REAL-TIME PRODUCT STRUCTURAL VALIDATION FOR FUSED FILAMENT FABRICATION

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Advisor: Austin Downey
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UNIVERSITY OF South Carolina

Contents

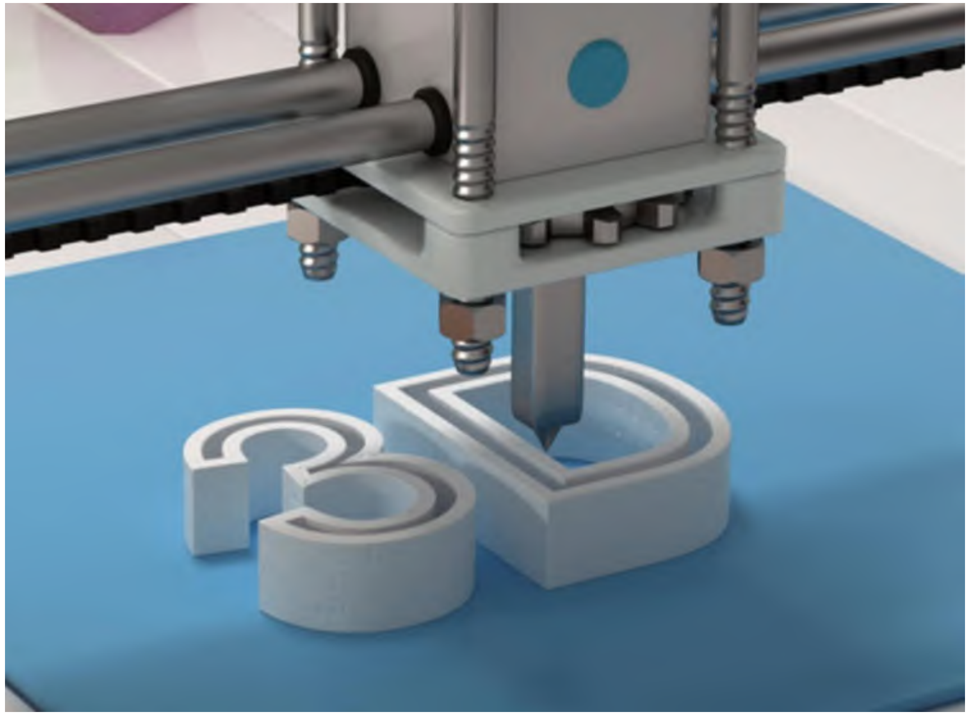
South Carolina

Objective

To reduce part-to-part variations and guarantee product structural quality during the printing is essential .

Algorithm for part structural quality guaranteeing should have the abilities:

- Cyber-physical defects detection
- Product structural validation
- Smart decision-making
- Quality damage warning



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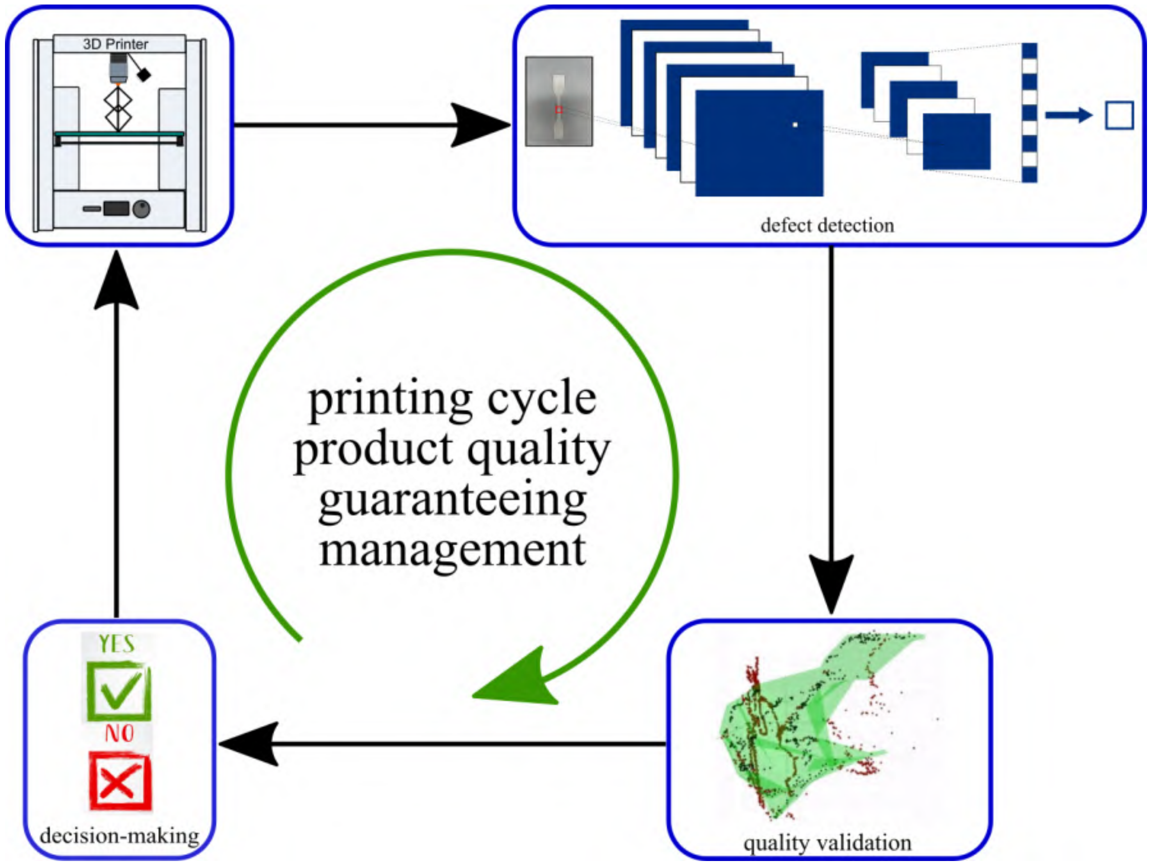
1. https://www.bcn3d.com/introduction-fff-3d-printing-technology-additive-manufacturing-basics/

Objective



Printing cycle quality guaranteeing: pull off and ready to go

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Motivation

Additive manufacturing technologies

- **Material Extrusion** → FFF
- **Vat Polymerization** → SLA, DLP
- **Power Bed Fusion (Polymers)** → SLS
- **Material Jetting** → Material Jetting, DOD
- **Blinder Jetting** → Blinder Jetting
- **Powder Bed Fusion (Metals)** → DMLS, SLM, EBM

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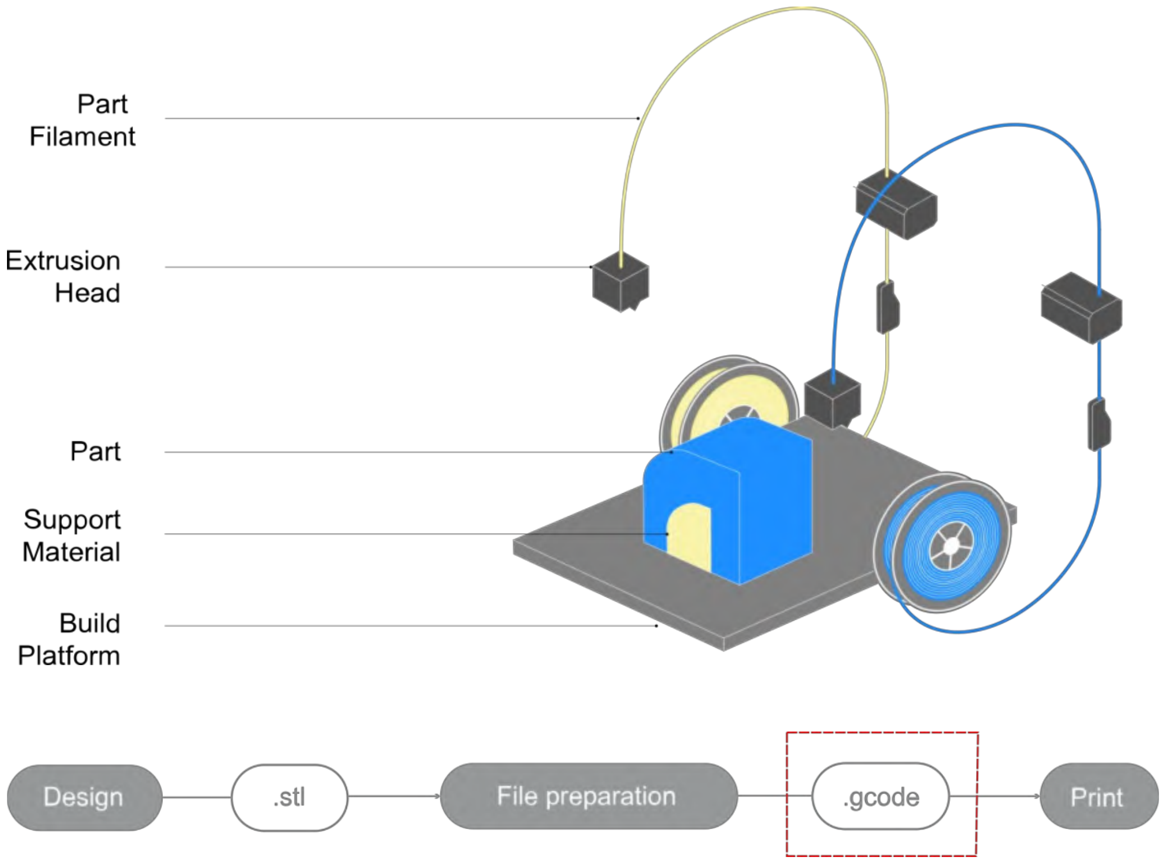
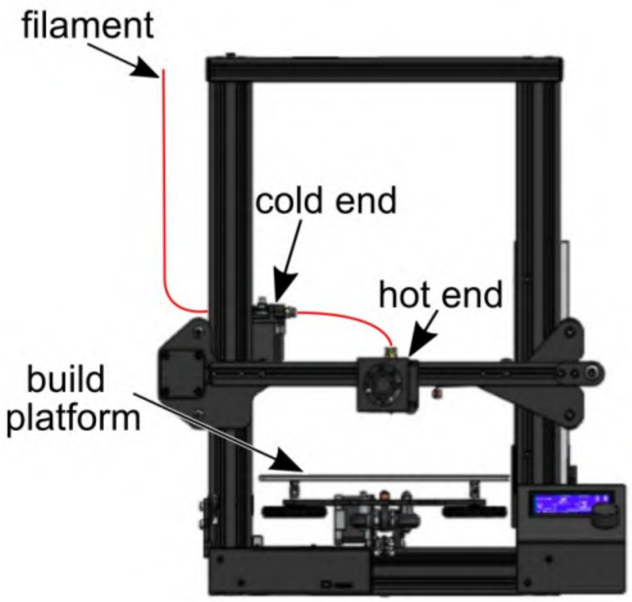
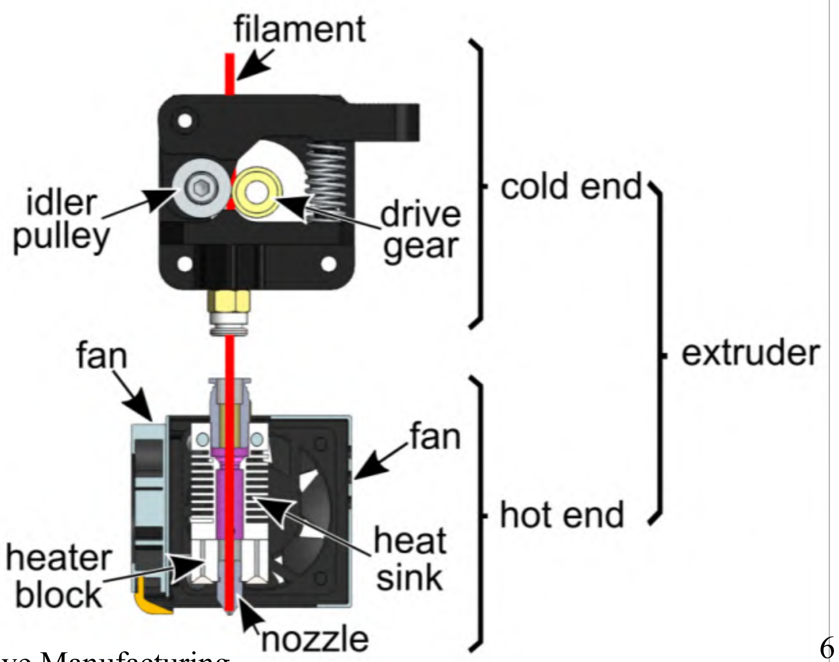
1. https://www.bcn3d.com/introduction-fff-3d-printing-technology-additive-manufacturing-basics/

Motivation







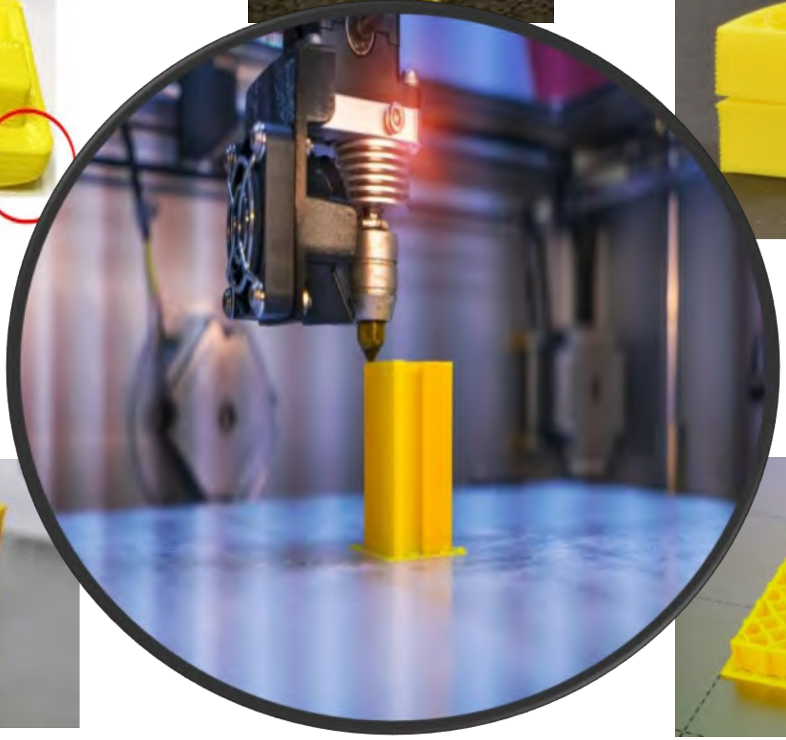
1. https://www.bcn3d.com/introduction-fff-3d-printing-technology-additive-manufacturing-basics
2. Fu Y, Downey A, Yuan L, Pratt A, Balogun Y. In situ monitoring for fused filament fabrication process: A review. Additive Manufacturing.

Motivation

Bonding

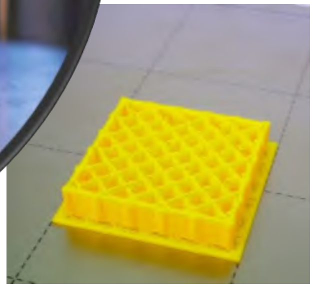
Warpage

Crack



Geometry

Infill



1. https://www.simplify3d.com/support/print-quality-troubleshooting/

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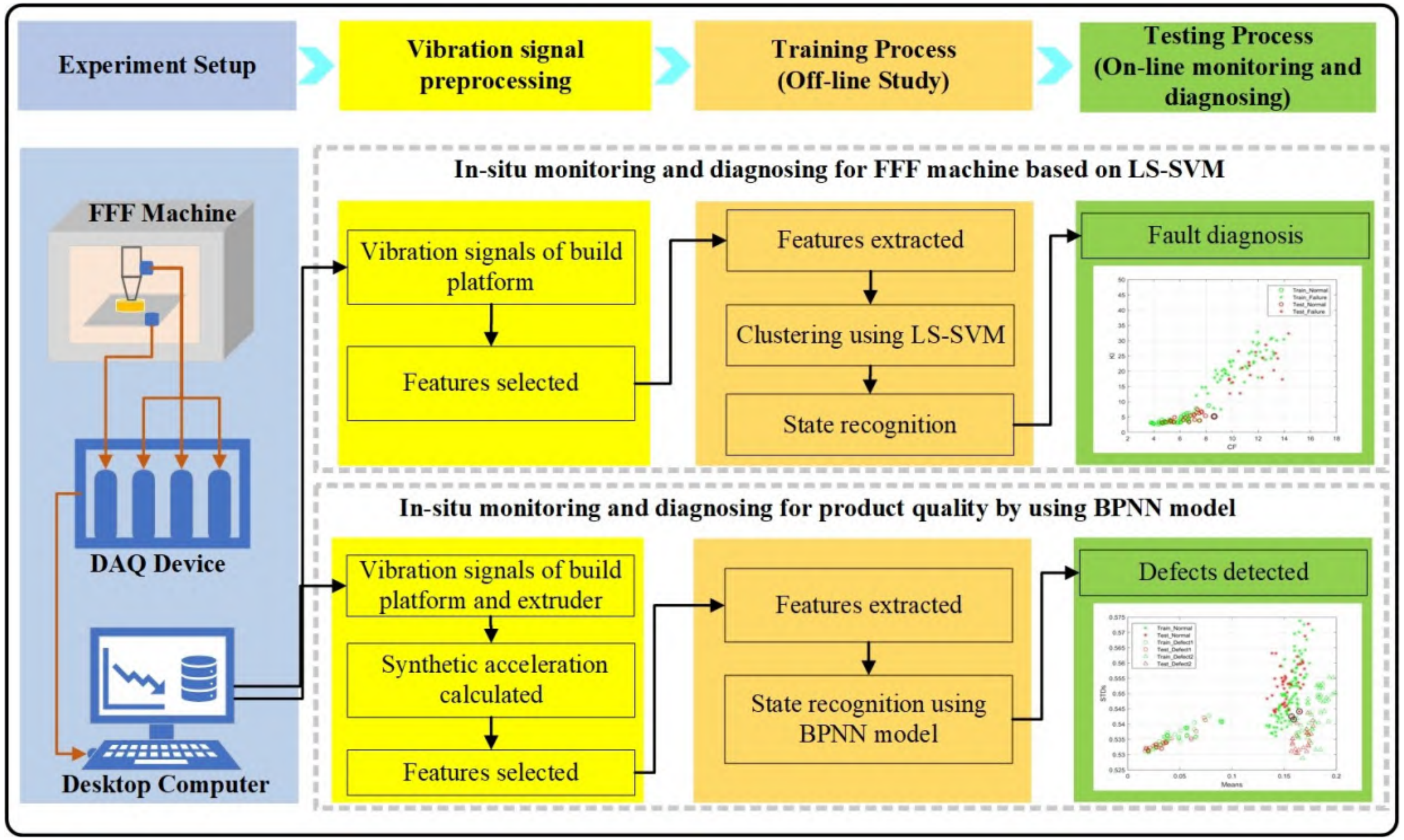
Literature Review

In situ monitoring for fused filament fabrication process: A review



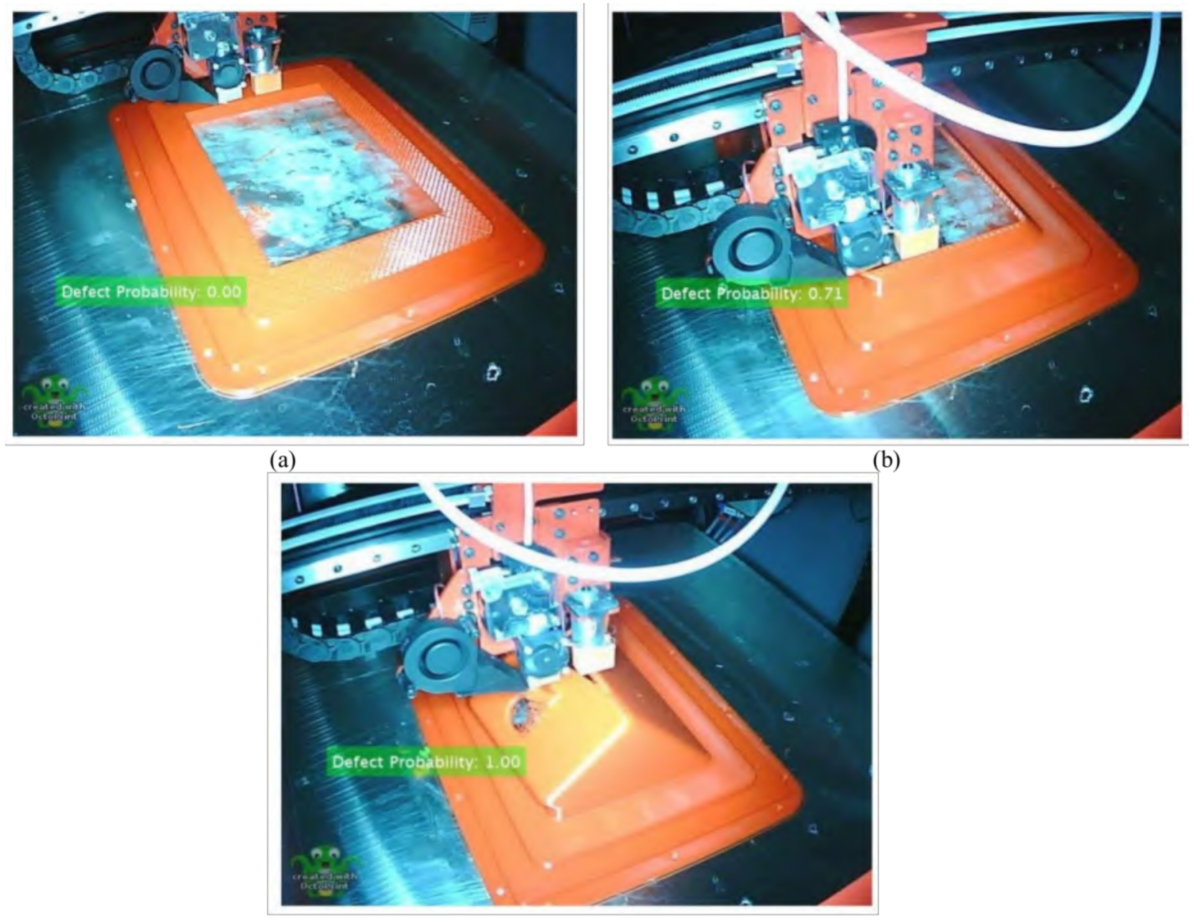
Defect: filament jam
Algorithm: LS-SVM
Accuracy: 90%

Defect: warpage and material stack
Algorithm: BPNN
Accuracy: 95%

1. Yongxiang Li, Wei Zhao, Qiushi Li, Tongcai Wang, and Gong Wang. In-situ monitoring and diagnosing for fused filament fabrication process based on vibration sensors. Sensors, 19(11):2589, 2019.

Literature Review

In situ monitoring for fused filament fabrication process: A review



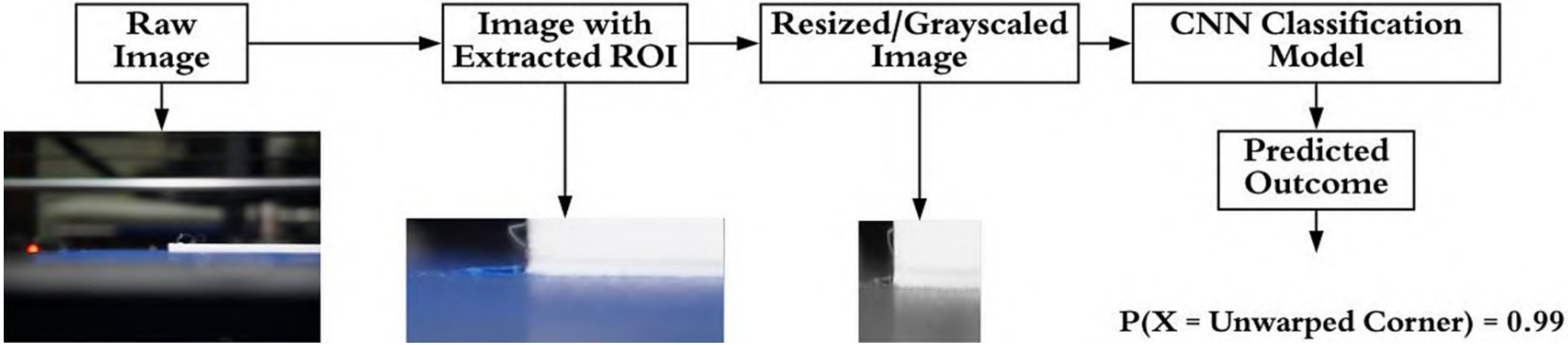
(a) (b) (c)

Defect: printing product quality (good/defect)
Algorithm: SVM, CNN
Accuracy: 98.2%, 99.5%

1. Barath Narayanan Narayanan, Kelly Beigh, Gregory Loughnane, and Nilesh U. Powar. Support vector machine and convolutional neural network basedAwwal, and Khan M. Iftekharuddin, editors, Applications of Machine Learning. SPIE, September 2019. approaches for defect detection in fused filament fabrication. In Michael E. Zelinski, Tarek M. Taha, Jonathan Howe, Abdul A.

Literature Review

In situ monitoring for fused filament fabrication process: A review



Defect: warpage
Algorithm: CNN
Accuracy: 99.3%

1. Aditya Saluja, Jiarui Xie, and Kazem Fayazbakhsh. A closed-loop in-process warping detection system for fused filament fabrication using convolutional neural networks. Journal of Manufacturing Processes, 58:407–415, October 2020.

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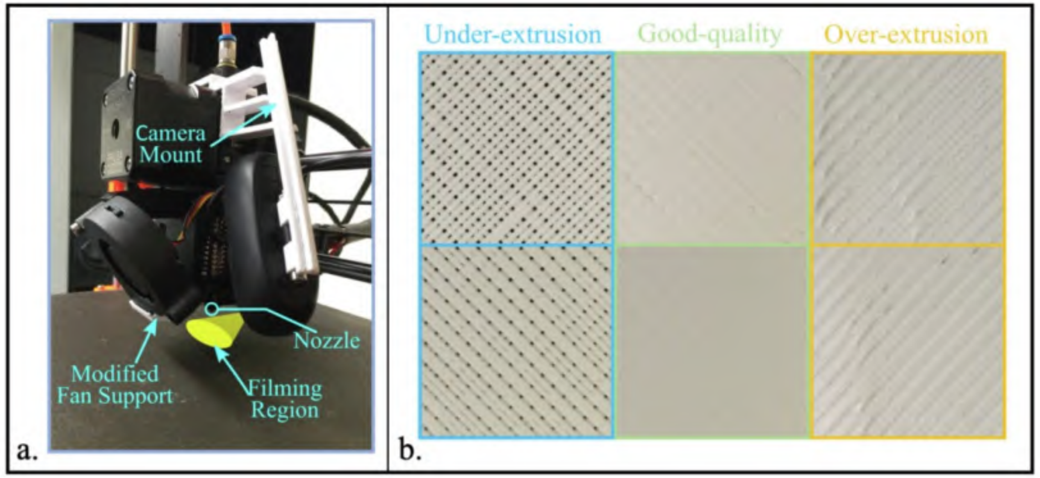
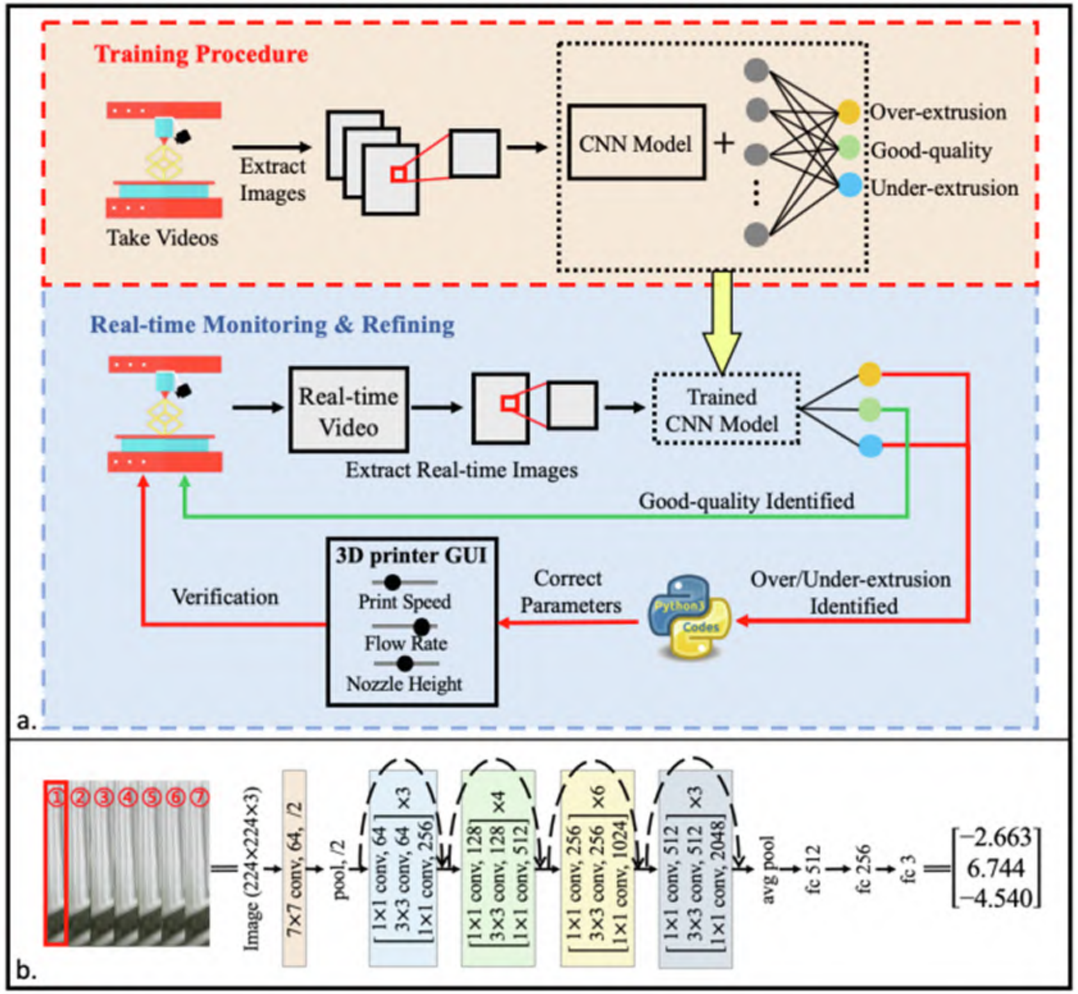
Literature Review

In situ monitoring for fused filament fabrication process: A review





Defect: over-extrusion, under-extrusion, good quality

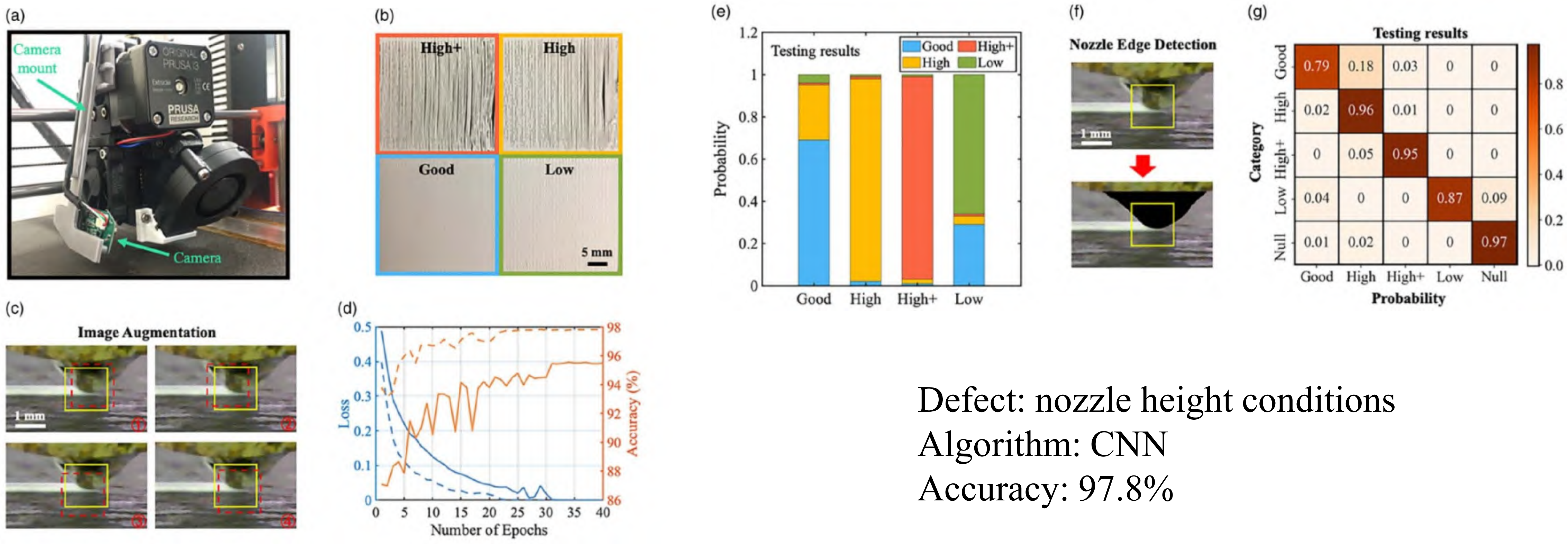
Algorithm: DCNN

Accuracy: 94%

1. Zeqing Jin, Zhizhou Zhang, and Grace X. Gu. Autonomous in-situ correction of fused deposition modeling printers using computer vision and deep learning. Manufacturing Letters, 22:11–15, October 2019.

Literature Review

In situ monitoring for fused filament fabrication process: A review

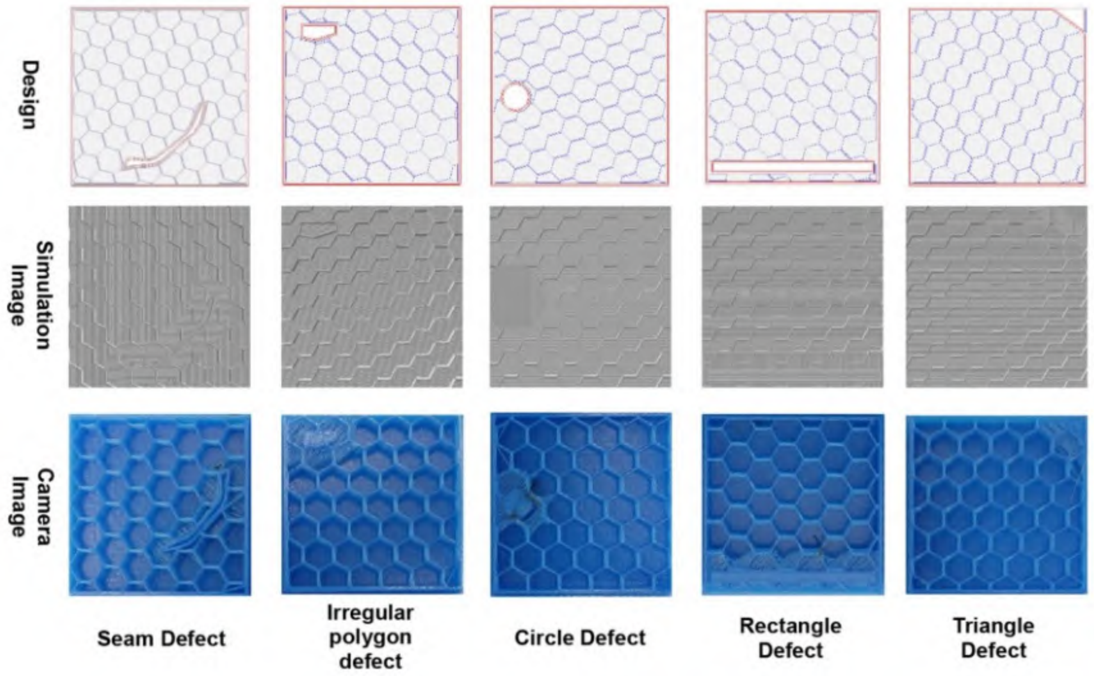


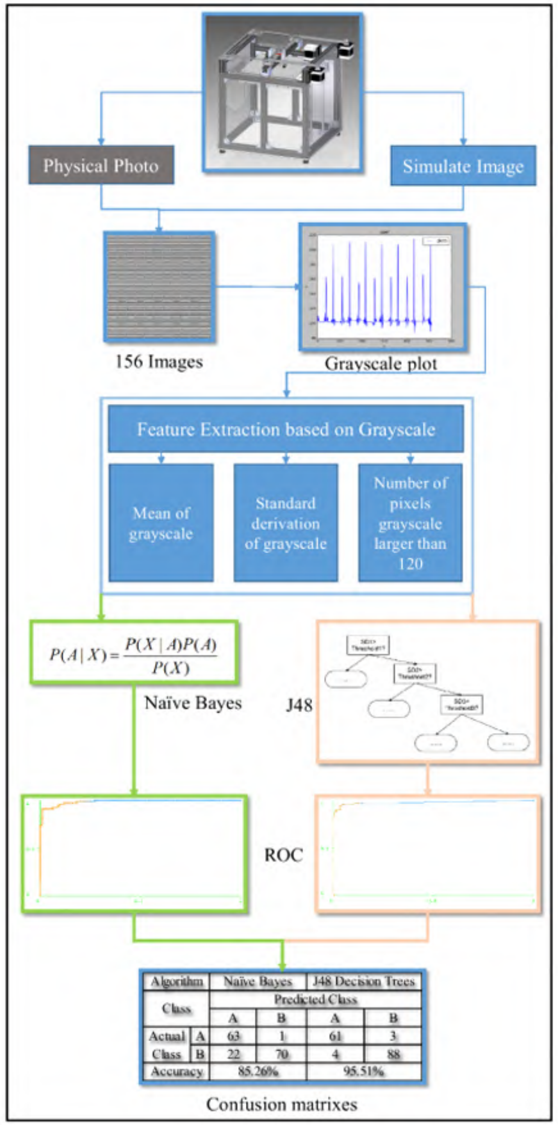
Defect: nozzle height conditions
Algorithm: CNN
Accuracy: 97.8%

1. Zeqing Jin, Zhizhou Zhang, and Grace X. Gu. Automated real-time detection and prediction of interlayer imperfections in additive manufacturing processes using artificial intelligence. Advanced Intelligent Systems, 2(1):1900130, December 2019.

Literature Review

In situ monitoring for fused filament fabrication process: A review





Defect: infill defects
Algorithm: naive Bayes classifiers, J48 decision tree
Accuracy: 85.26%, 95.51%

1. Mingtao Wu, Vir V Phoha, Young B Moon, and Amith K Belman. Detecting malicious defects in 3d printing process using machine learning and image classification. In ASME 2016 International Mechanical Engineering Congress and Exposition. American Society of Mechanical Engineers Digital Collection, 2016.

Summary

From the "in situ monitoring for fused filament fabrication process: A review" paper, we concluded that:

- Defect detection had been widely studied.
- Defect-based product structural validation was ignored.
- More advanced system should integrate real-time feedback and defect mitigating.

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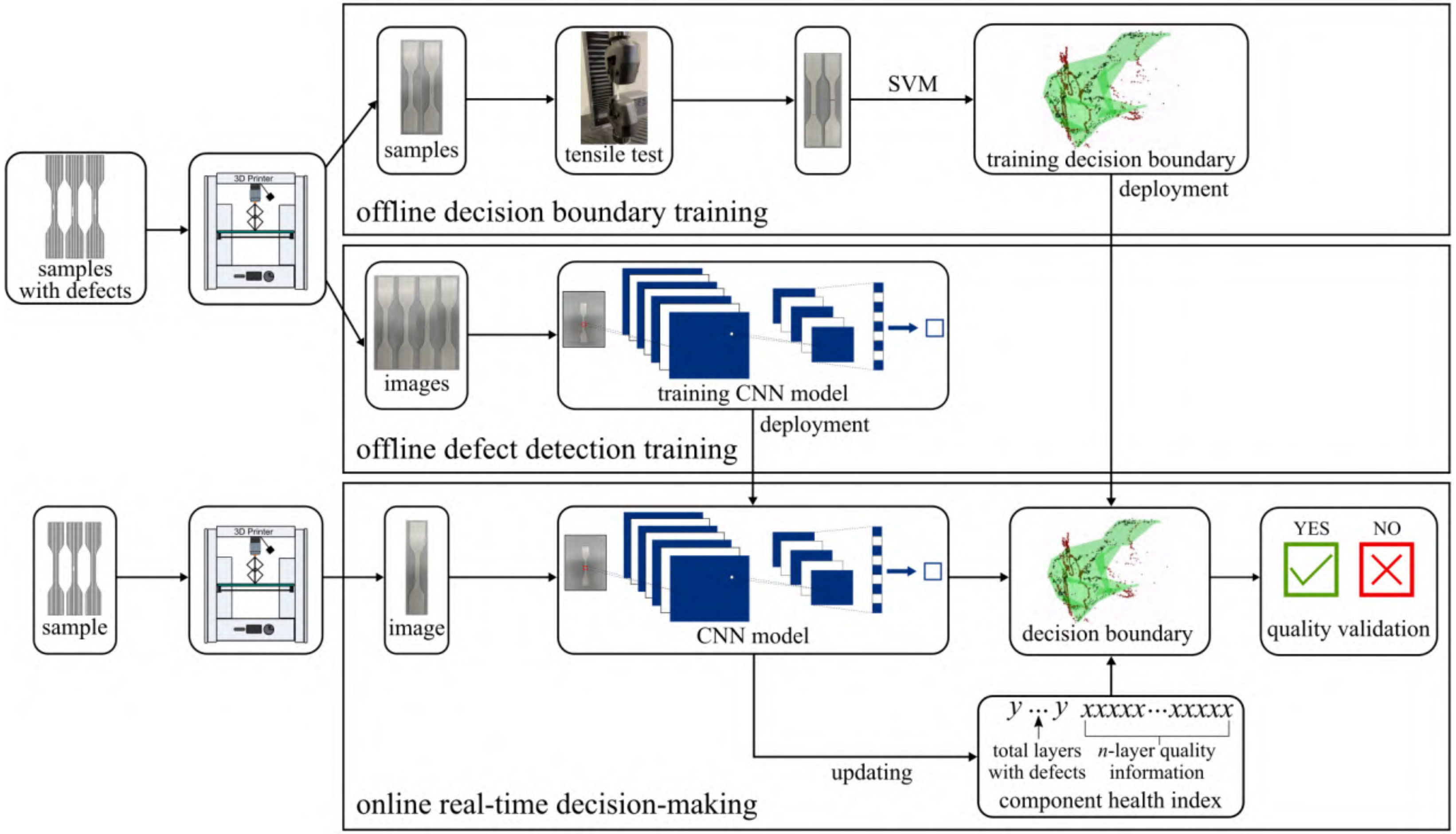
Real-time structural validation for FFF

Diagram of real-time structural validation



- offline decision boundary training
- offline defect detection training
- online real-time decision-making

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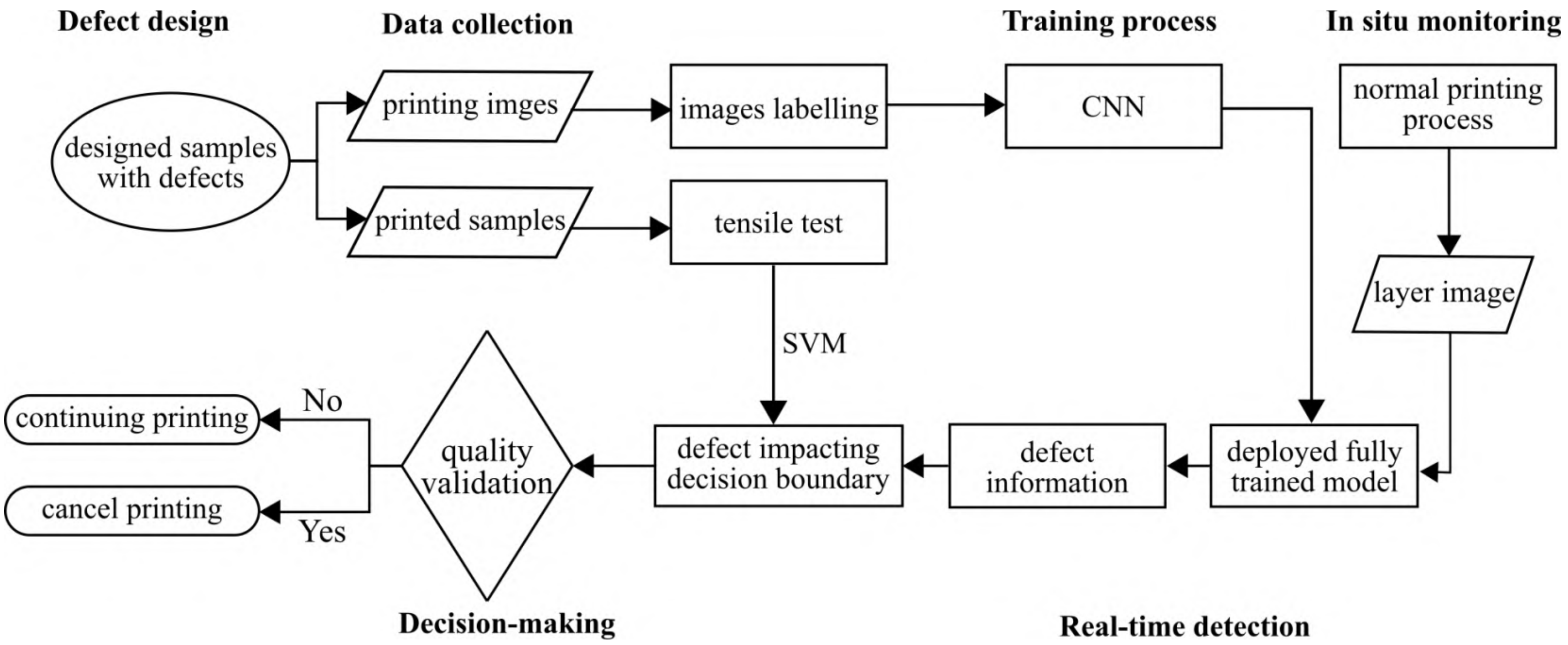
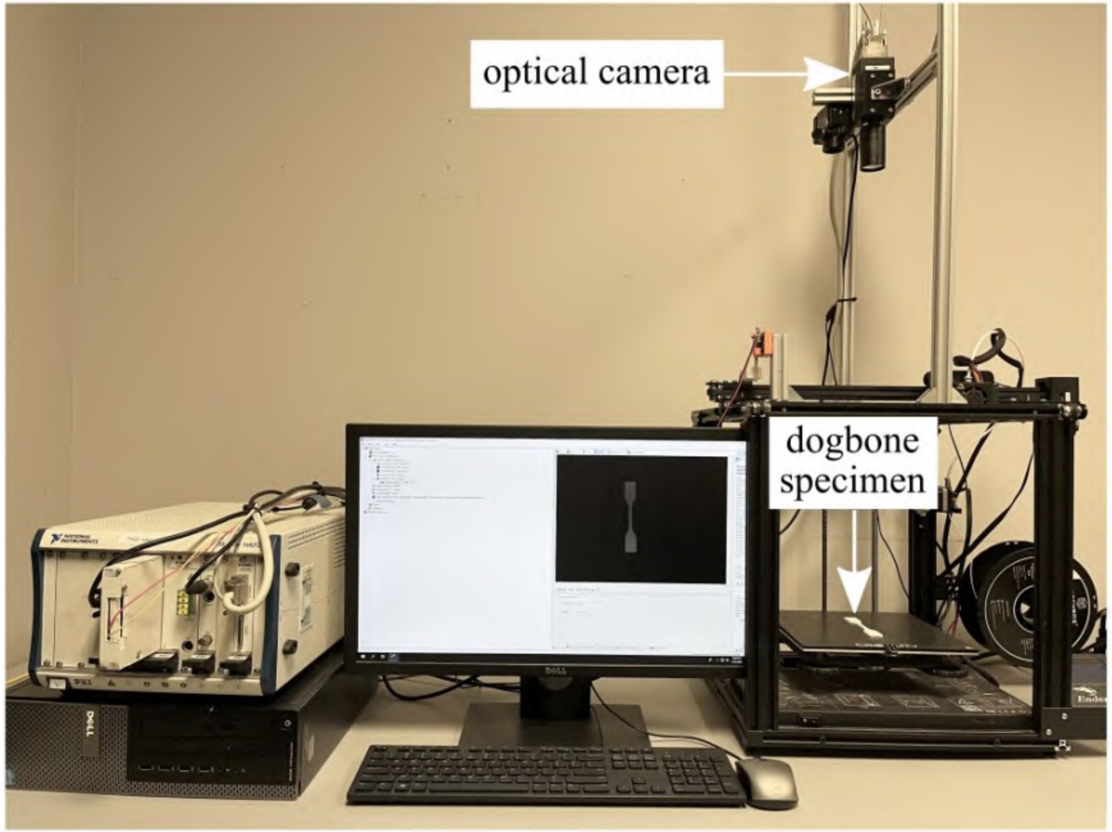
Real-time structural validation

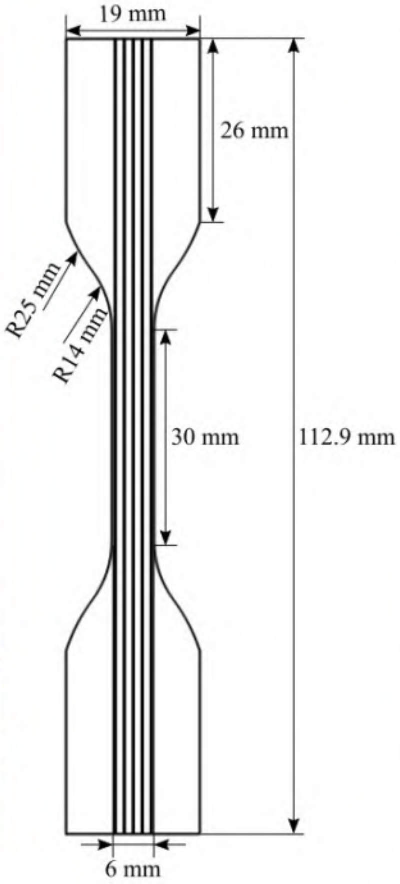
Flowchart of real-time structural validation

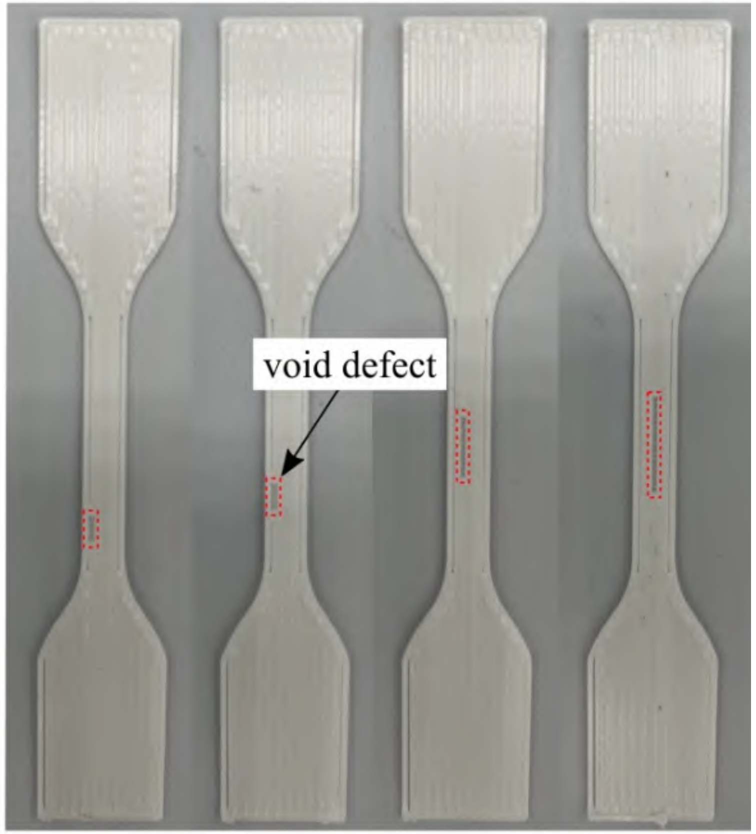


Real-time structural validation

Experimental platform and designed sample

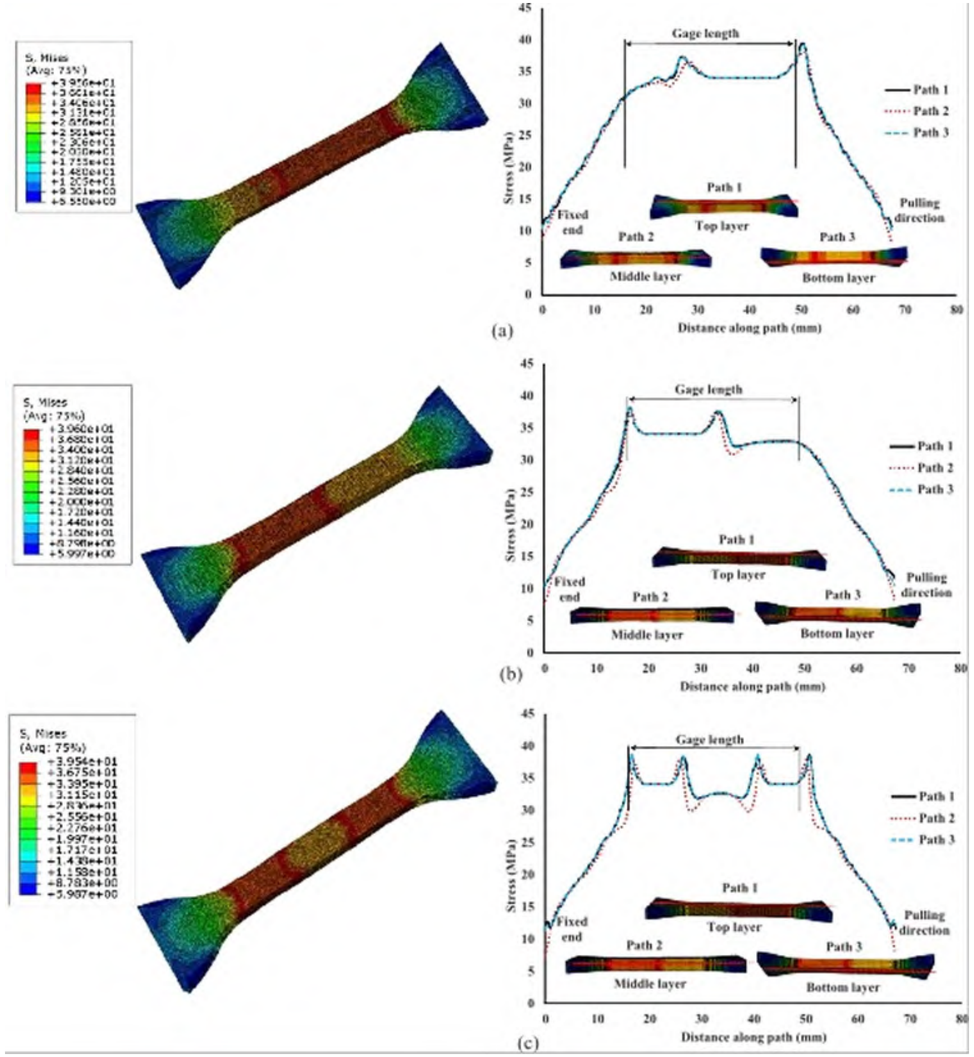


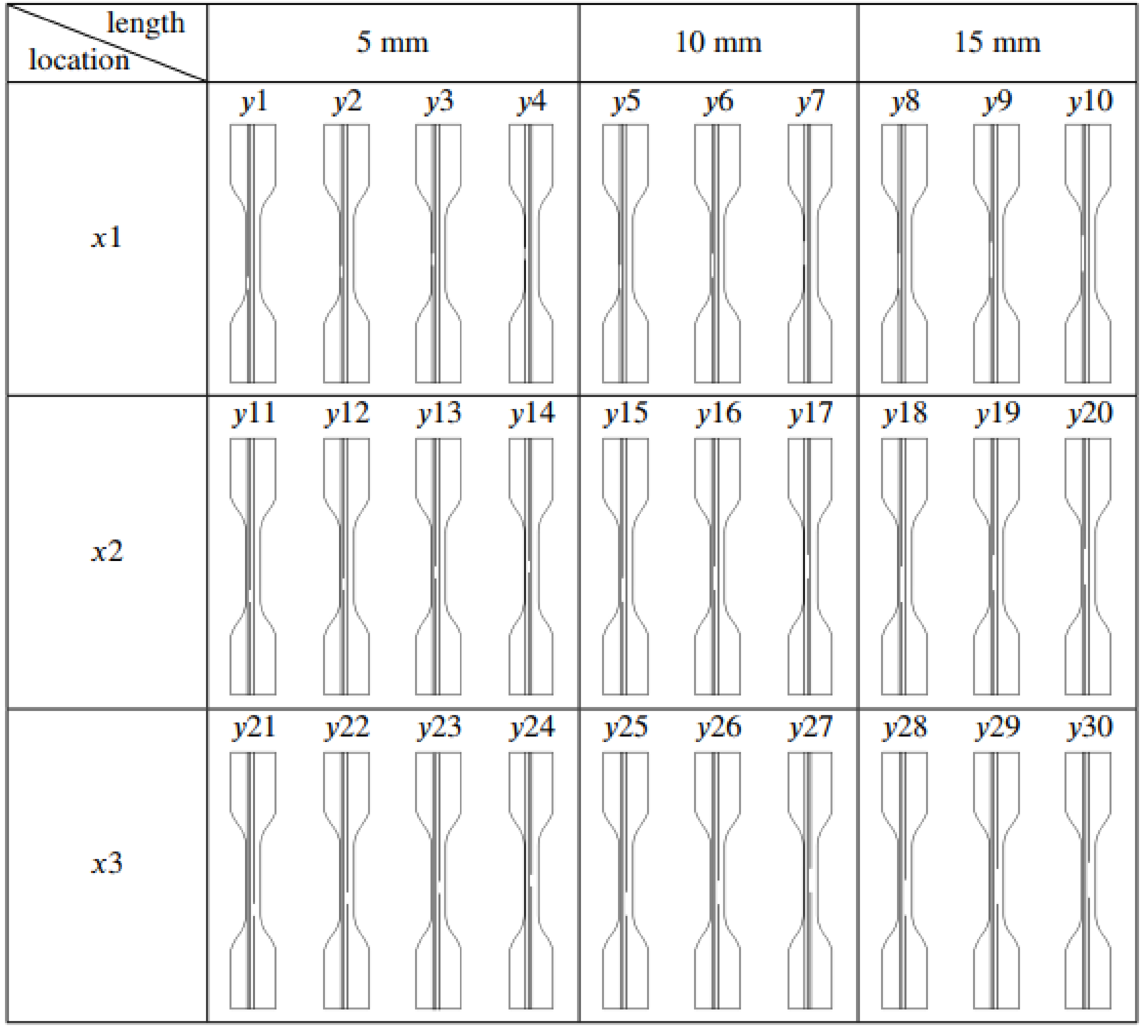




Real-time structural validation

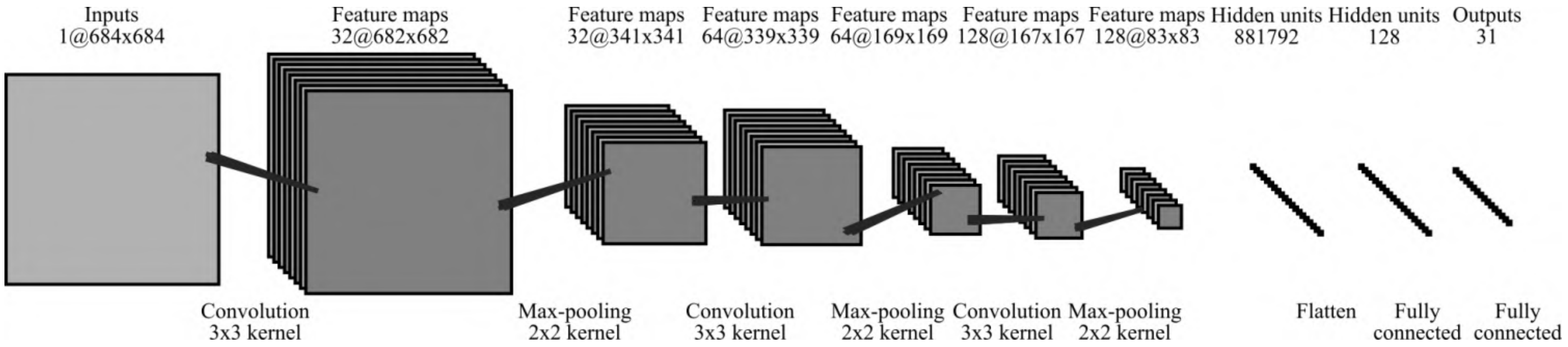
Designed defect with different lengths and locations within the dogbone specimen

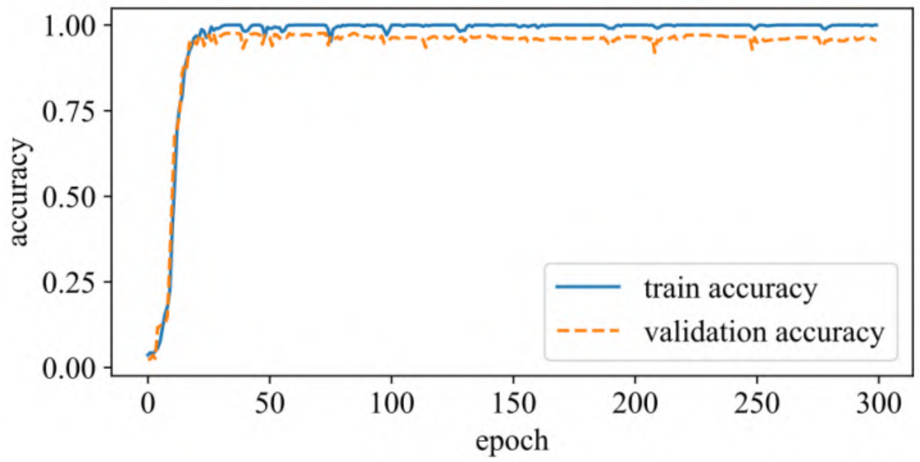




Real-time structural validation

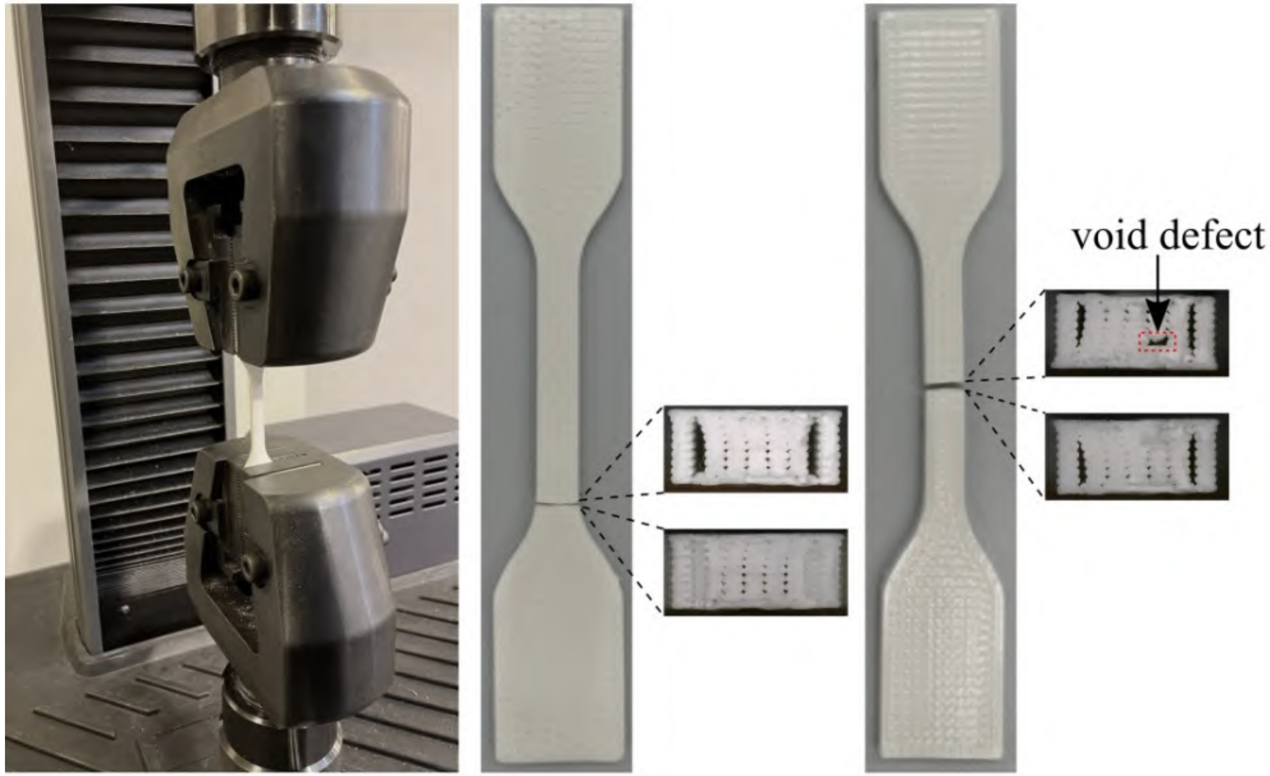
Designed data-driven CNN model structure

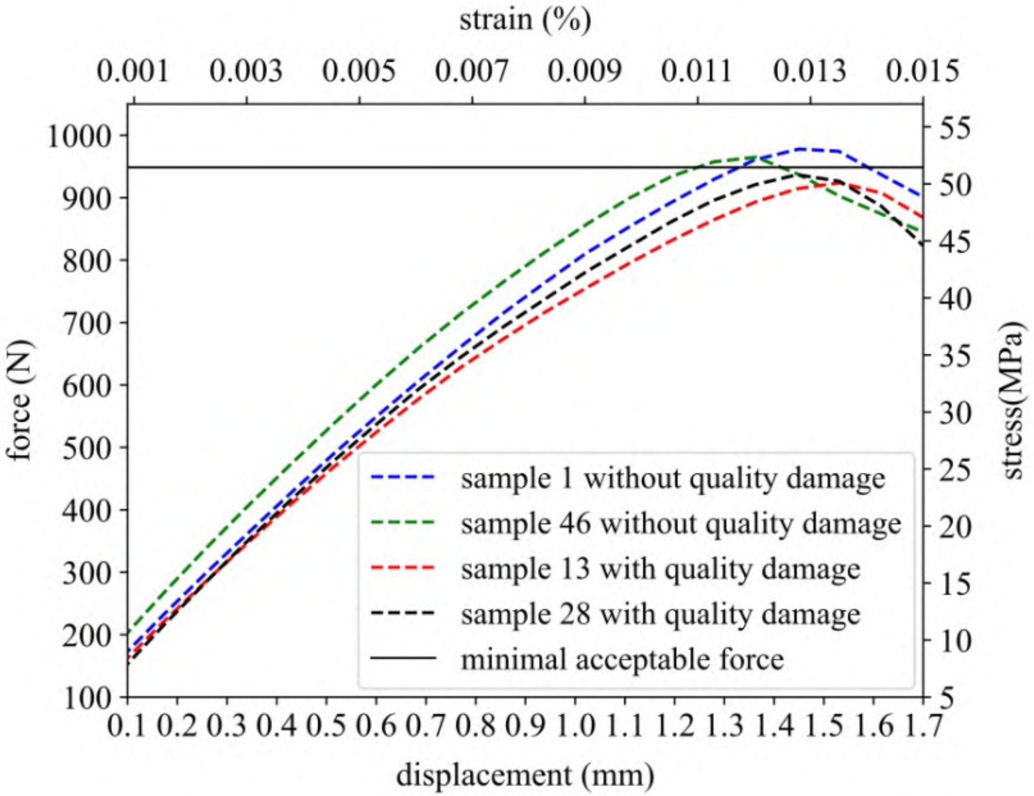




Real-time structural validation

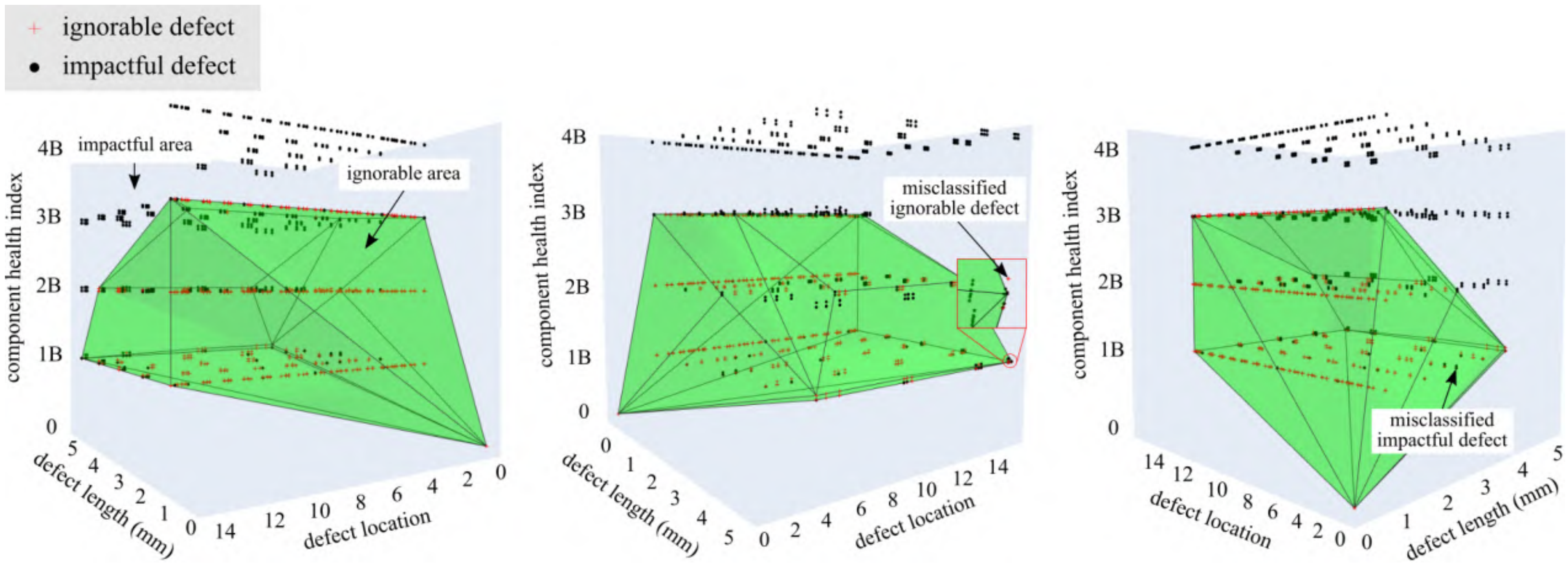
Printed sample and tensile test result

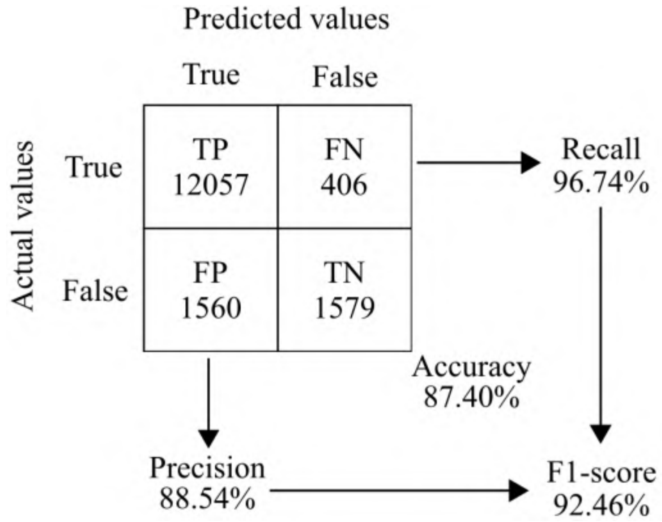


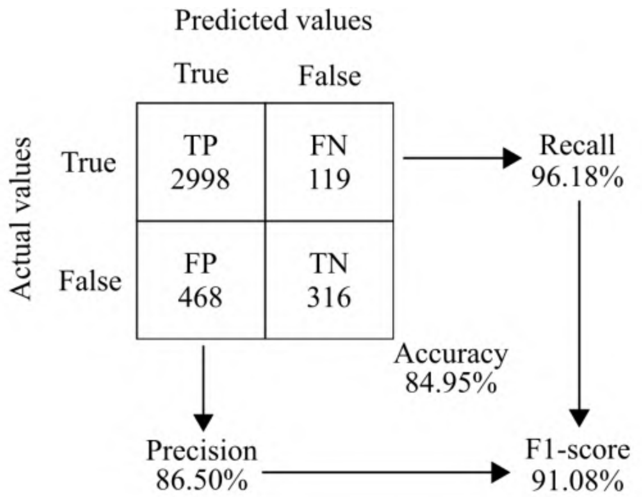


Real-time structural validation

Defect impact decision boundary and confusion matrix

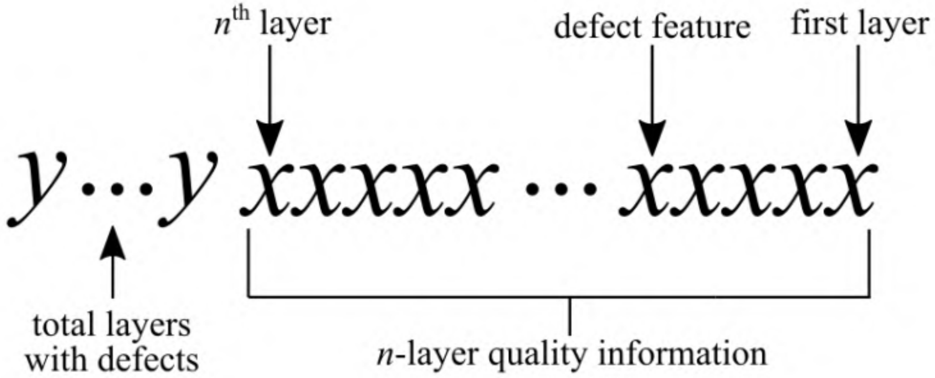


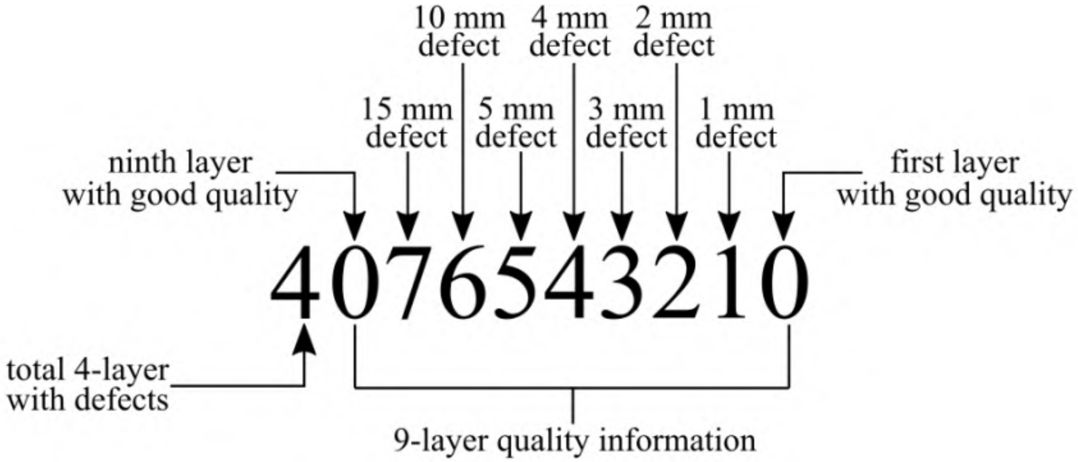


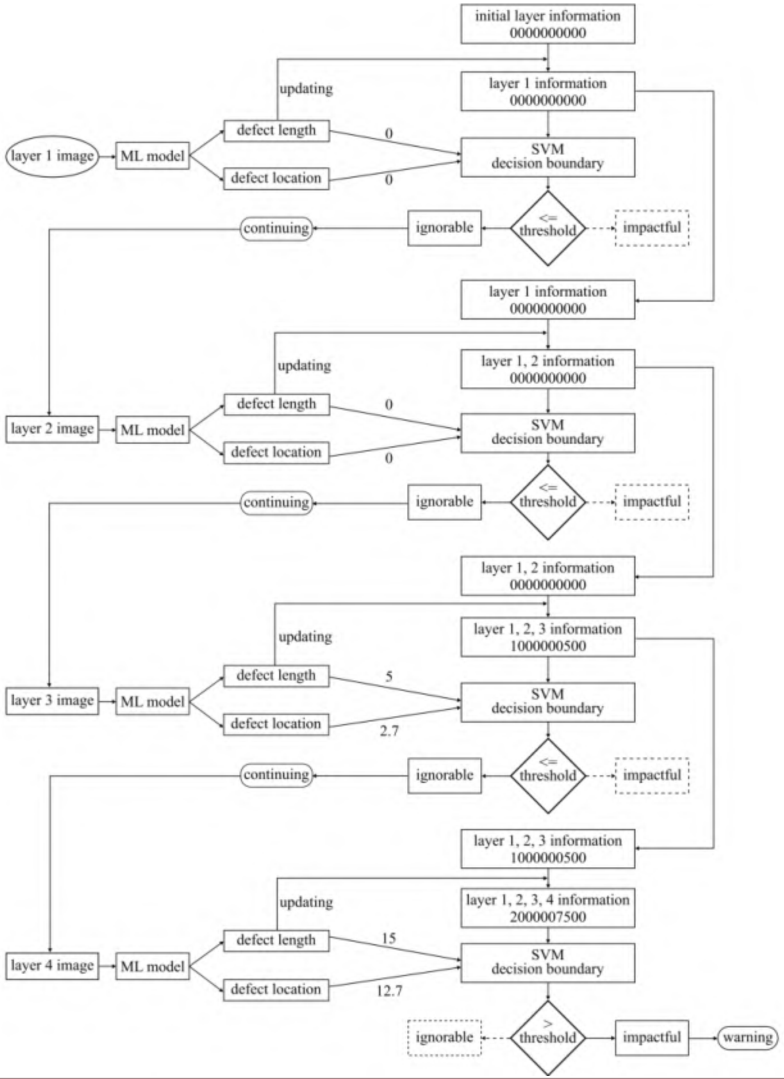


Real-time structural validation

Proposed component health index and structural validation visualization

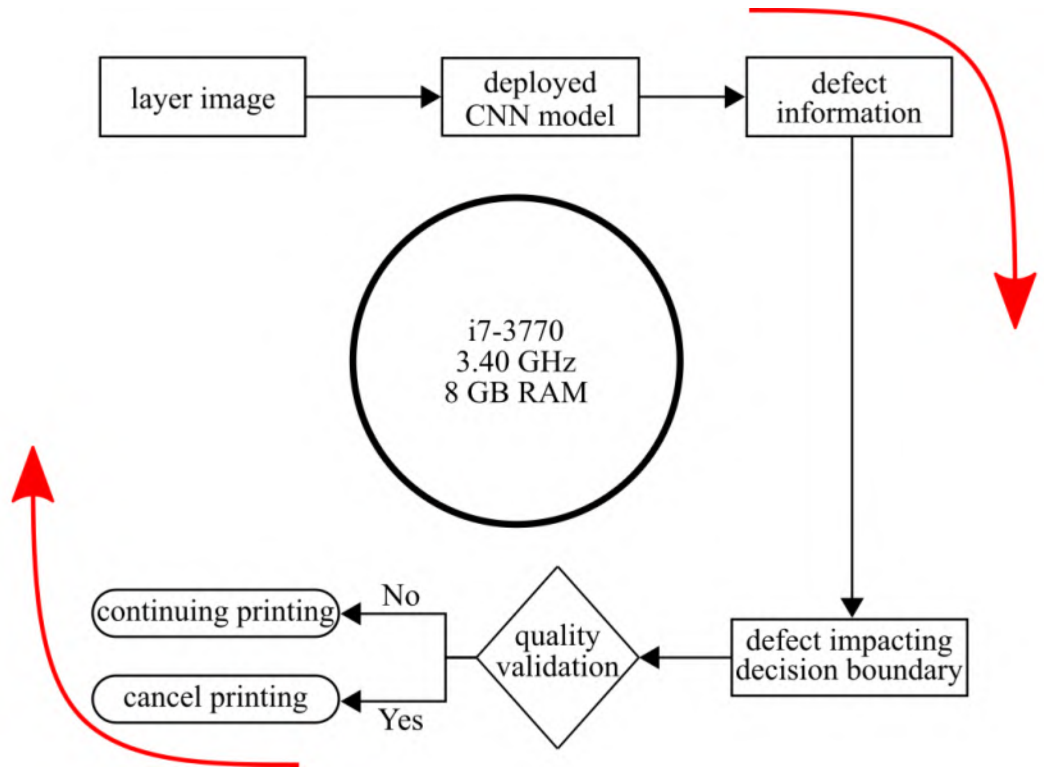


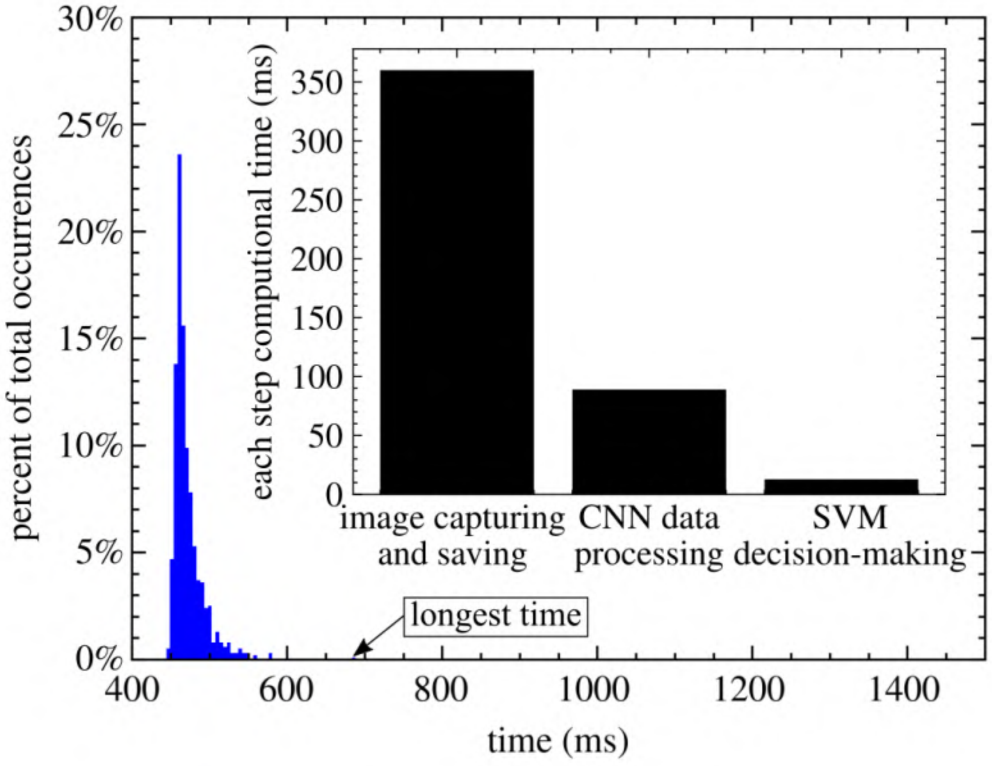




Real-time structural validation

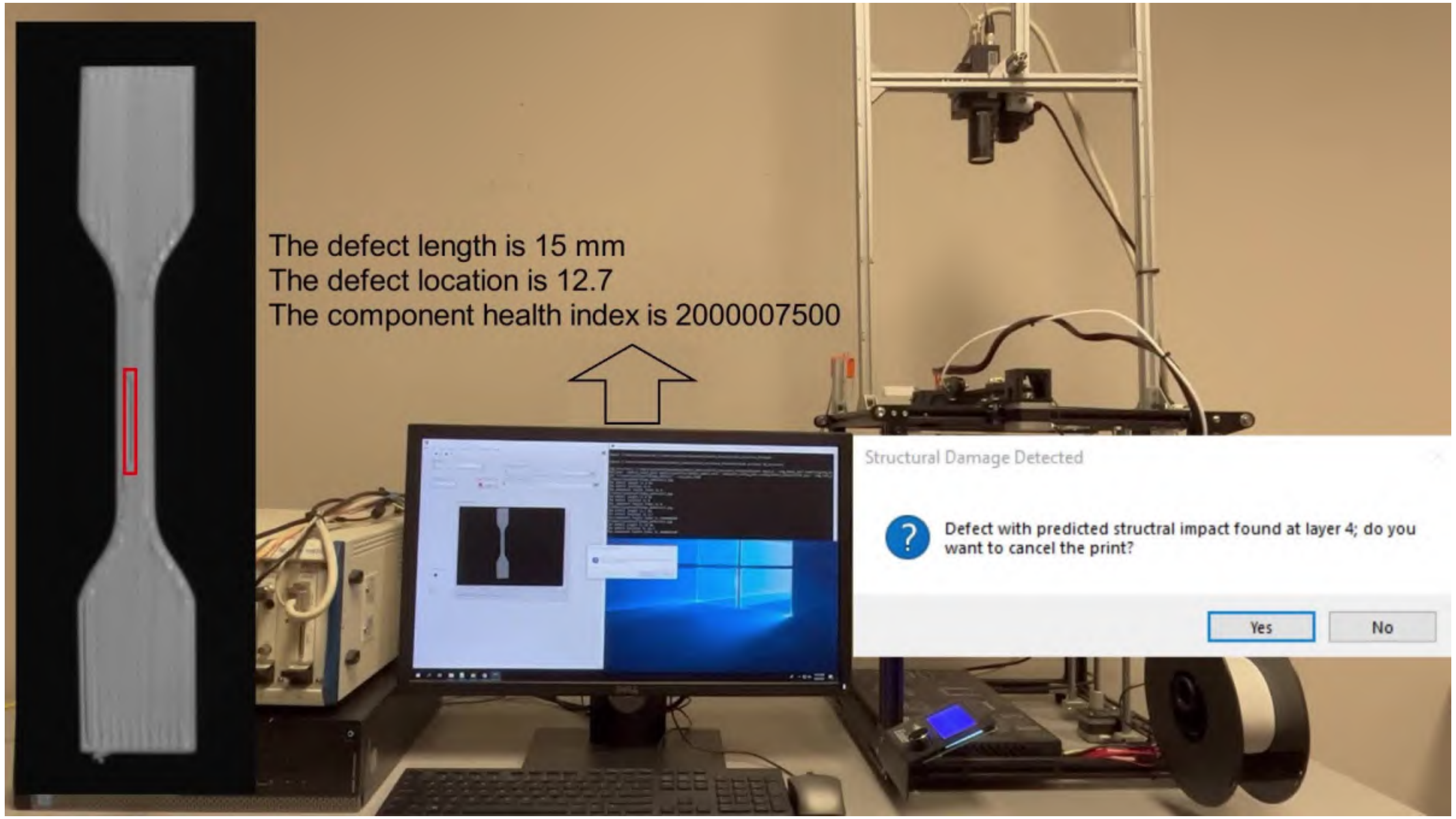
Time range calculation for the real-time structural validation





Real-time structural validation

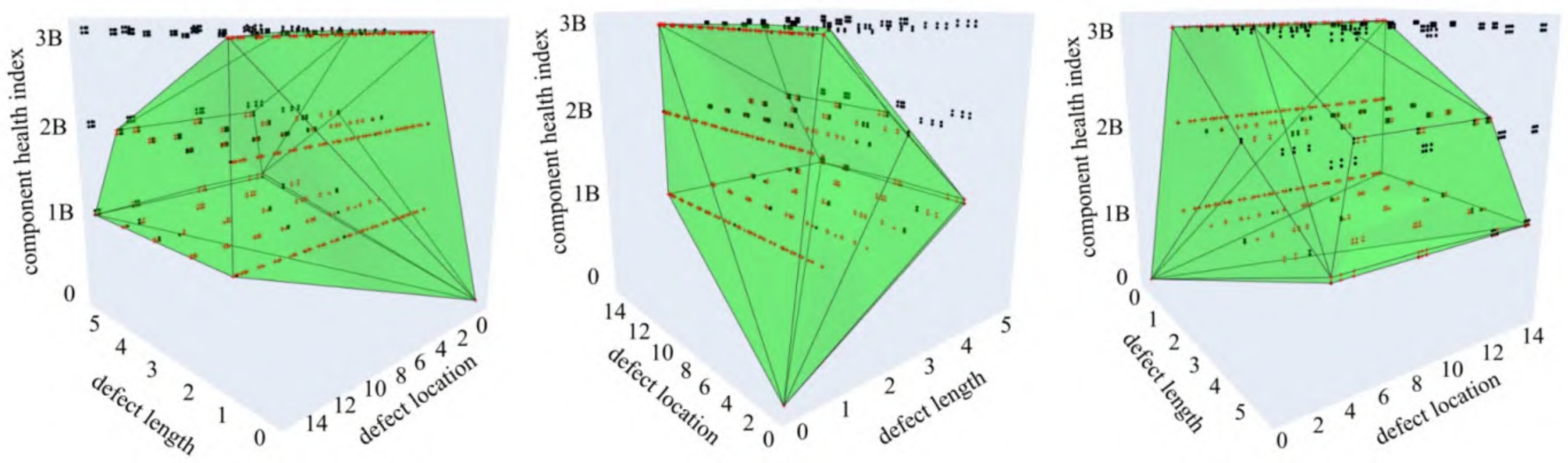
Warning window



Real-time structural validation

Video of real-time structural validation

Real-time Product Structural Quality Validation for Material Extrusion Additive Manufacturing



Summary

Achievements of structural quality validation for FFF:

- Defect detection with machine learning algorithm.
- Structural validation based on decision boundary from support vector machine.
- A novel component health index that links the features of defects across layers.
- Smart decision-making algorithm based on defect impact.

Limitations:

- Supervised learning can only predict the known defects.
- Defect impact decision boundary is accurate but still has errors.
- Component health index is complex and hard to record multiple defects on one layer.

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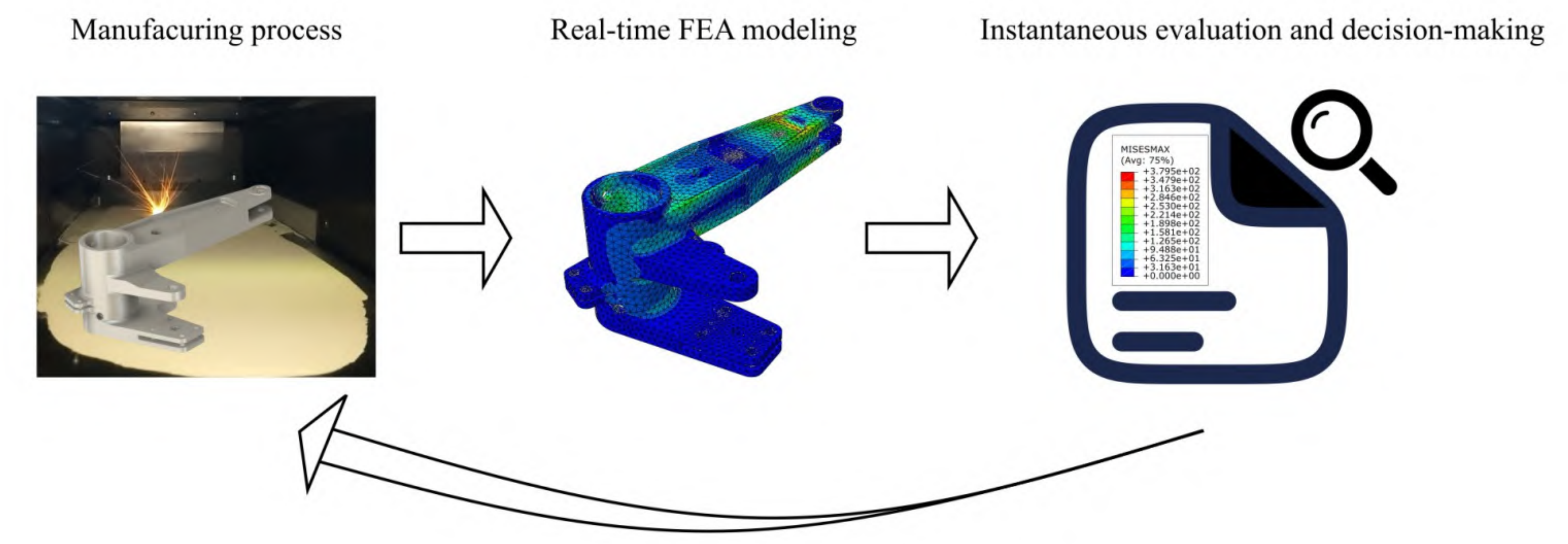
Real-time FEA for structural validation

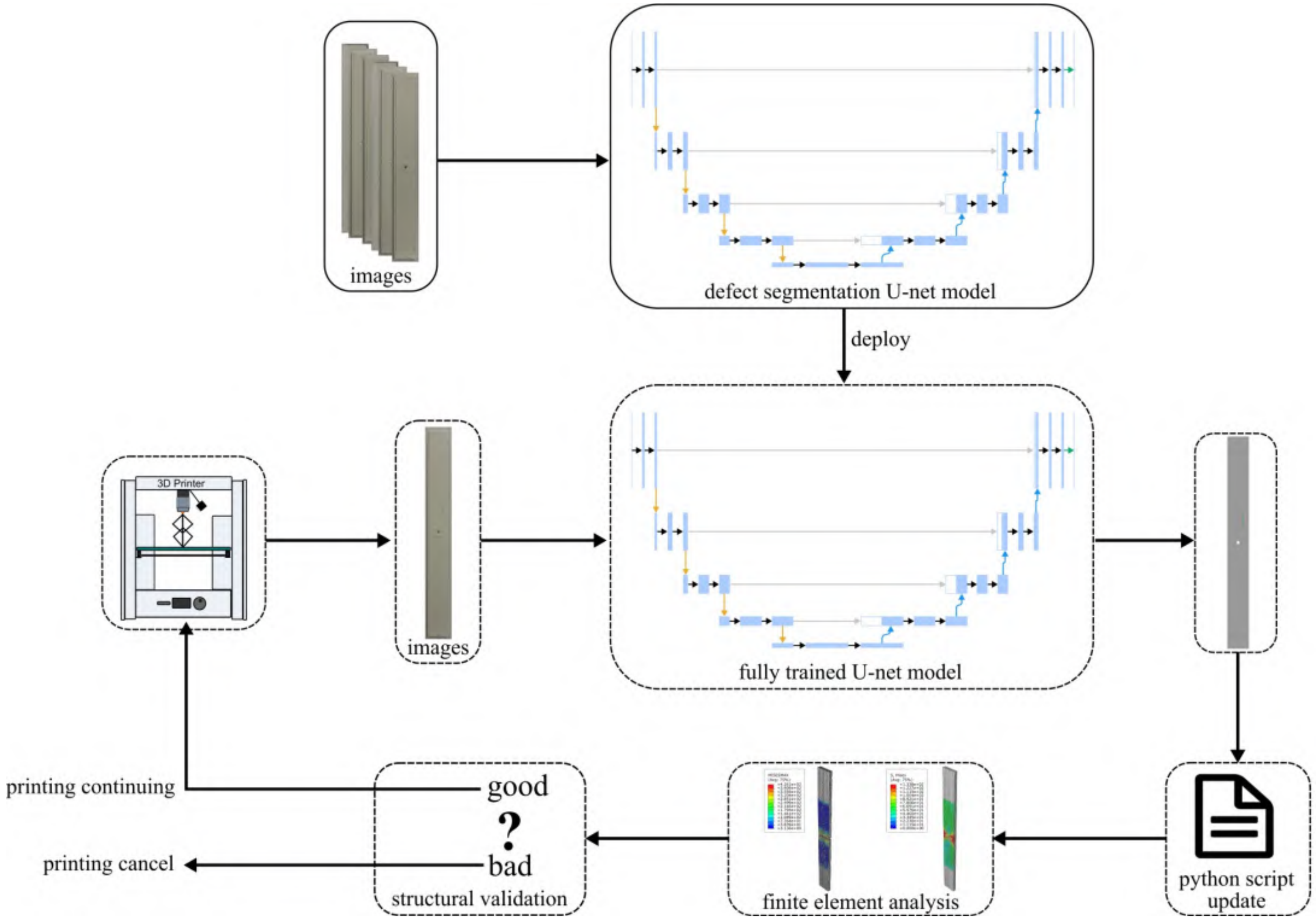
Objective of real-time FEA structural validation for FFF

To solve the limitations in the machine learning-based real-time structural validation for FFF, real-time FEA structural validation is proposed.



Real-time FEA for structural validation

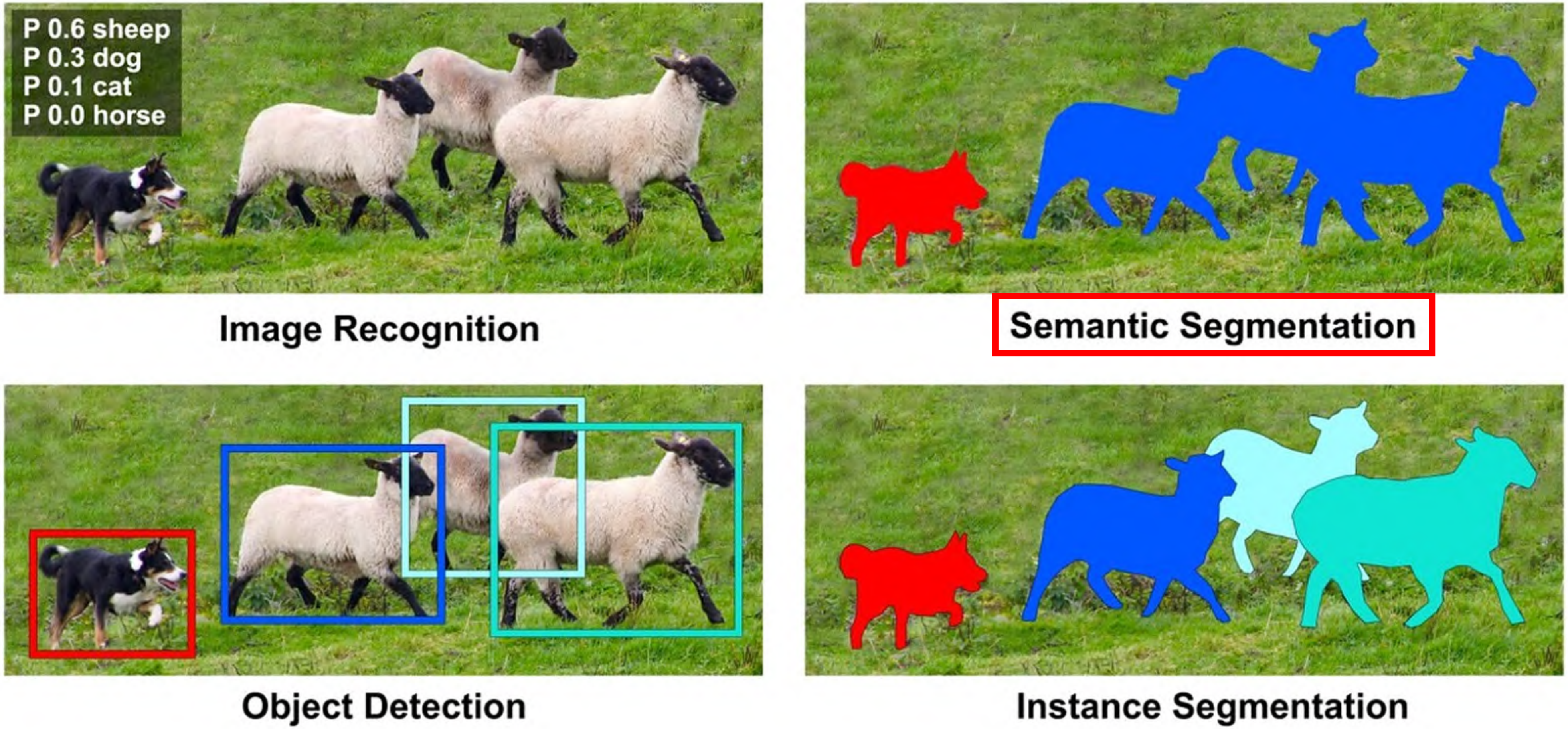
Diagram of the real-time FEA structural validation



- offline defect segmentation model training
- online defect segmentation
- online real-time FEA structural validation

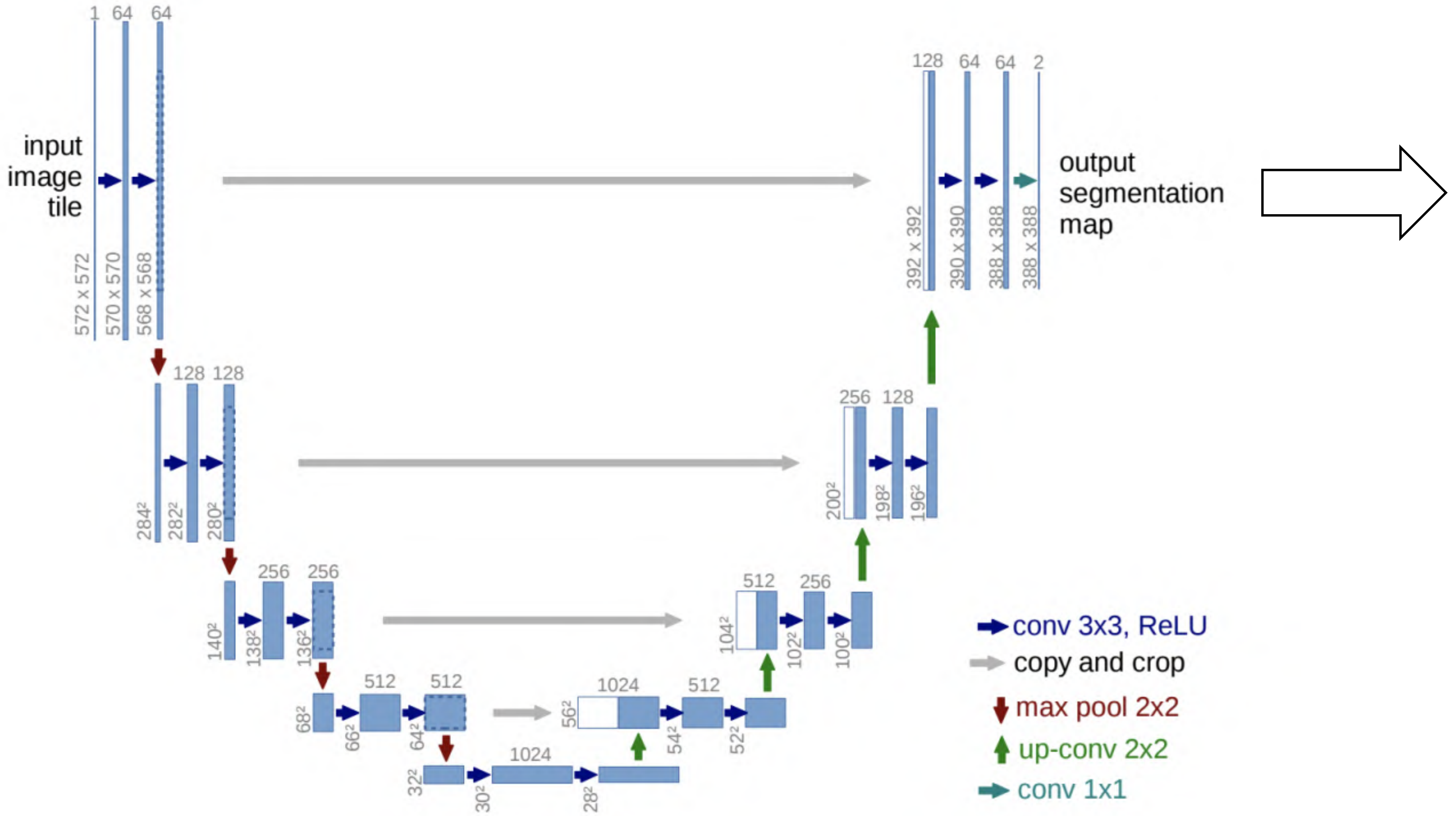
Real-time FEA for structural validation

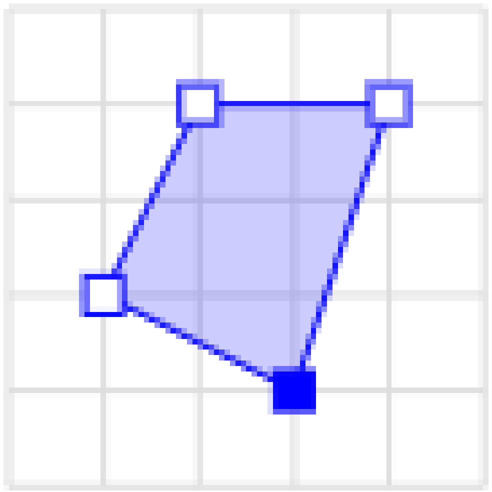
Image segmentation



Real-time FEA for structural validation

Image segmentation model – UNet

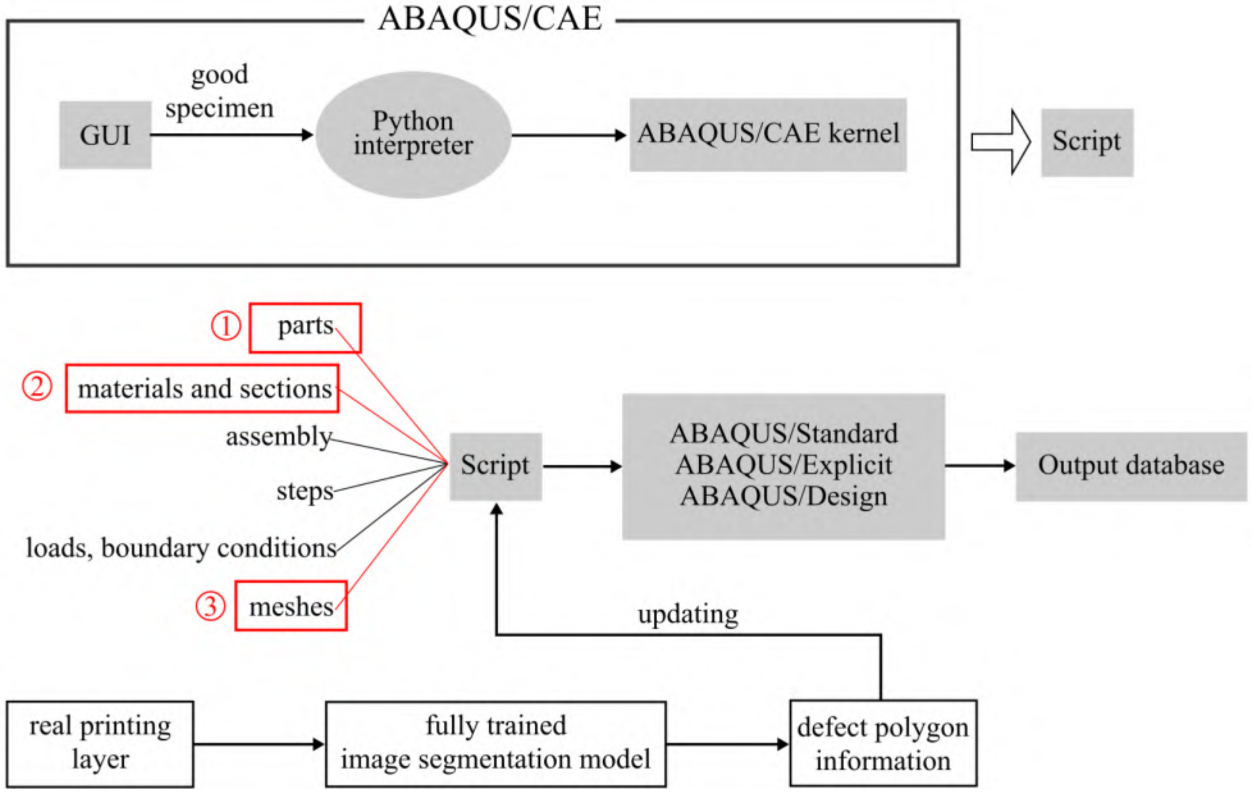


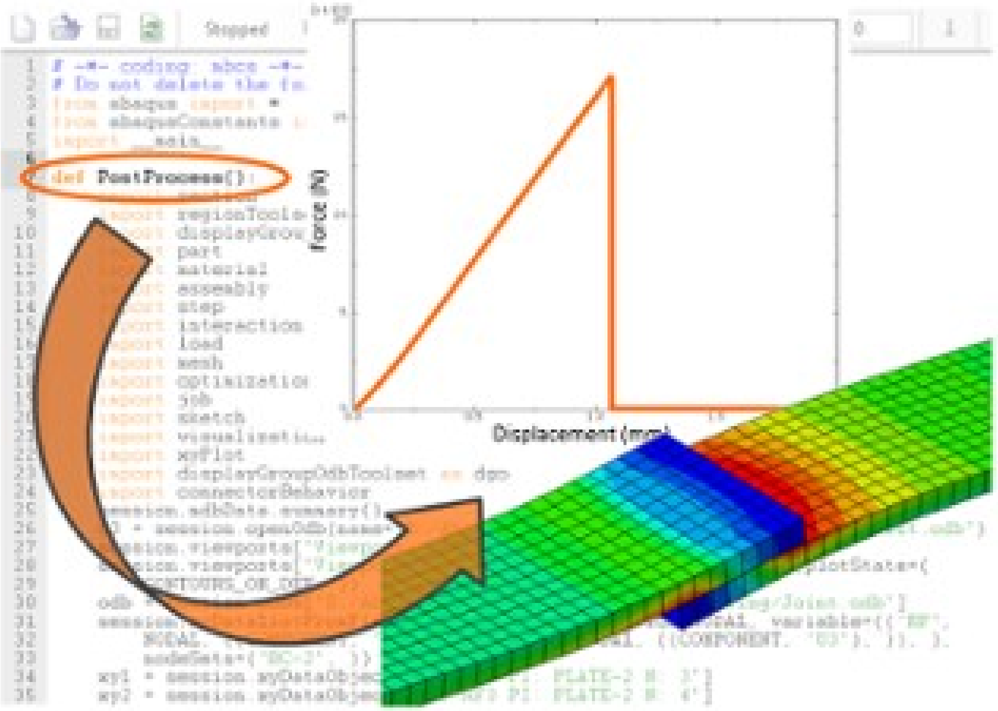


Polygon Line

Real-time FEA for structural validation

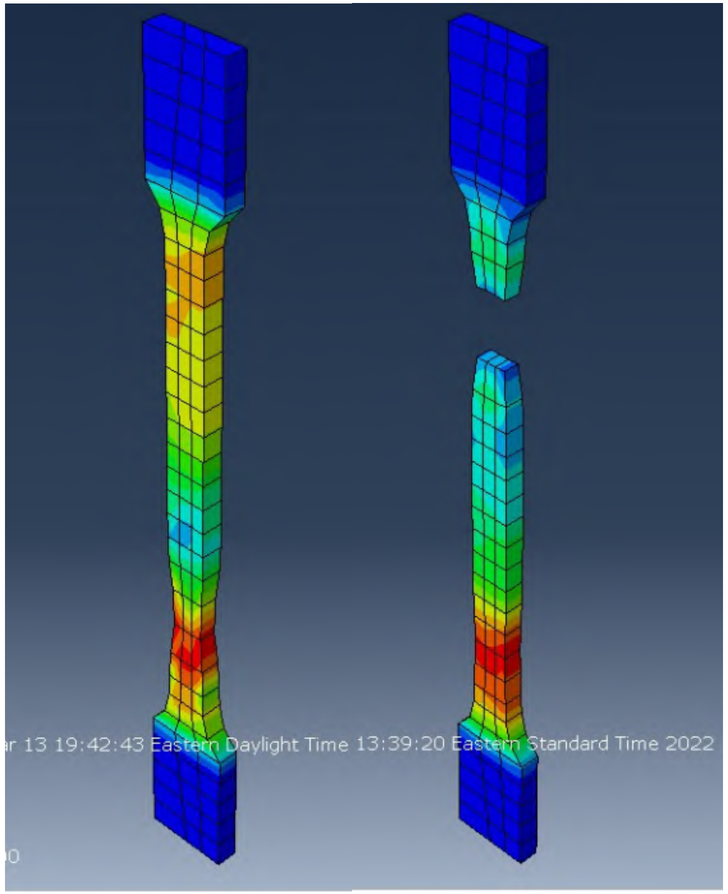
Abaqus interactive products (Abaqus/CAE)





Real-time FEA for structural validation

Generated Abaqus Python script




```
from part import *
from material import *
from assembly import *
from load import *
from mesh import *
from optimization import *
from job import *
from sketch import *
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mdb.models['Model-1'].sketches['__profile__'].Line(point1=(0.0, 30.0), point2=(
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mdb.models['Model-1'].rootAssembly.regenerate()
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mdb.jobs['TensileTest'].submit(consistencyChecking=OFF, datacheckJob=True)
```

Real-time FEA for structural validation

Abaqus model updating

```
from part import *
from material import *
from assembly import *
from load import *
from mesh import *
from optimization import *
from job import *
from sketch import *
mdb.models['Model-1'].ConstrainedSketch(name='__profile__', sheetSize=200.0)
mdb.models['Model-1'].sketches['__profile__'].Line(point1=(0.0, 0.0), point2=(
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mdb.models['Model-1'].sketches['__profile__'].Line(point1=(0.0, 30.0), point2=(
    15.0, 30.0))
mdb.models['Model-1'].sketches['__profile__'].Line(point1=(15.0, 30.0), point2=
    (15.0, -25.0))
mdb.models['Model-1'].Part(dimensionality=THREE_D, name='Dogboen_test', type=
    DEFORMABLE_BODY)
mdb.models['Model-1'].parts['Dogboen_test'].BaseSolidExtrude(depth=5.0, sketch=
    mdb.models['Model-1'].sketches['__profile__'])
mdb.models['Model-1'].Material(name='PLAMaterial')
mdb.models['Model-1'].materials['PLAMaterial'].Density(table=((7.8e-09, ), ))
mdb.models['Model-1'].materials['PLAMaterial'].Elastic(table=((210000.0, 0.3), ))
mdb.models['Model-1'].materials['PLAMaterial'].Plastic(table=((770.0, 0.0), (
    800.0, 0.01), (830.0, 0.02), (850.0, 0.1), (900.0, 0.15), (930.0, 0.35), (
    960.0, 1.0), (1050.0, 3.0)))
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mdb.models['Model-1'].parts['Dogboen_test'].generateMesh()
mdb.models['Model-1'].rootAssembly.regenerate()
mdb.Job(activateLoadBalancing=False, atTime=None, contactPrint=OFF)
mdb.jobs['TensileTest'].submit(consistencyChecking=OFF, datacheckJob=True)
```

Module import
Creat sketch object
Draw model sketch
Creat model
Extrude sketch
Property setting
Boundary condition setting
Job submitting


```
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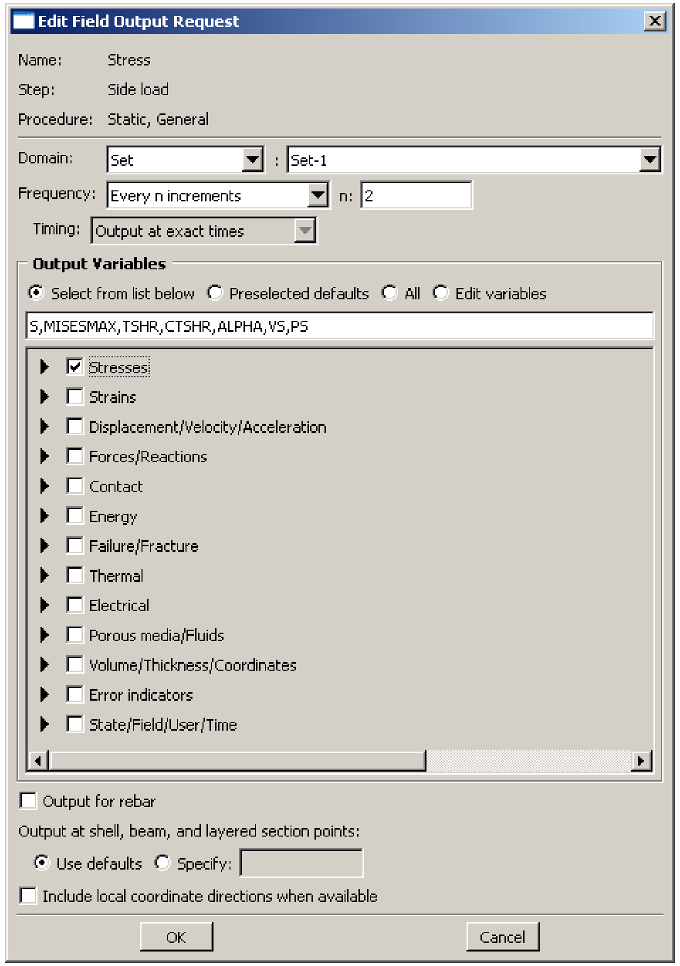
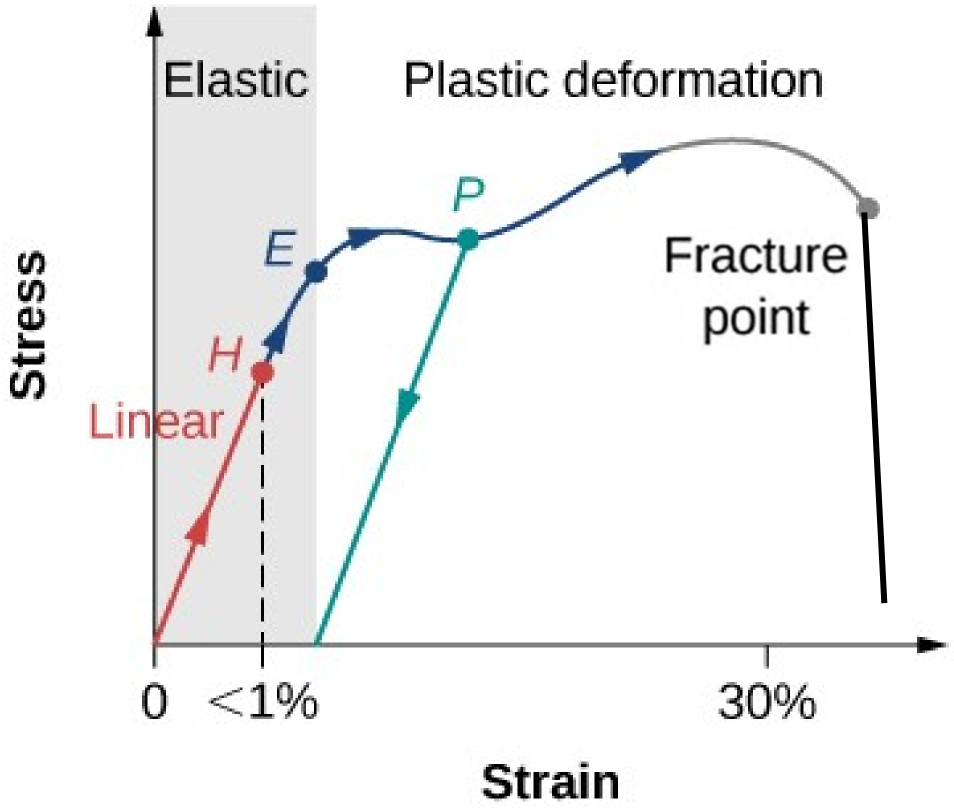
Real-time FEA for structural validation

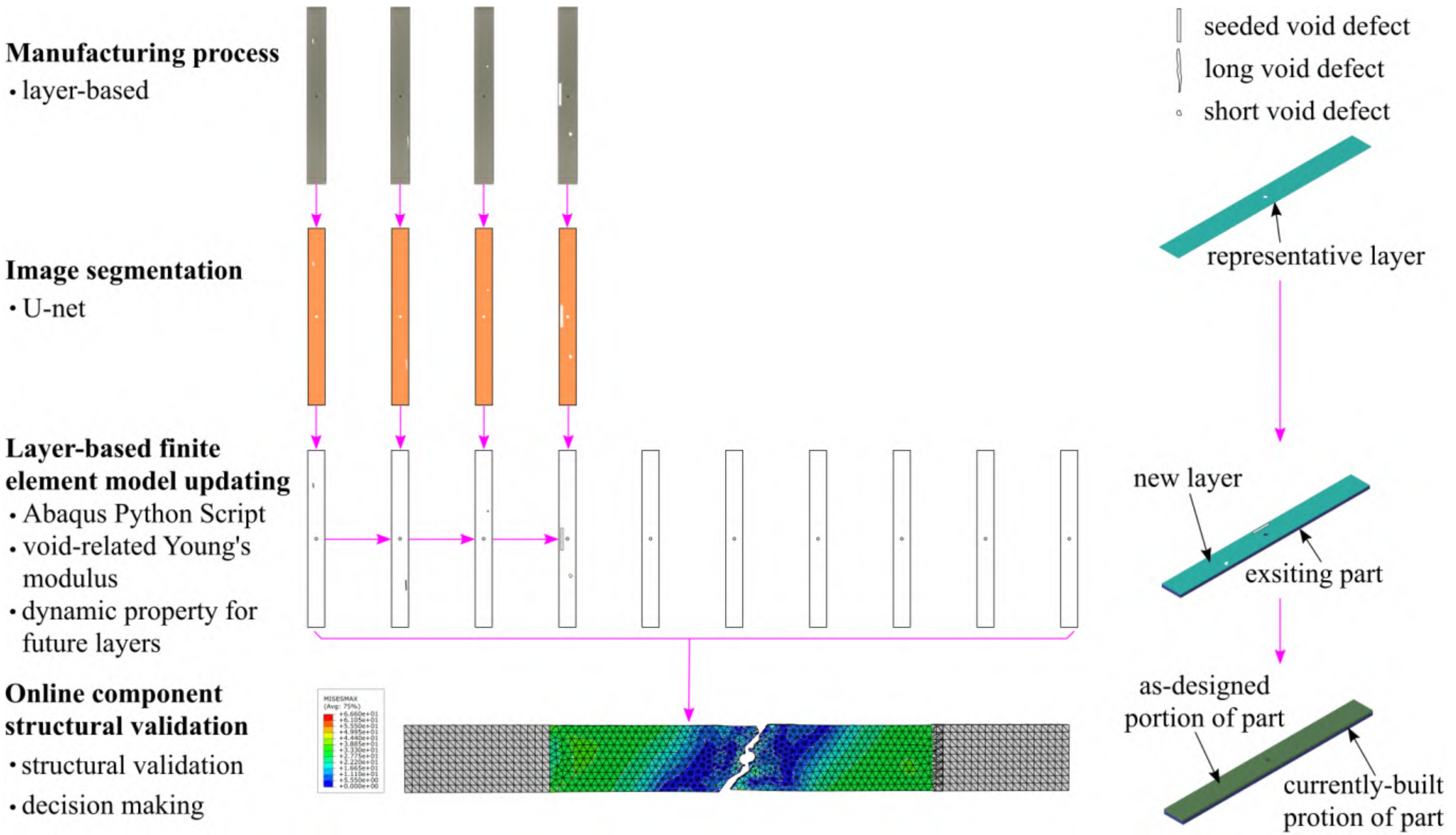
Abaqus output dataset





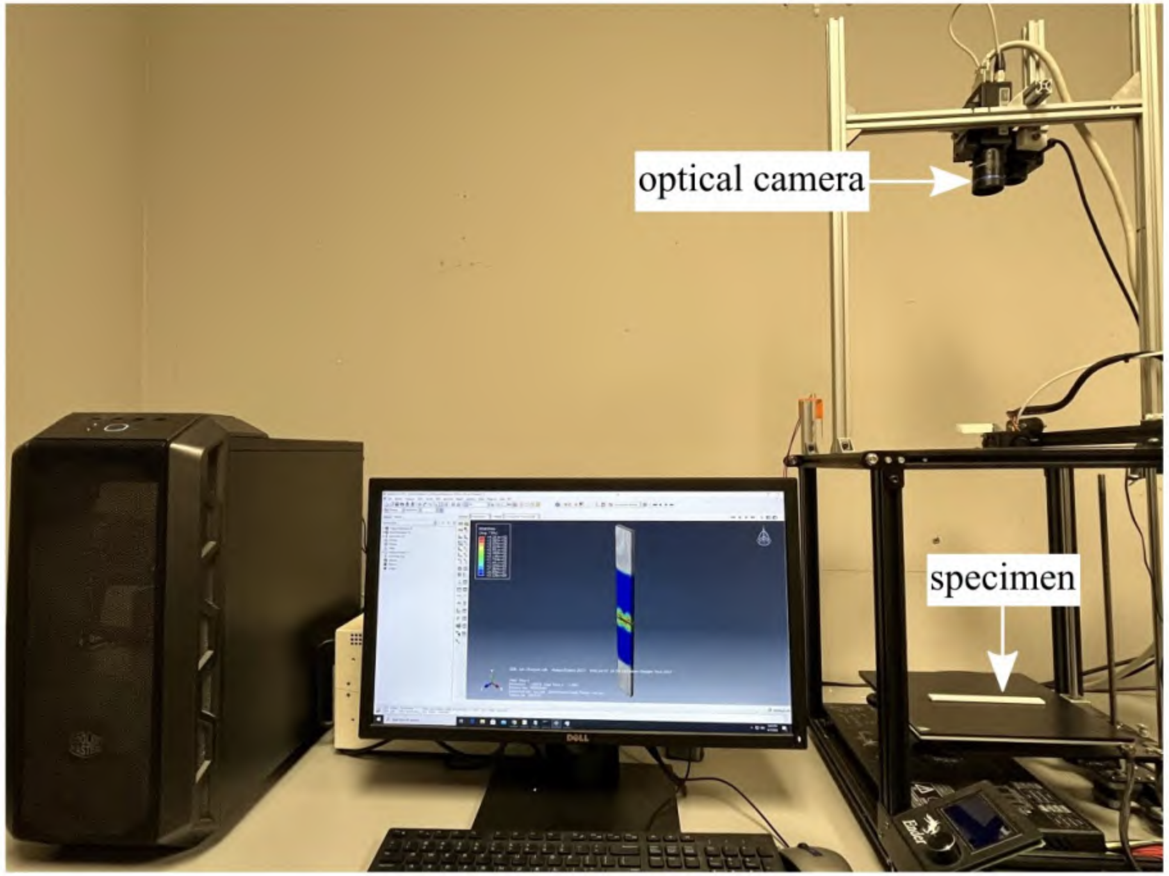
Real-time FEA for structural validation

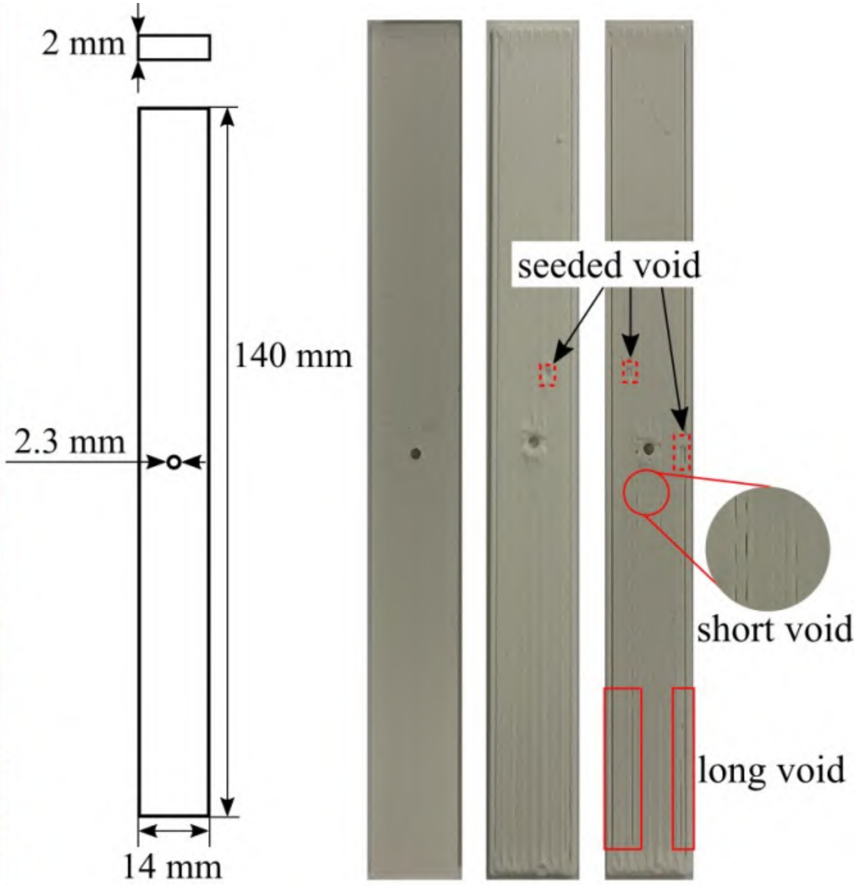
Principle of real-time FEA structural validation



Real-time FEA for structural validation

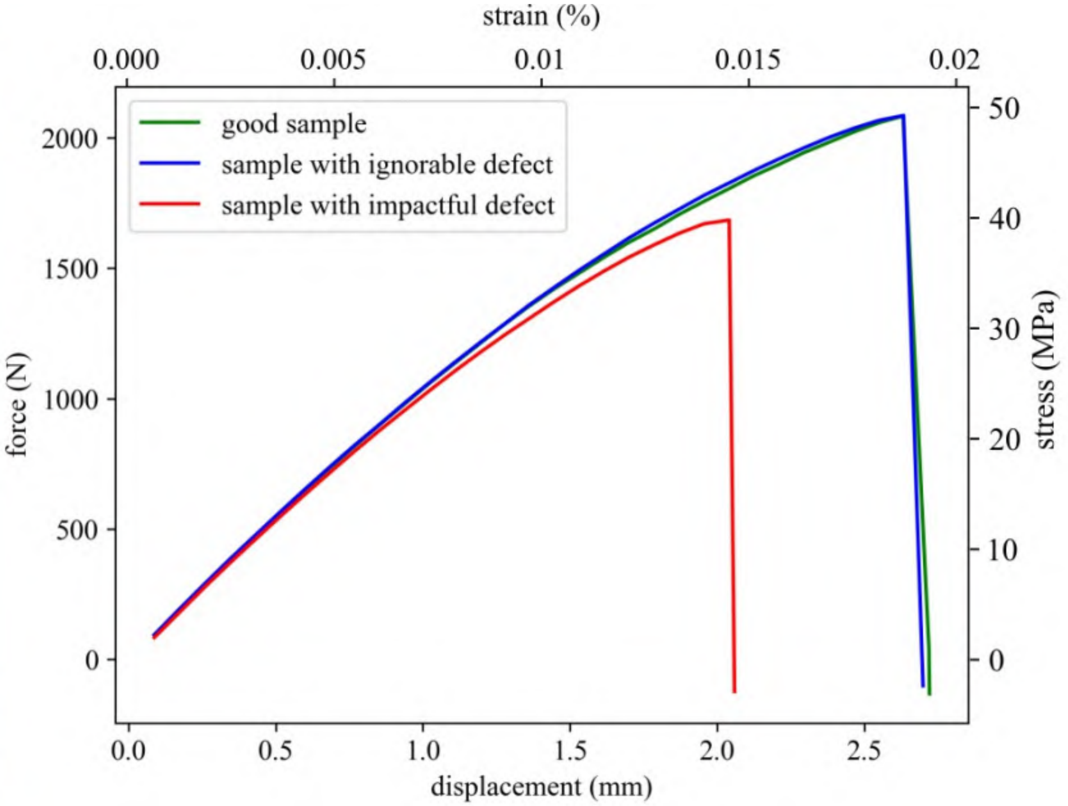
Experimental platform and designed specimen with defects





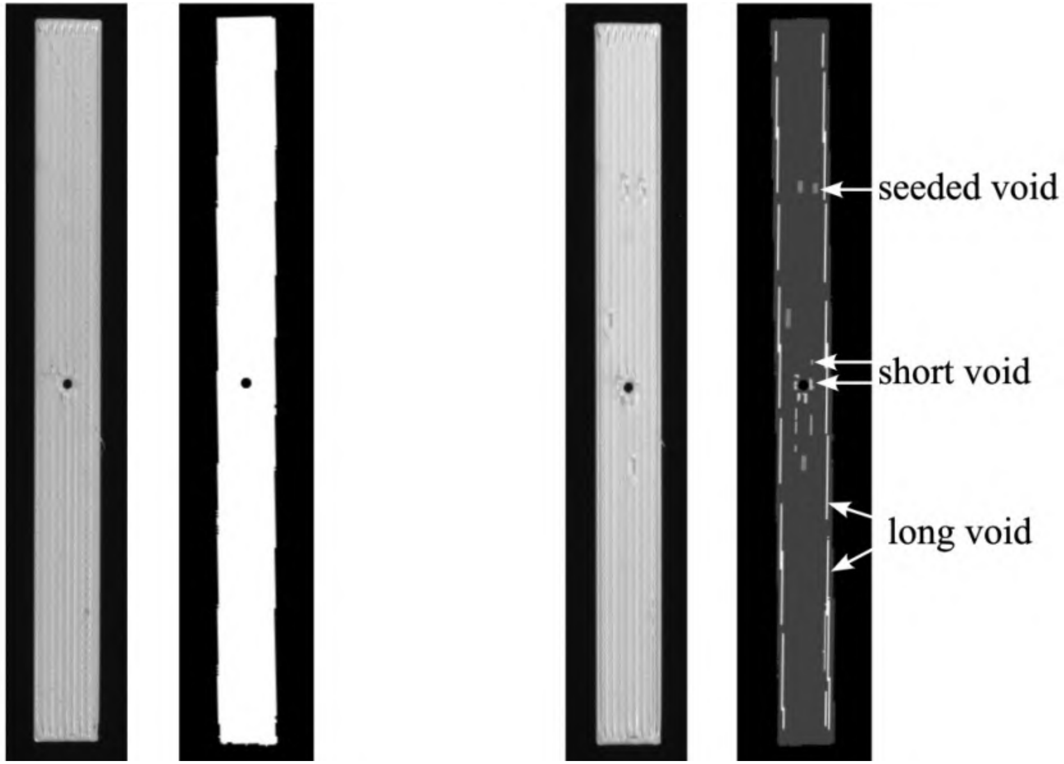
Real-time FEA for structural validation

Tensile test result



Real-time FEA for structural validation

Image segmentation result and dynamic material property



Based on the research from Dewey et al., the basic form of the equation for Young's modulus is:

$E_p = E_0(1 - aP)$

where E_p is Young's modulus of the void body,

E_0 is the modulus of a non-void body of the same material,

a is a constant dependent on Poisson's ratio of the matrix material,

P is the volume void.

- IoU for training data: 95.32%
- IoU for test data: 92.79%

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Real-time FEA for structural validation

Abaqus FEA setting

Property	Density (g/mm^3)	Young's modulus (MPa)	Poisson's ratio	Yield stress (MPa)	Yield strain (mm)	Elongation at break (%)
Value	1.36	3600	0.4	49.56	2.27	1.62

- Simulation software: Abaqus explicit scheme
- Boundary condition:
  Fixed side U1 = U2 = U3 = UR1 = UR2 = UR3 = 0
  Load side U1 = U3 = UR1 = UR2 = UR3 = 0, U2 = 3
- Mesh size: 1 mm
- Element shape: 4-node linear tetrahedron (C3D4)

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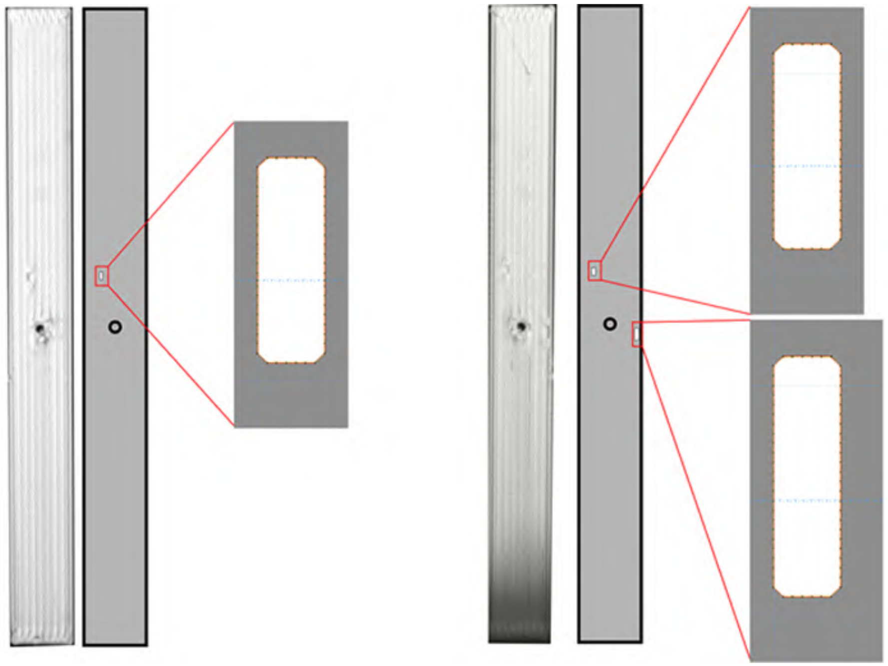
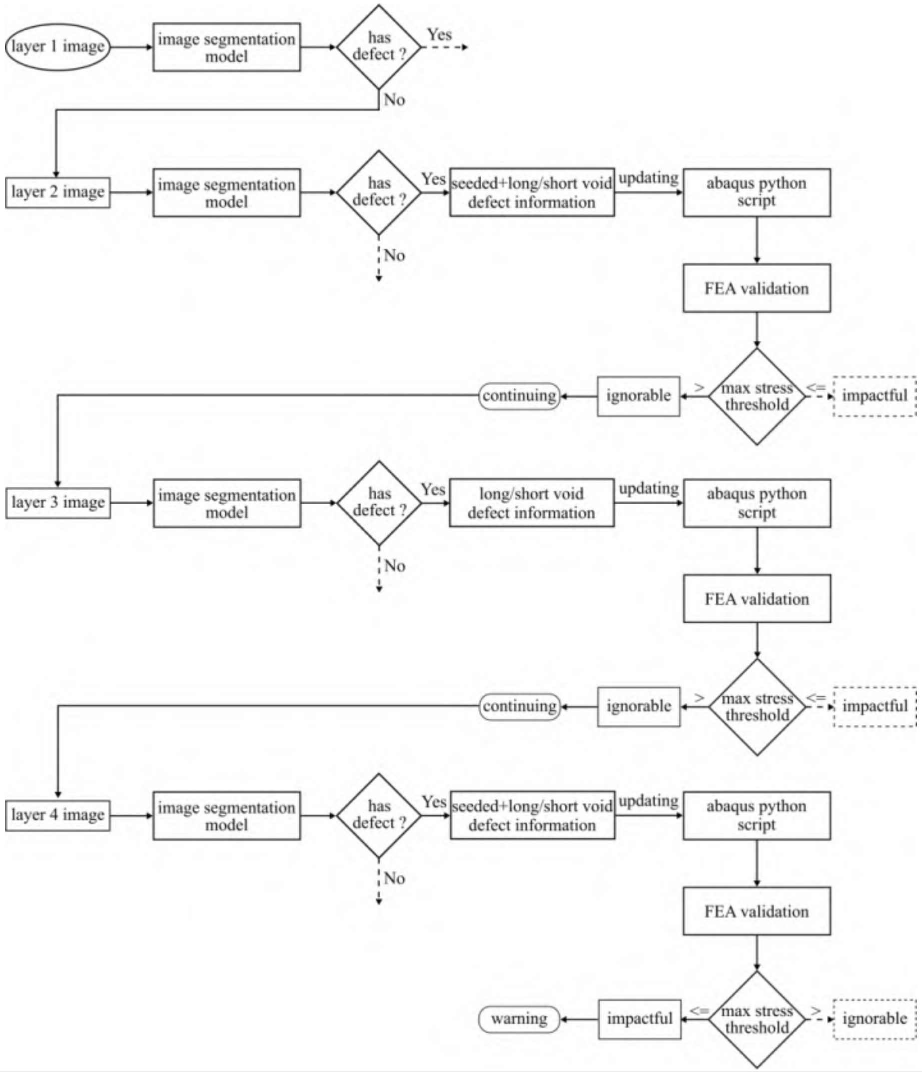
Real-time FEA for structural validation

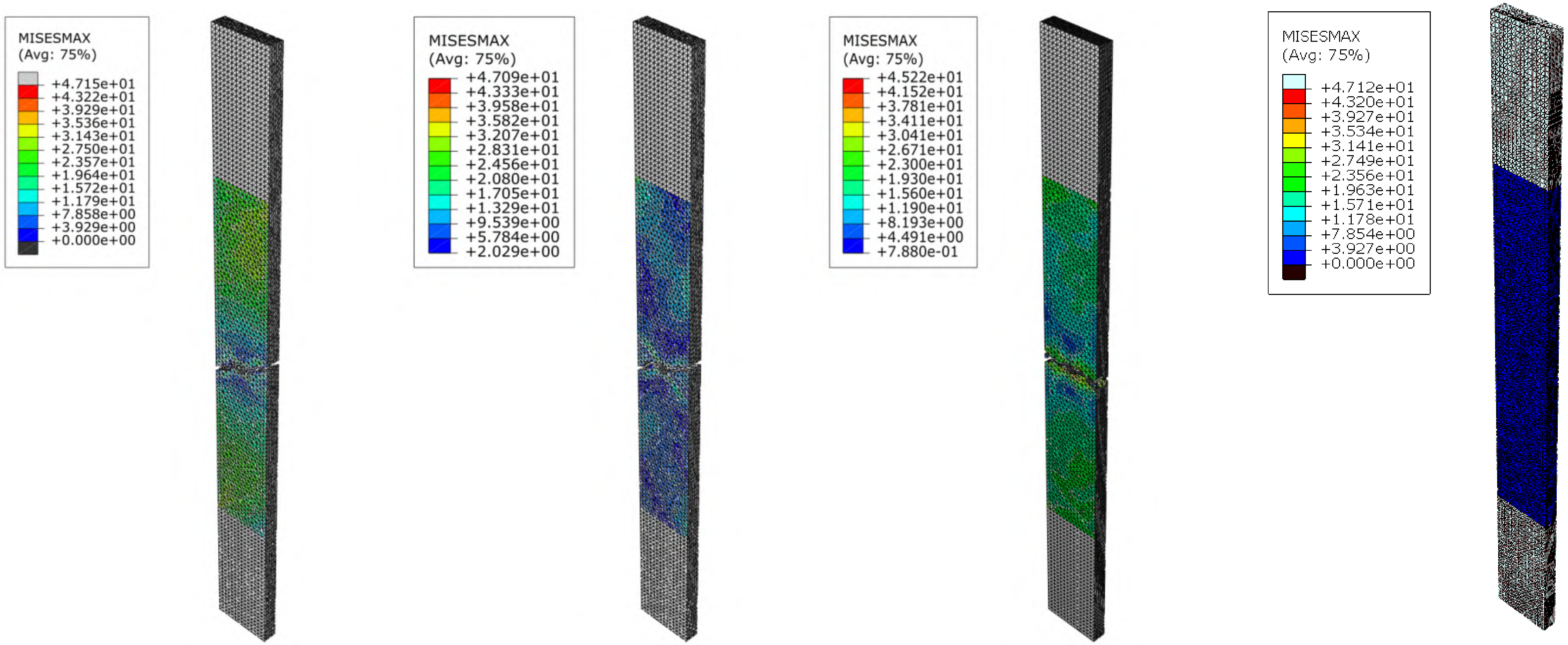
Real-time FEA structural validation process





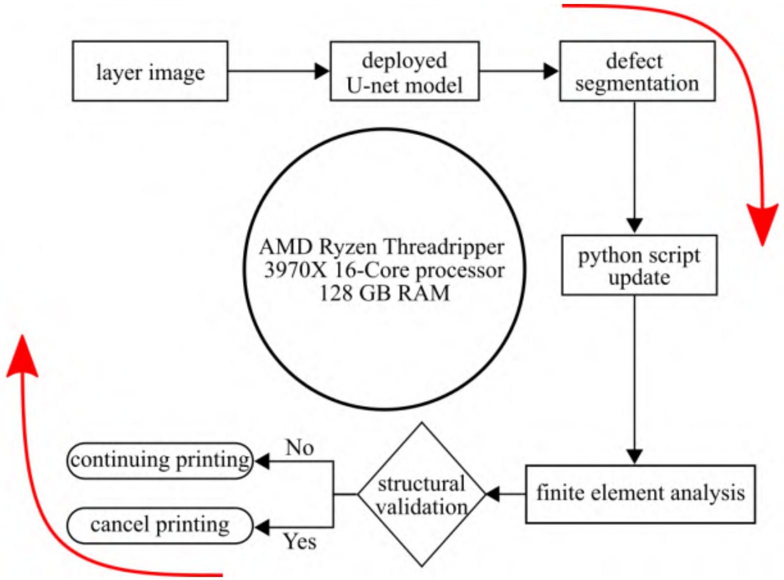
Real-time FEA for structural validation

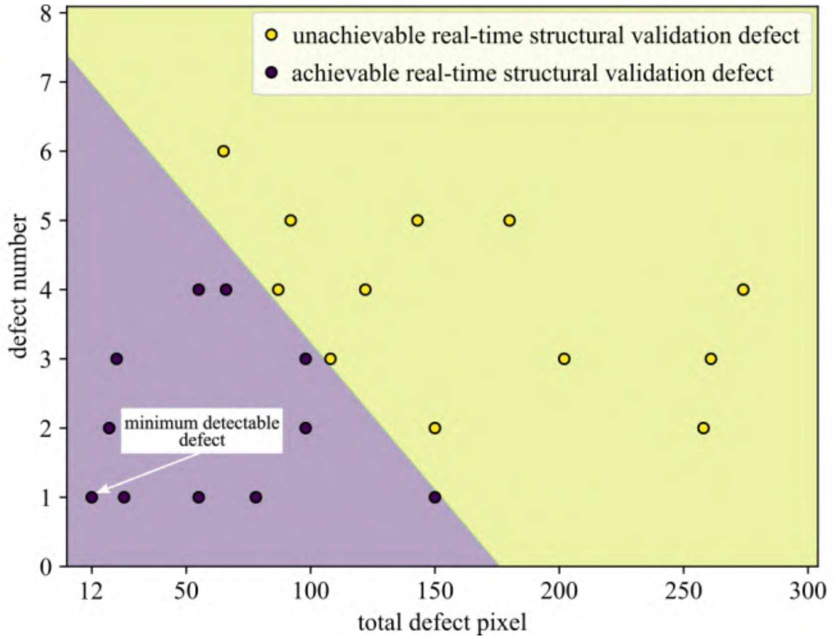
Abaqus simulation result

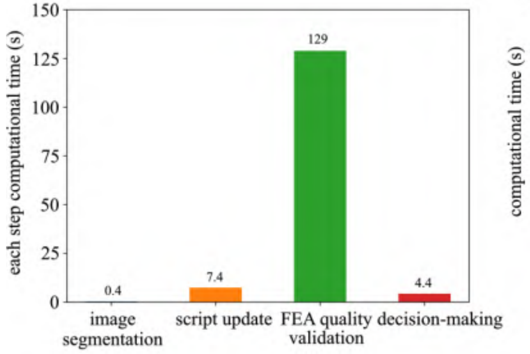


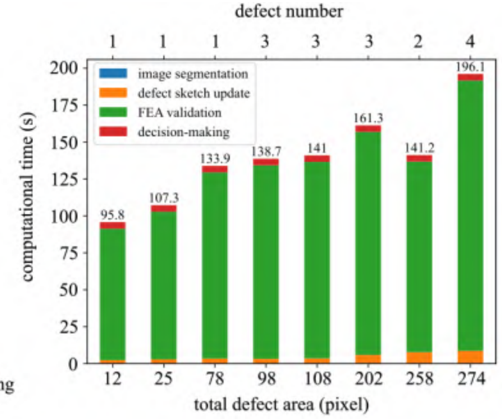
Real-time FEA for structural validation

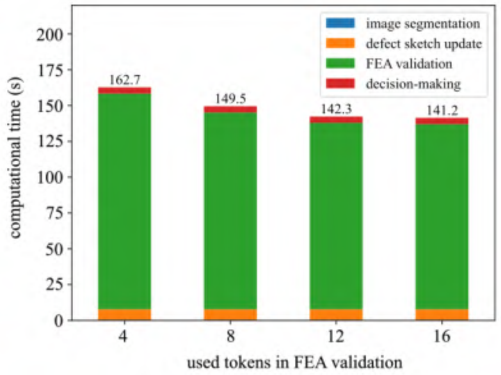
Computational time calculation











Real-time FEA for structural validation

Maximum stress extraction and warning window

```
"""
odbMaxMises.py
Code to determine the location and value of the maximum
von-mises stress in an output database.
Usage: abaqus python odbMaxMises.py -odb odbName
       -elset(optional) elsetName
Requirements:
1. -odb    : Name of the output database.
2. -elset  : Name of the assembly level element set.
             Search will be done only for element belonging
             to this set. If this parameter is not provided,
             search will be performed over the entire model.
3. -help   : Print usage
"""

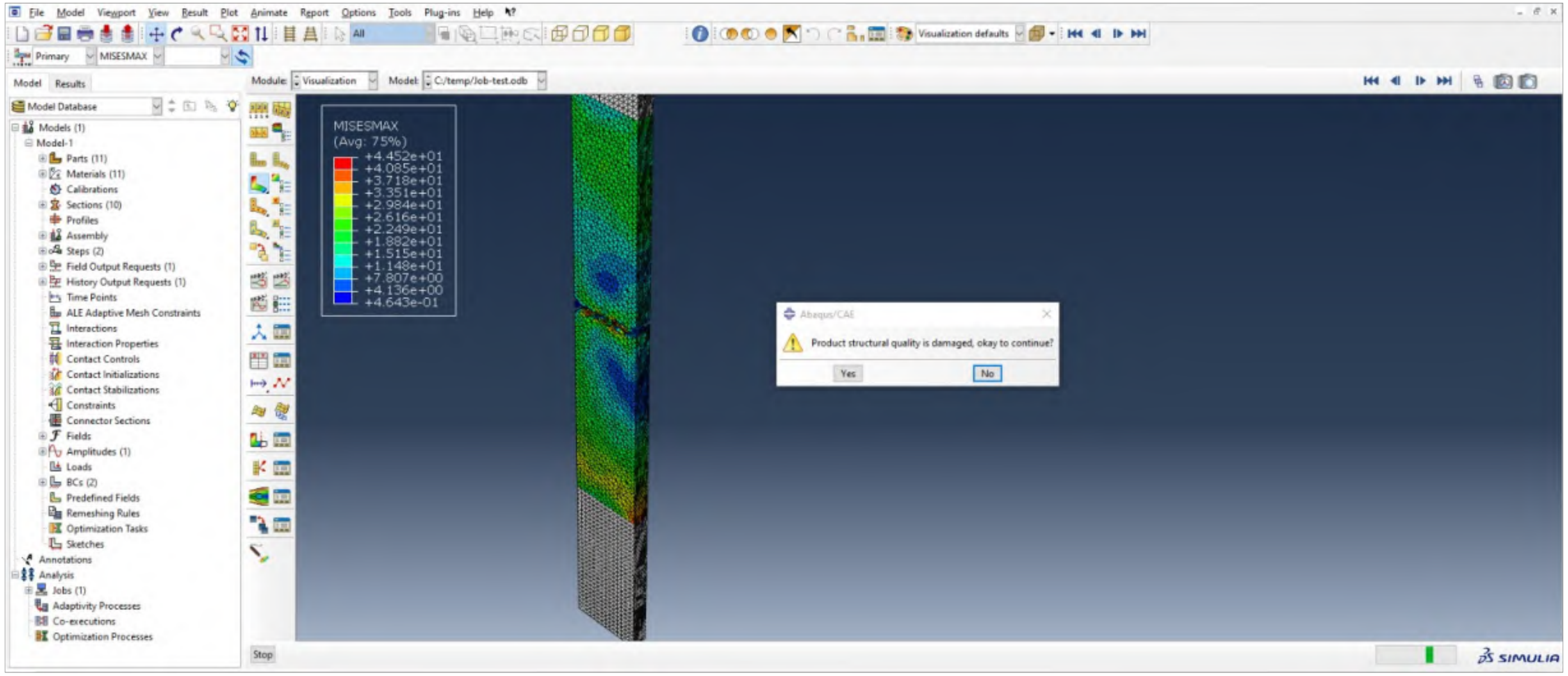
#~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
from odbAccess import *
from sys import argv,exit

#~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~

def rightTrim(input,suffix):
    if (input.find(suffix) == -1):
        input = input + suffix
    return input
#~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~

def getMaxMises(odbName,elsetName):
    """ Print max mises location and value given odbName
        and elset(optional)
    """
    elset = elemset = None
    region = "over the entire model"
    """ Open the output database """
    odb = openOdb(odbName)
    assembly = odb.rootAssembly

    """ Check to see if the element set exists
        in the assembly
    """
    if elsetName:
        try:
            elemset = assembly.elementSets[elsetName]
            region = " in the element set : " + elsetName;
        except KeyError:
            print ('An assembly level elset named %s does' \
                   'not exist in the output database %s' \
                   % (elsetName, odbName))
            odb.close()
            exit(0)
```



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Real-time FEA for structural validation

A summery of real-time FEA structural validation

Achievements of real-time FEA structural validation:

- Defect segmentation and defect information extraction.
- Model updating Abaqus Python script file generation.
- Dynamic specimen layer properties (void-related Young's modulus).
- Real-time FEA structural validation.
- Maximum stress based decision-making system.

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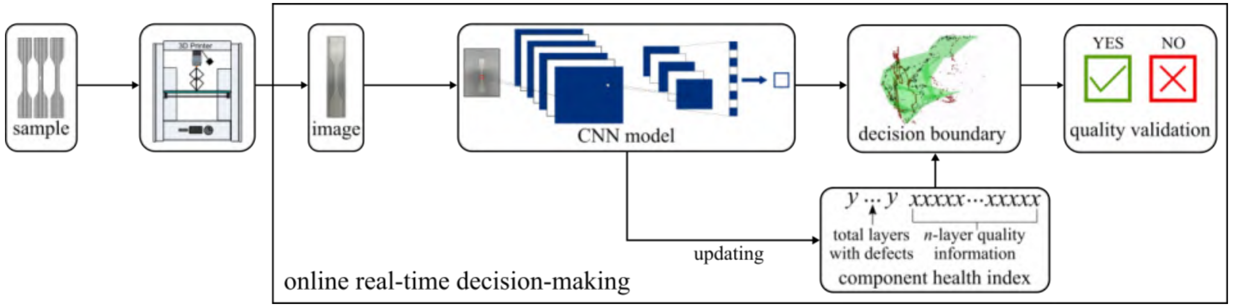
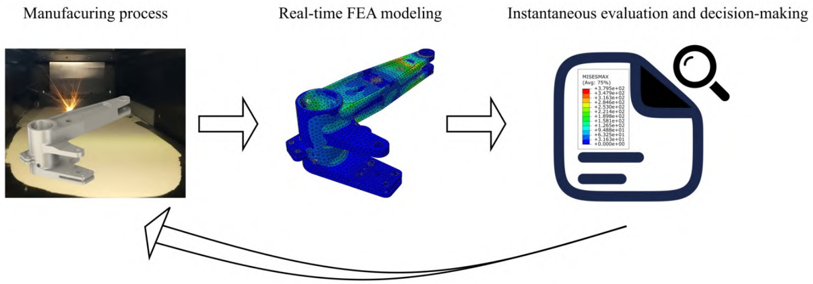
Contents

Contributions

Key Contributions in the field of real-time structural validation for FFF

- Defect detection with machine learning and computer vision.
- A novel component health index that links the features of defects across layers.
- Dynamic specimen layer properties.
- Structural validation based on defect impact decision boundary and FEA result.
- Smart decision-making algorithm based on defect impact.

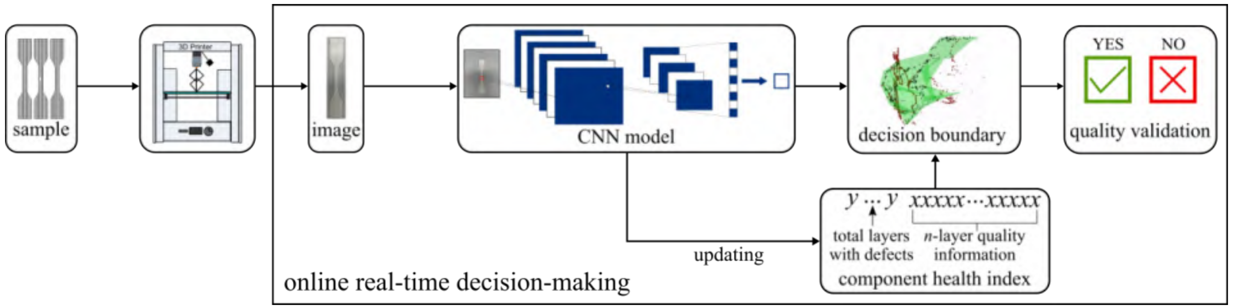


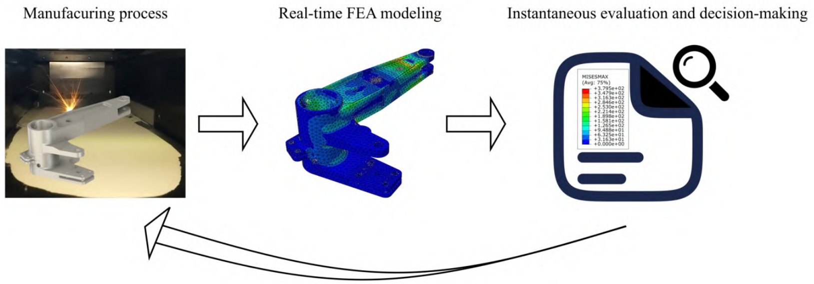


Summary

A summery of the research presented in this work.

- Reviewed the current in situ monitoring research for FFF.
- Presented a machine learning-based real-time structural validation for FFF.
- Presented a defect segmentation-based real-time FEA structural validation for FFF.





Publications

1. **Fu Y**, Downey A, Yuan L, et al. In situ structural validation of components manufactured using fused filament fabrication[C]. Nondestructive Characterization and Monitoring of Advanced Materials, Aerospace, Civil Infrastructure, and Transportation XV. International Society for Optics and Photonics, 2021, 11592: 115921E.
2. **Fu Y**, Downey A, Yuan L, et al. In situ monitoring for fused filament fabrication process: A review[J]. **Additive Manufacturing**, 2021, 38: 101749.
3. **Fu Y**, Downey A R J, Yuan L, et al. Machine learning algorithms for defect detection in metal laser-based additive manufacturing: A review[J]. **Journal of Manufacturing Processes**, 2022, 75: 693-710.
4. **Fu Y**, Downey A, Yuan L, et al. Towards Online Structural Validation for Fused Filament Fabrication. QNDE presentation, 2021.
5. **Fu Y**, Downey A, Yuan L, et al. Real-time structural validation for material extrusion additive manufacturing. **Additive Manufacturing** 65 (2023): 103409.
6. **Fu Y**, Downey A, Yuan L, et al. Real-time splatter tracking in laser powder bed fusion additive manufacturing. In NDE 4.0, Predictive Maintenance, Communication, and Energy Systems: The Digital Transformation of NDE 2023 Apr 25 (Vol. 12489, pp. 121-127). SPIE.
7. **Fu Y,** Joud S, Downey AR, Yuan L, Zhang T, Kiracofe D. Investigating Compressing Particle Damper Pockets in Beams Manufactured by Laser Powder Bed Fusion Additive Manufacturing. In Society for Experimental Mechanics Annual Conference and Exposition 2023 Jun 5 (pp. 139-144). Cham: Springer Nature Switzerland.
8. **Fu Y**, Downey A, Yuan L, et al. Real-time finite element analysis for online structural component. Additive Manufacturing (In process)

THANK YOU

Questions?

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