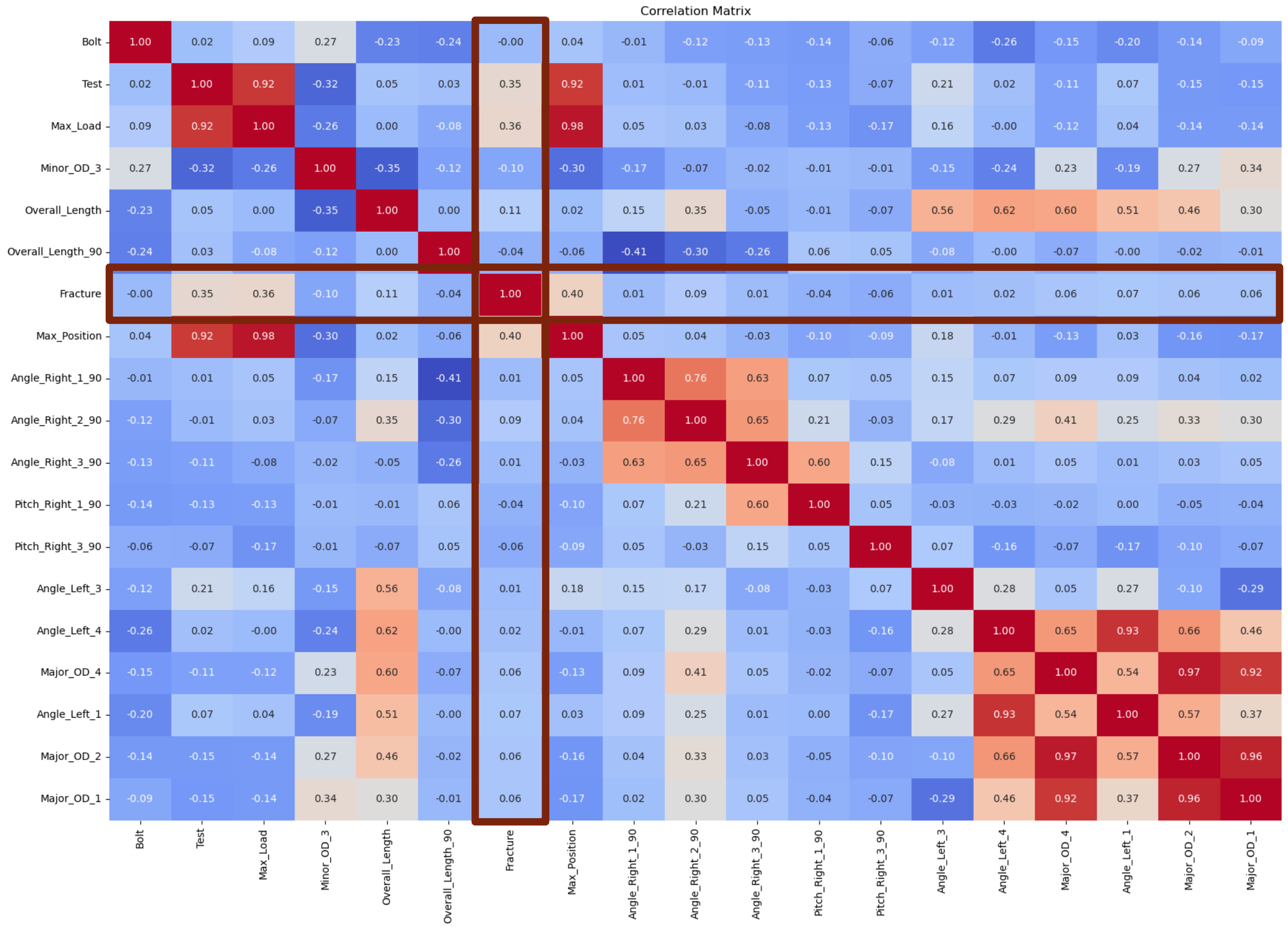

Azure Digital Twin Model

Data Exploration – Correlation Matrix

- Used to identify relationships between dataset features.
- **High Correlation Insights**
  - Max Load -> Max Position
  - Max Position -> Fracture
  - Max Load -> Fracture

Dimensionally, high correlation shows part to part similarity.

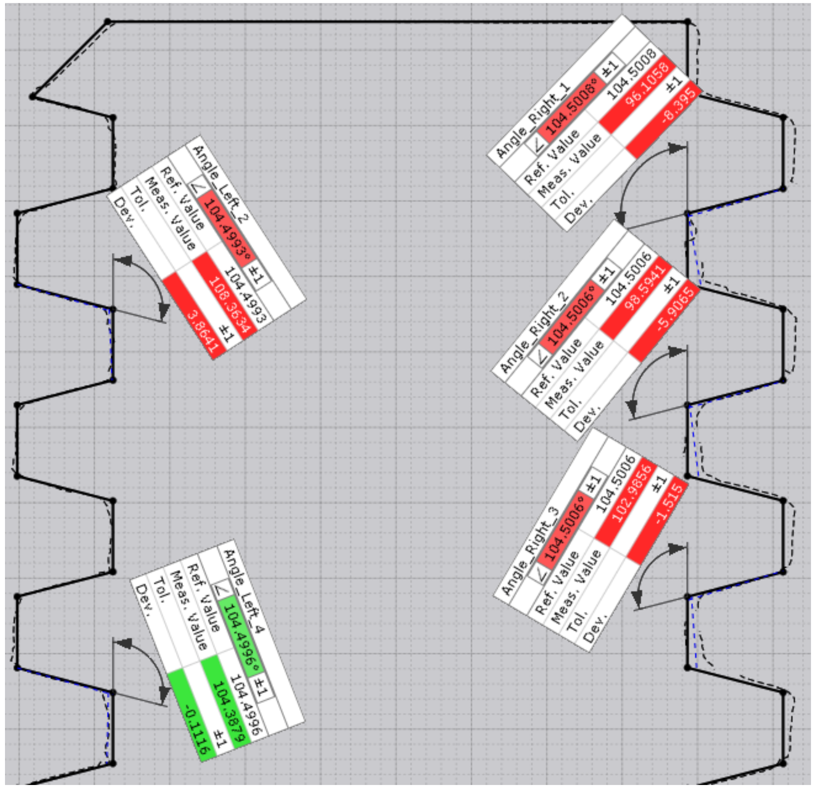
- **Low Correlation Insights**
  - Overall Length -> Fracture



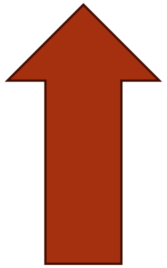
Data Exploration – Descriptive Statistics

- Ability to give insight to understanding the dataset.
- Focus on Standard Deviation across Bolt + Test Combinations.
- **Top 11** Features with Highest Standard Deviation are Dimensional Features.
- **Top 5** Features of these 11 are all Thread Angles in region of force application.
- **Question:** Is this a manufacturing issue or related to tensile testing?

Feature	Angle_Right_1	Angle_Right_2	Angle_Right_3	Angle_Left_4	Angle_Left_2
Standard Deviation (degrees)	20.19	19.73	18.76	14.24	13.24



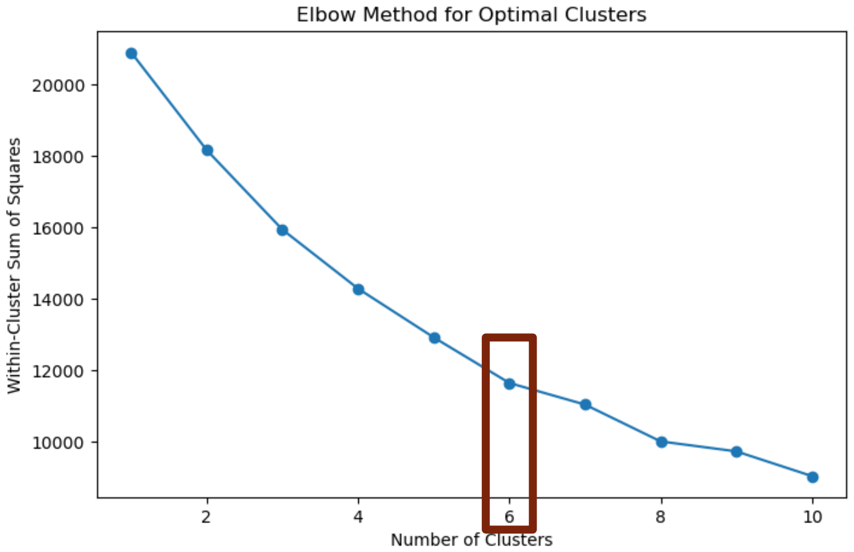
Example Depiction from Dataset

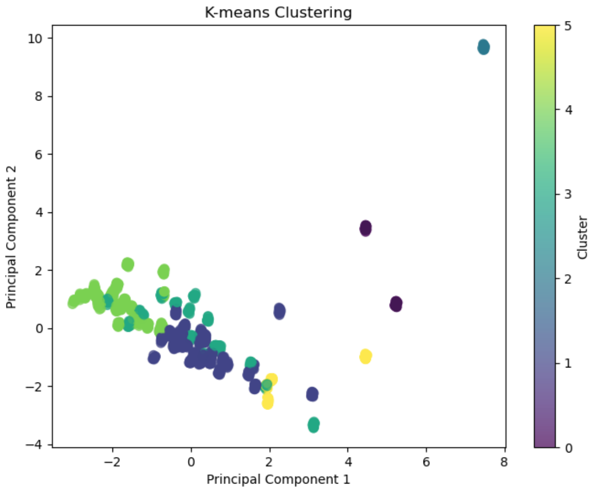


Direction of Force

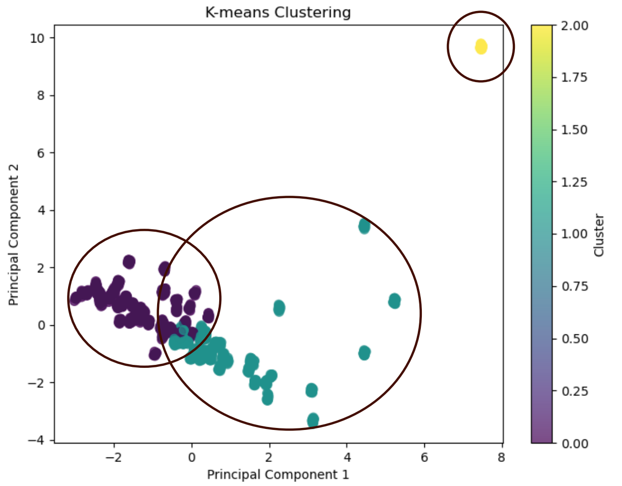
Data Exploration – K Mean Clusters

- Investigate grouping within dataset using Principal Component Analysis (PCA)
- Optimal Clusters Initialized based on Elbow Method.
- Unclear data separation led to a reduction in clusters.





N = 6 clusters

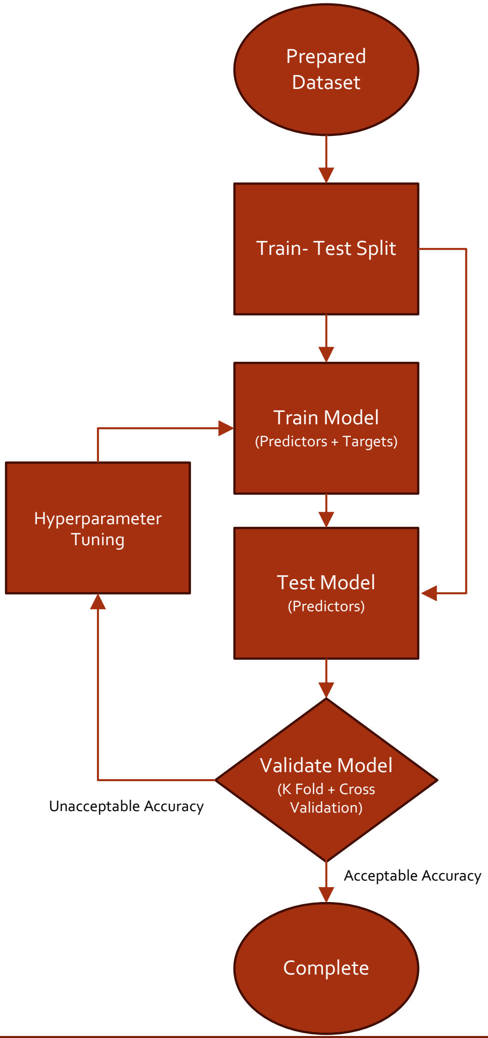


N = 3 clusters

Model Design – Random Forest

- Why Random Forest?
  - Efficient in handling high dimensionality data
  - Splits data into separate decision trees to run predictions.
  - Excellent at solving Classification Problems.
  - Ability to draw connections in nonlinear data.
- Train / Test Data Split
  - Predictors: 70% (770 items)
  - Targets: 30% (330 items)
  - Randomized selection to reduce potential bias
- Validation
  - Stratified K Folds
    - N=10 splits
  - Confusion Matrix
  - Classification Report

Model Selection



Process Validation

Confusion Matrix (TP,TN,FP,FN)

	Predicted Positive	Predicted Negative
Actual Positive	316	0
Actual Negative	0	14

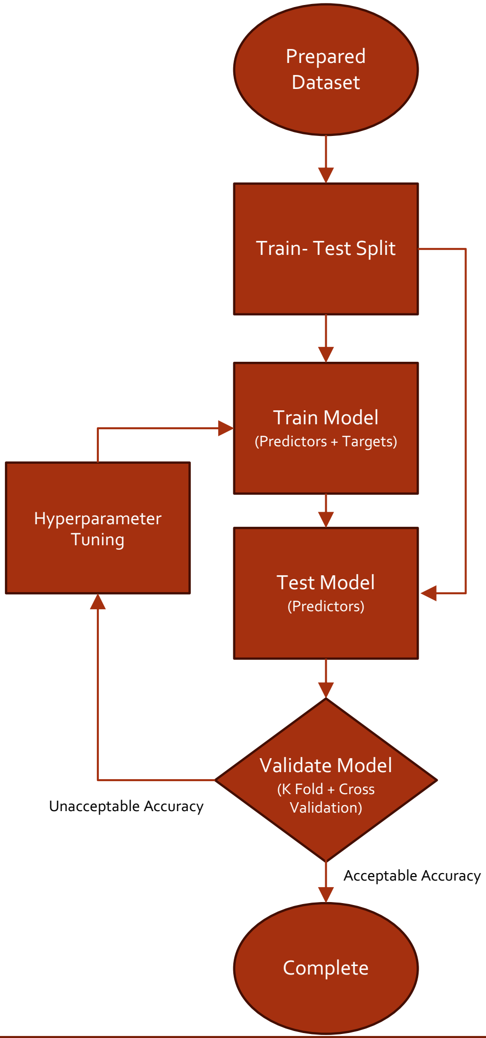
Classification Report

	Precision	Recall	F1-Score	Support
True Positives	1.0	1.0	1.0	316
True Negatives	1.0	1.0	1.0	14

Model Design – Decision Tree

- Why Decision Tree?
  - More efficient overall model
  - Splits data into separate branches of a single tree to run predictions.
  - Prone to overfitting
- Train / Test Data Split
  - Predictors: 70% (770 items)
  - Targets: 30% (330 items)
  - Randomized selection to reduce potential bias
- Validation
  - Stratified K Folds
    - N=10 splits
  - Confusion Matrix
  - Classification Report

Model Selection



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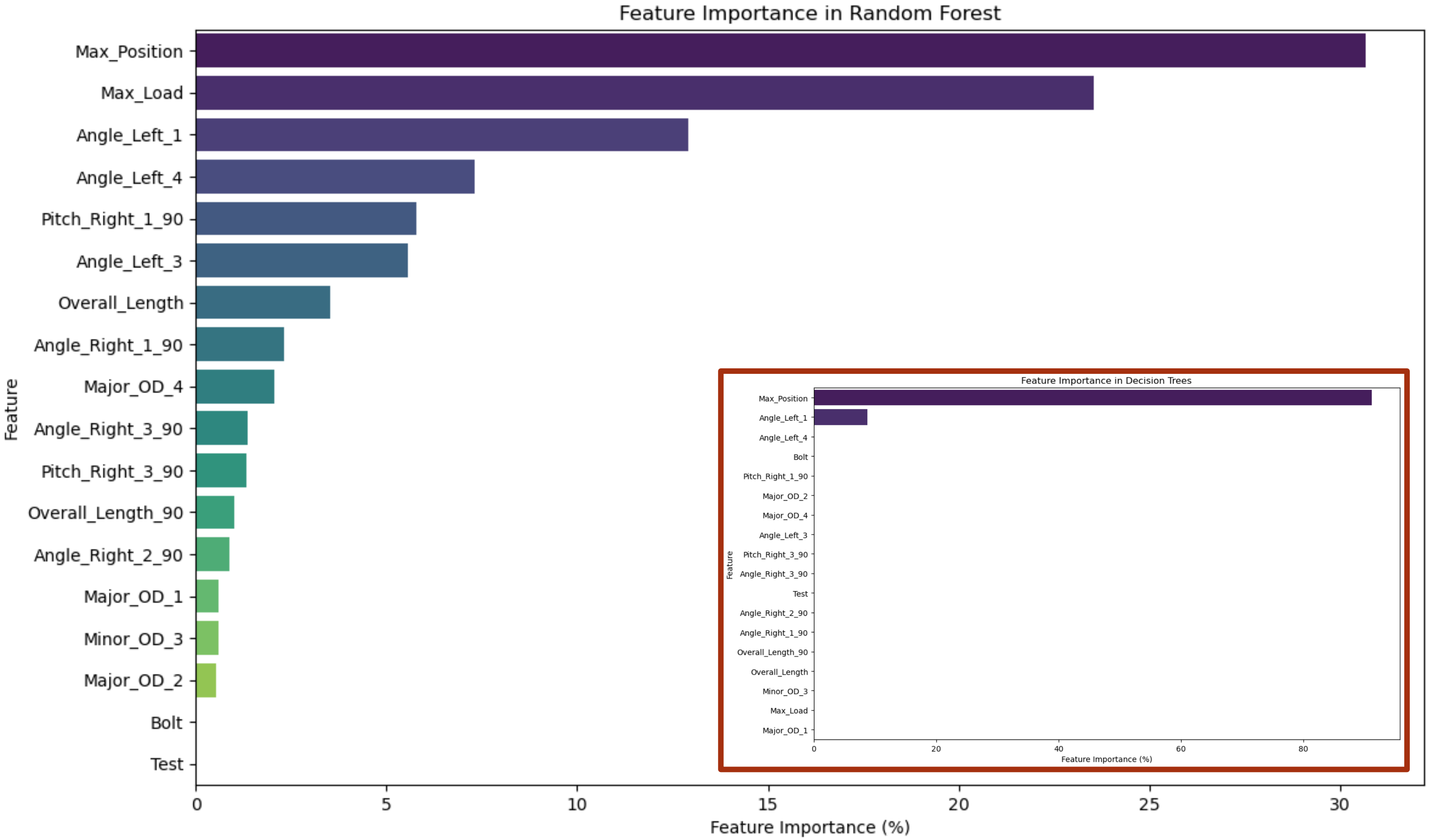
True Positives	1.0	1.0	1.0	316
True Negatives	1.0	1.0	1.0	14

Evaluation

- Both Decision Tree and Random Forest models are accurate for this prediction.
- Feature Importance Analysis shows major difference in effectiveness.
  - Decision Trees:
    - Max Position, Left Thread Angle 1
  - Random Forest:
    - Max Position, Max Load, Left Thread Angle 1, many many more…
- Similar features are found to be important, at vastly different impact percentages.



Conclusion

- Digital Twins of Components and Equipment, Quality Inspection or not, provide an effective platform for asset specific data ingestion, visualization, and future prediction.
  - Increased insight for many functions, including engineering, quality, manufacturing, and reliability.
  - Usage potential in all phases of product development cycle, from design to manufacturing and beyond.
  - Business impact is tangible; including cost savings, cost avoidance, and equipment uptime.

- For the core audience, an applicable approach for implementing a Digital Twin of Quality Inspection Equipment and of mechanical components was given using a real-world product reliability problem.

- Next Steps:
  - Extend Digital Twin database using materials of varying mechanical properties to find if feature importance can shift away from testing data towards dimensional data.
  - Find use case for Digital Twins at work, potentially using Plastic Injection Molding Machines and Molding Tools.