Towards Online Structural Validation for Fused Filament Fabrication

Presenter: Yanzhou Fu

Authors: Yanzhou Fu[1], Austin Downey[1], Lang Yuan[1], Yunusa Balogun[2], Pratt Avery[2]

1. Department of Mechanical Engineering, University of South Carolina
2. Naval Surface Warfare Center (Crane Division)

NASA SC Space Grant Consortium

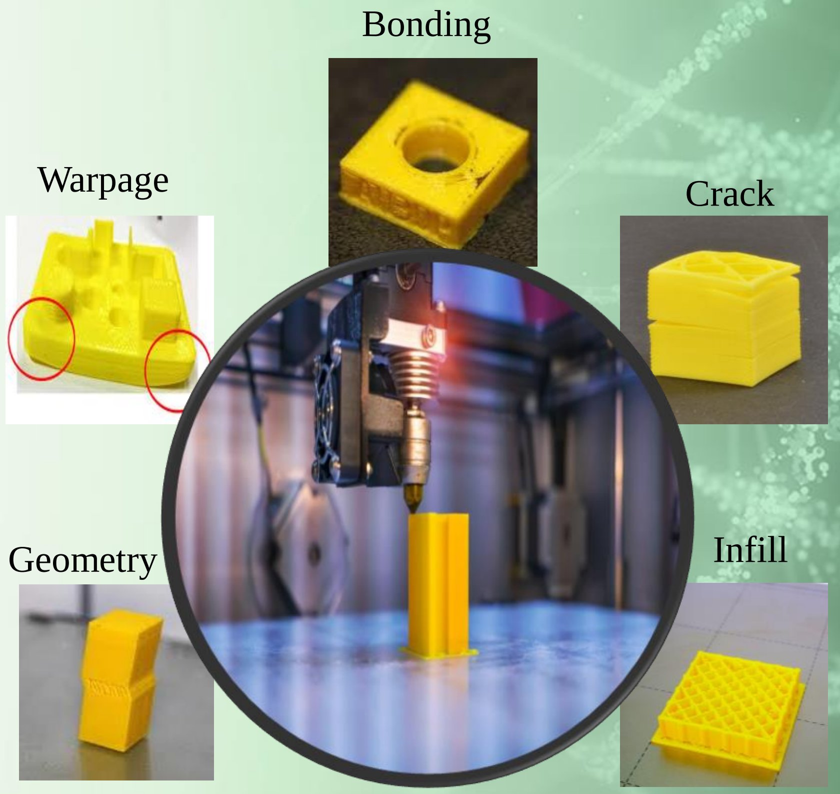
SCRA South Carolina Research Authority

U of SC South Carolina

Introduction

Contents

1. Research purpose
2. Prior work
3. Methodology
4. Results
5. Conclusion



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

Research purpose

Innovation:

No matter which defects are detected for FFF; the final purpose is guaranteeing the printed product quality for real-life utilization. But not all the defects will impact the product quality. So, we want to investigate **the printing product structure validation with different defect sizes' detection by using ML.**

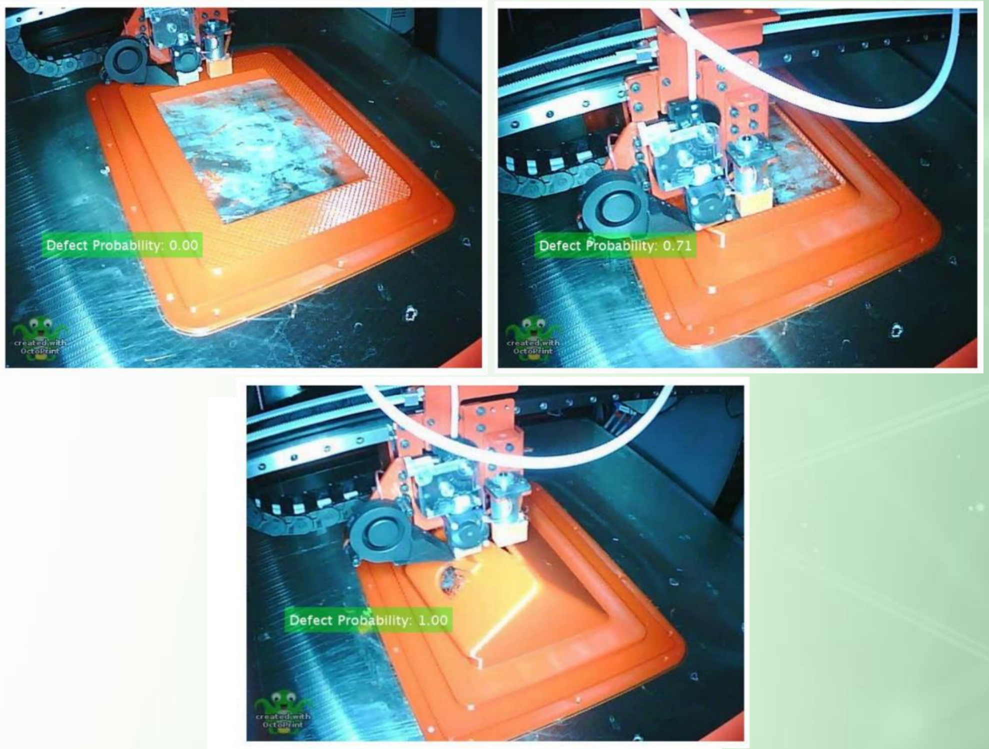
Research purpose:

1. In situ defect detection platform.
2. Decision boundary for different defect sizes impacting on product structure validation.
3. Defect size vs. model detection accuracy.
4. Online structural defect detection.

Product quality monitoring

Product structural quality monitoring

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

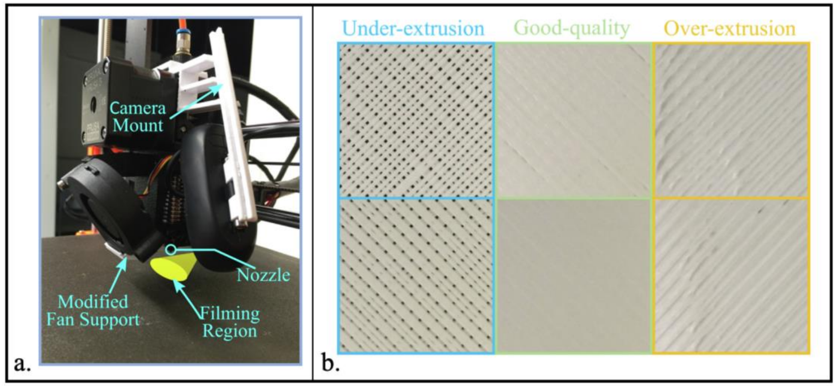


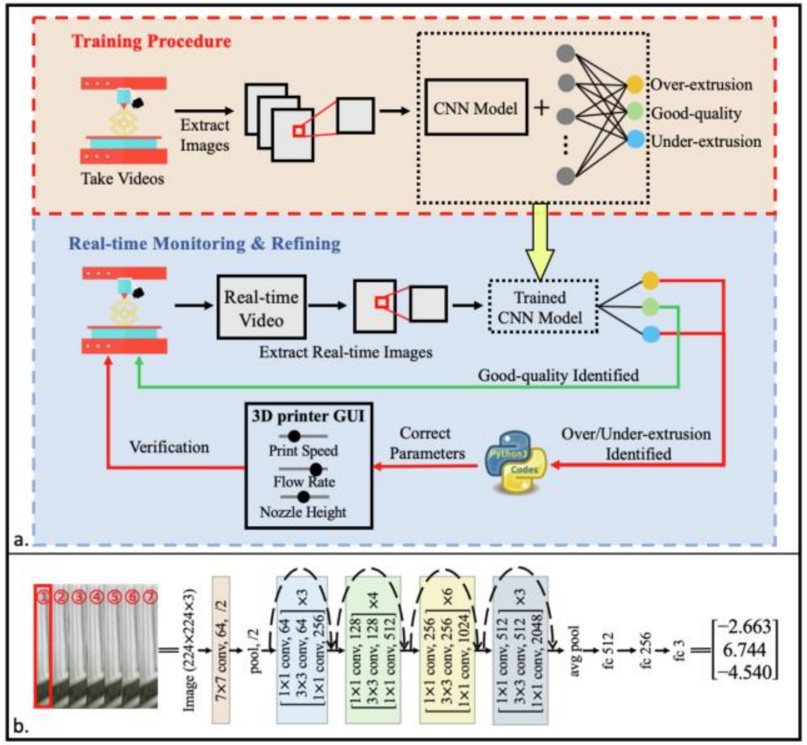
1. Barath Narayanan, Kelly Beigh, Gregory Loughnane, Nilesh U. Powar, Support vector machine and convolutional neural network based approaches for defect detection in fused filament fabrication, Applications of Machine Learning, SPIE, 2019.

Extrusion defect detection

Product bonding quality monitoring

- Defect: good quality, over-extrusion, under-extrusion
- Algorithm: DCNN
- Accuracy: 94%



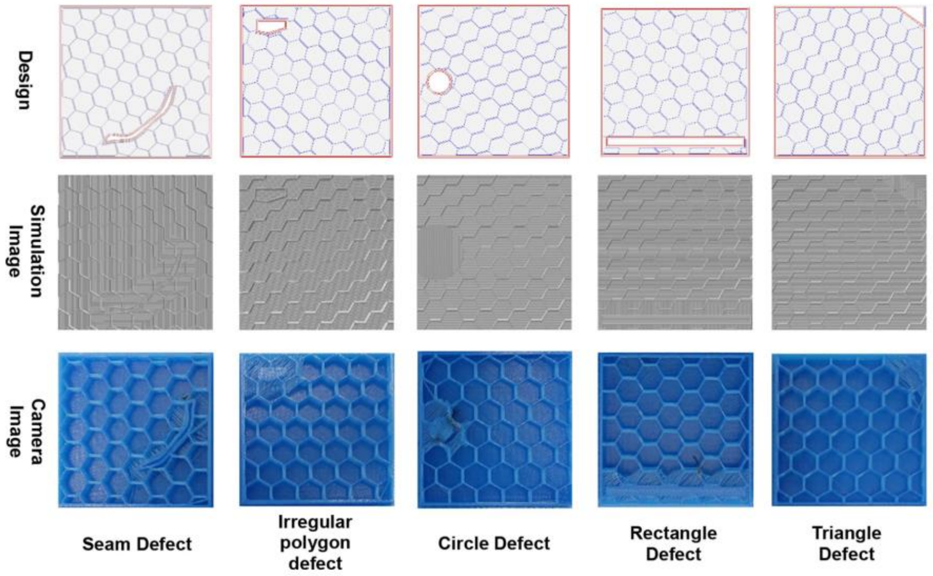


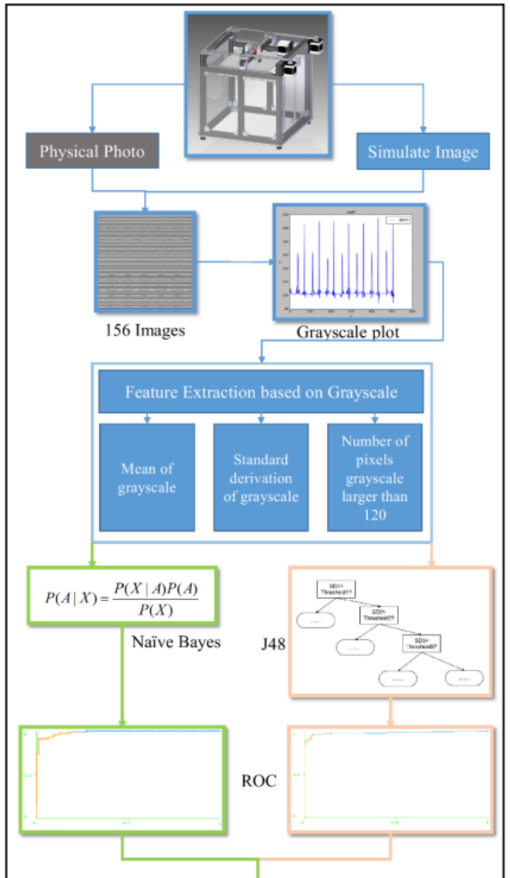
1. Zeqing Jin, Zhizhou Zhang, and Grace X. Gu. Autonomous in-situ correction of fused deposition modeling printers using computer vision and deep learning. Manufacturing Letters, 22:11–15, October 2019.

Infill defect detection

Product infill quality detection

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





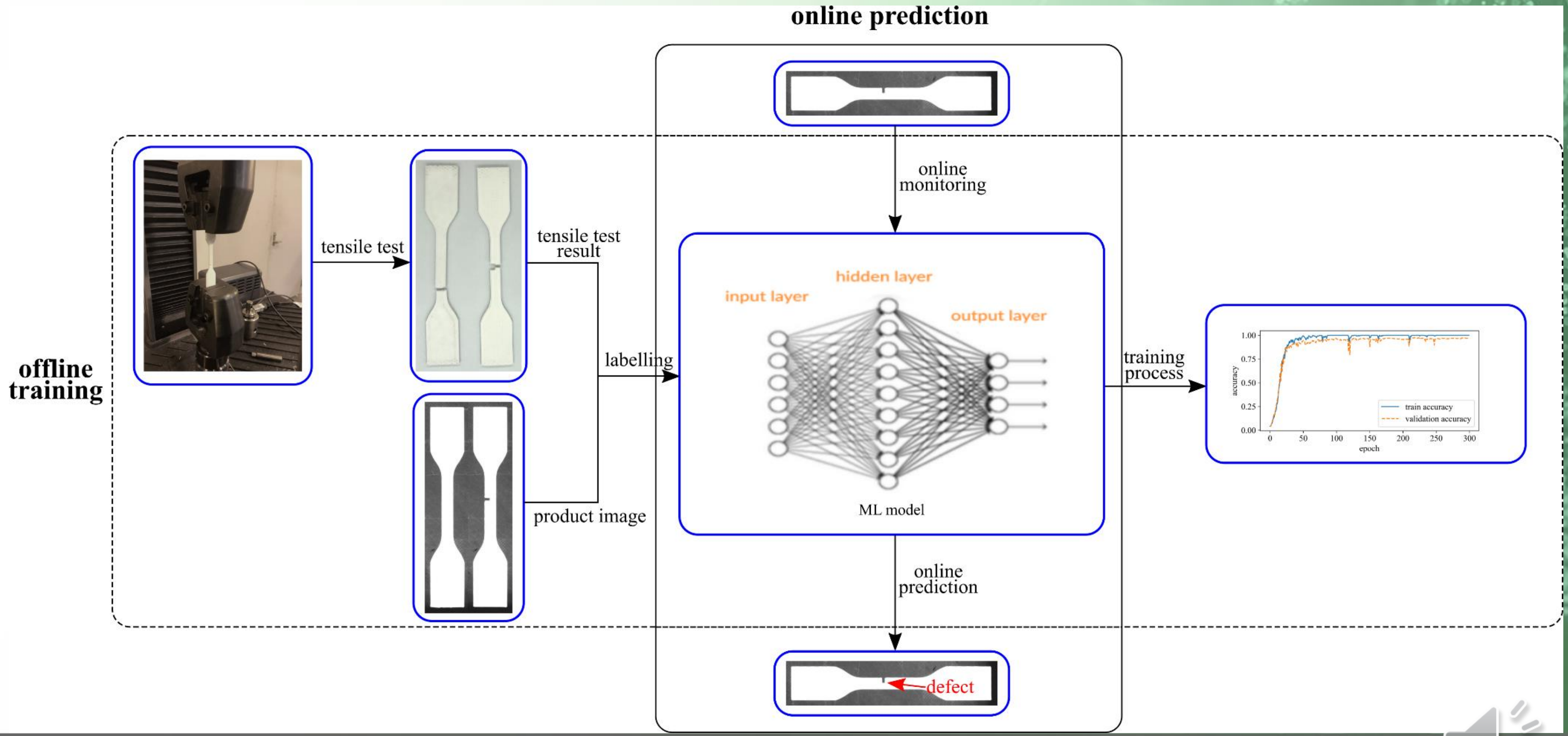
Algorithm		Naïve Bayes		J48 Decision Trees	
Class		Predicted Class			
		A	B	A	B
Actual Class	A	63	1	61	3
	B	22	70	4	88
Accuracy		85.26%		95.51%	

Confusion matrixes

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.

Process development

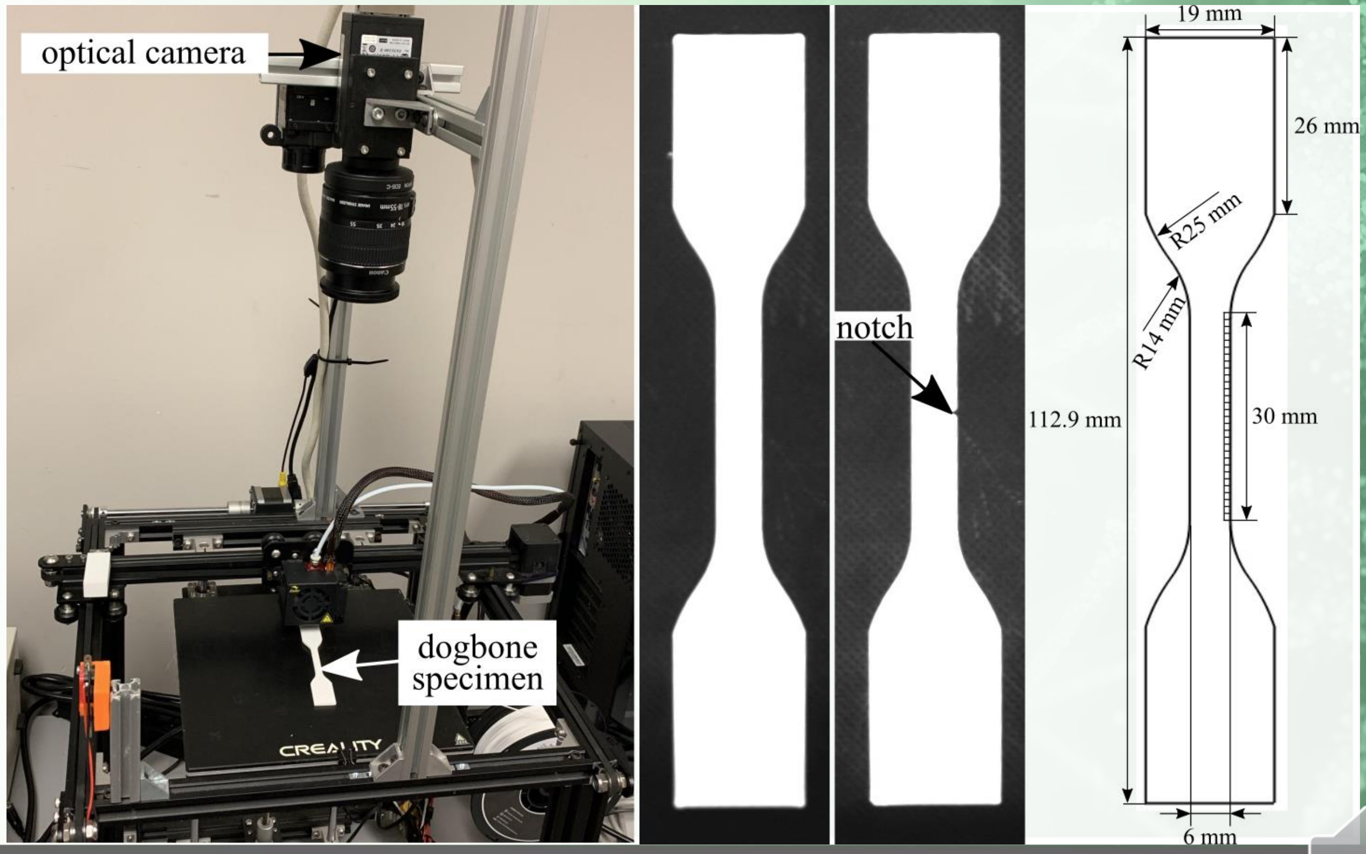
Diagram for the experiment methodology.



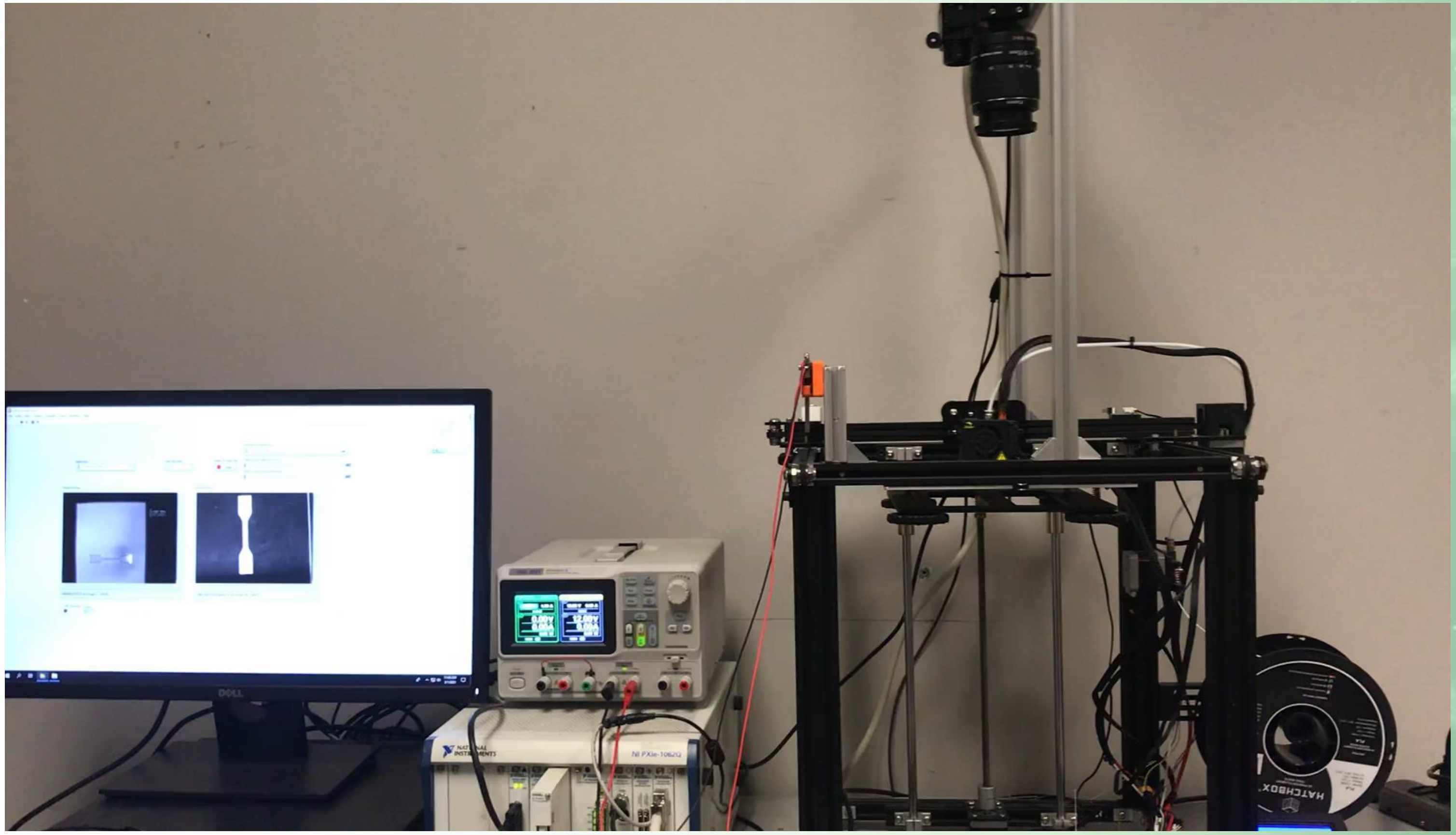
Experimental setup

Defect detection platform and specimen for the FFF printing process

- defect detection platform
- good quality specimen and specimen with defect (1 mm x 1 mm)
- specimen's dimension



Data collection

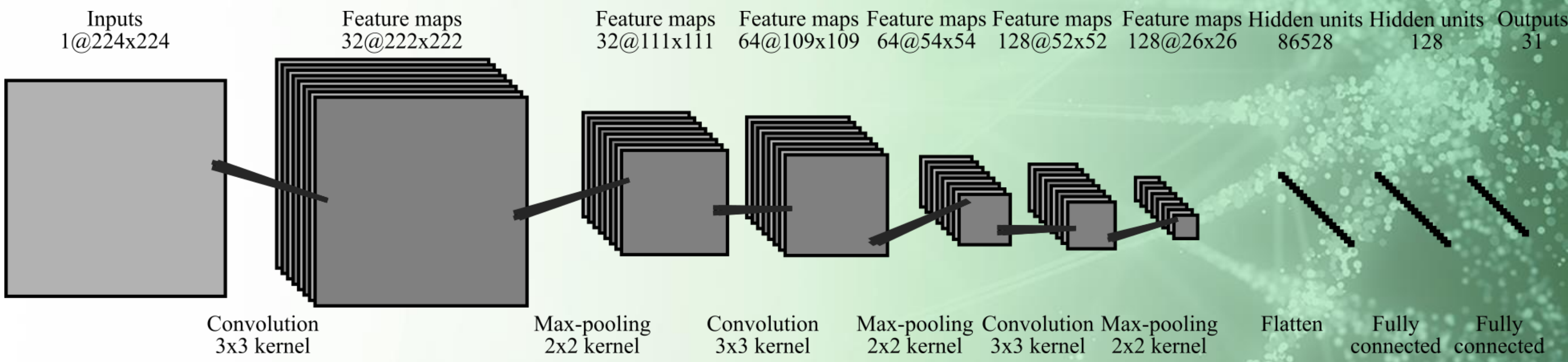


Video for the data collection process.

Deep learning architecture

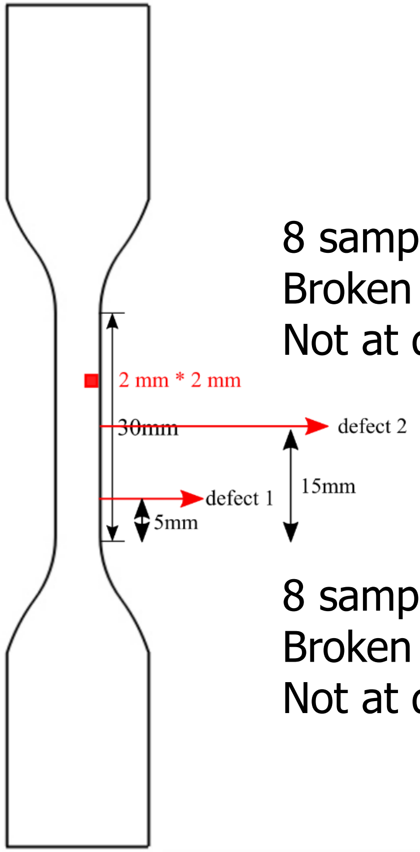
Designed CNN model structure based on LeNet 5

- 3 convolutional layer
- 3 max pooling layer
- 2 fully connected hidden layer



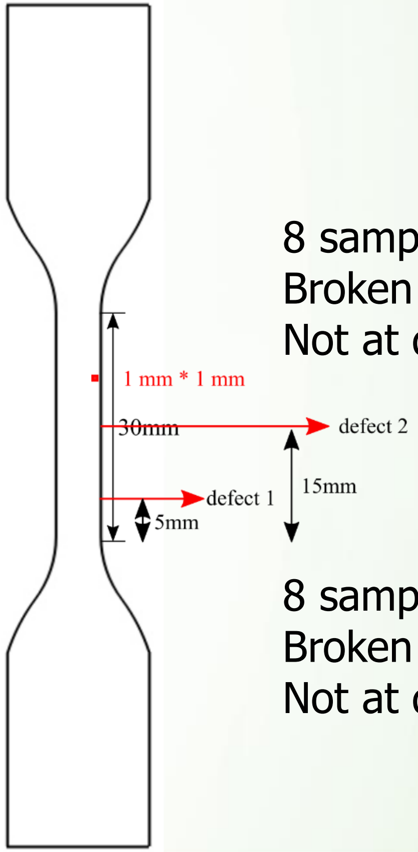
1. LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P., \Gradient-based learning applied to document recognition," Proceedings of the IEEE 86(11), 2278-2324 (1998).

Designed impactful defects



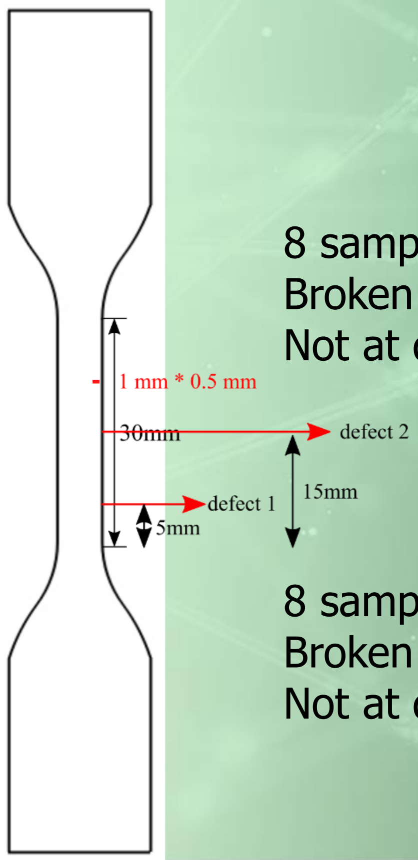
8 samples for defect 1
Broken at defect: 8
Not at defect : 0

8 samples for defect 2
Broken at defect: 8
Not at defect: 0



8 samples for defect 1
Broken at defect: 8
Not at defect: 0

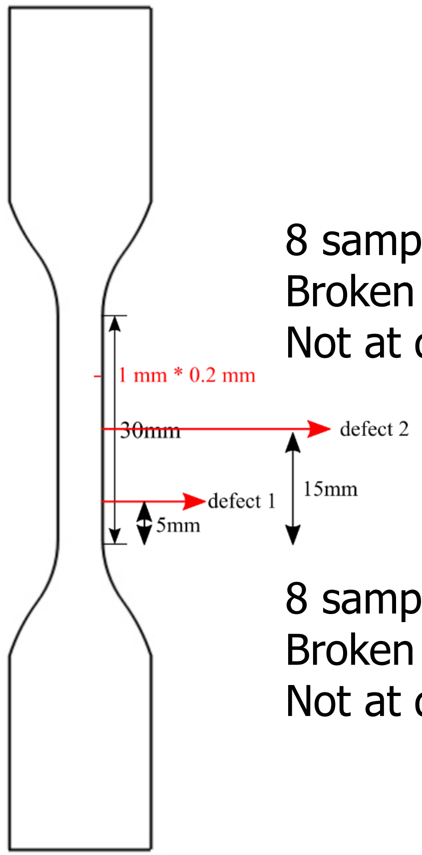
8 samples for defect 2
Broken at defect: 8
Not at defect: 0



8 samples for defect 1
Broken at defect: 8
Not at defect: 0

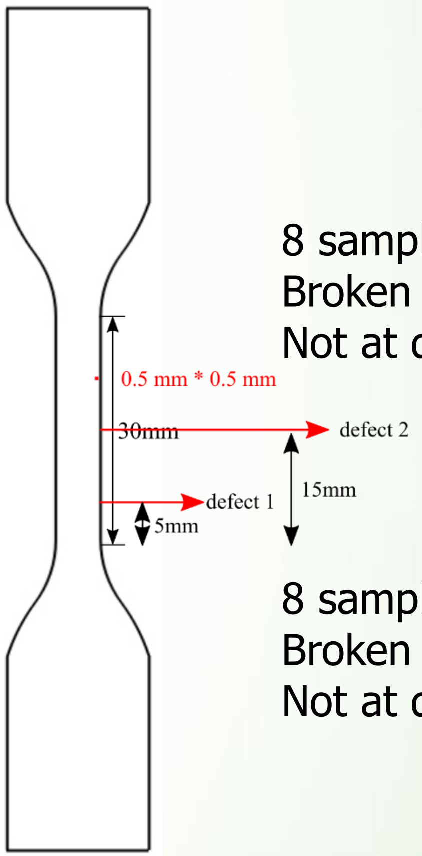
8 samples for defect 2
Broken at defect: 8
Not at defect: 0

Designed marginal defects



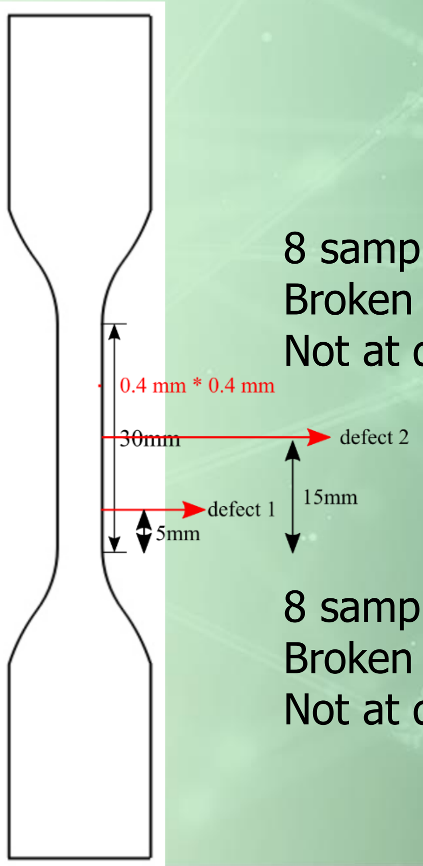
8 samples for defect 1
Broken at defect: 5
Not at defect: 3

8 samples for defect 2
Broken at defect: 8
Not at defect: 0



8 samples for defect 1
Broken at defect: 6
Not at defect: 2

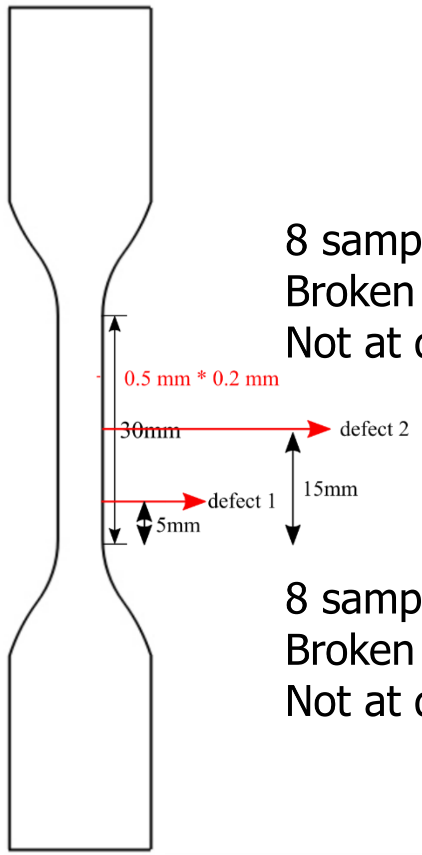
8 samples for defect 2
Broken at defect: 5
Not at defect: 3



8 samples for defect 1
Broken at defect: 0
Not at defect: 8

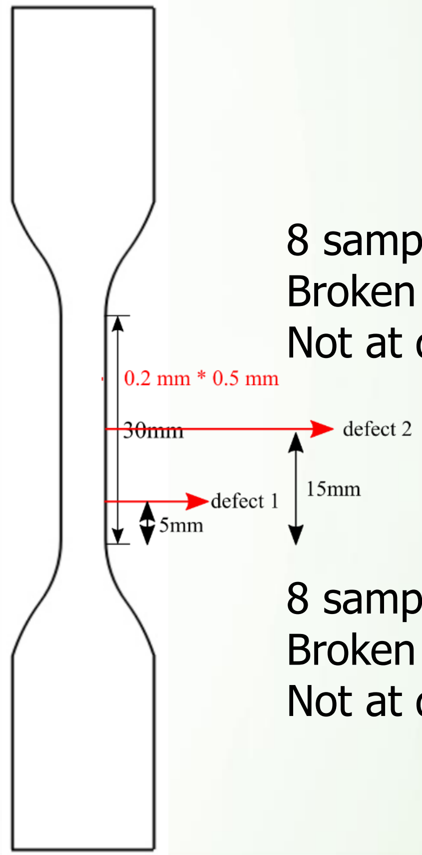
8 samples for defect 2
Broken at defect: 0
Not at defect: 8

Designed negligible defects



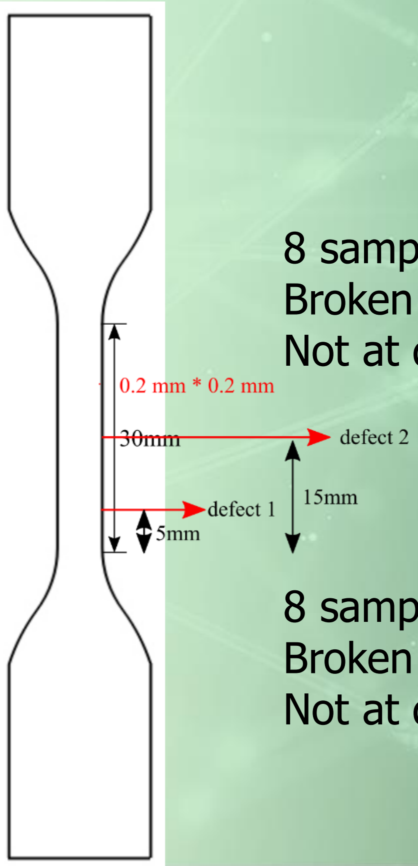
8 samples for defect 1
Broken at defect: 0
Not at defect: 8

8 samples for defect 2
Broken at defect: 0
Not at defect: 8



8 samples for defect 1
Broken at defect: 0
Not at defect: 8

8 samples for defect 2
Broken at defect: 0
Not at defect: 8



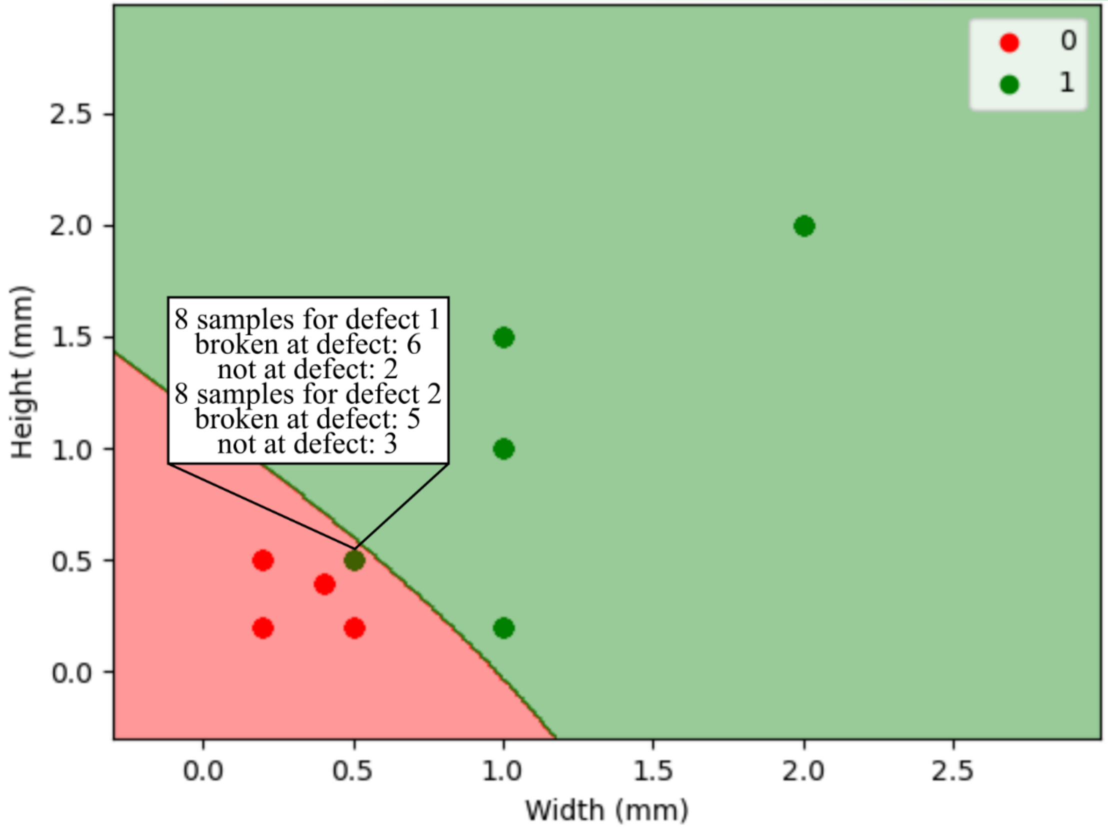
8 samples for defect 1
Broken at defect: 0
Not at defect: 8

8 samples for defect 2
Broken at defect: 0
Not at defect: 8

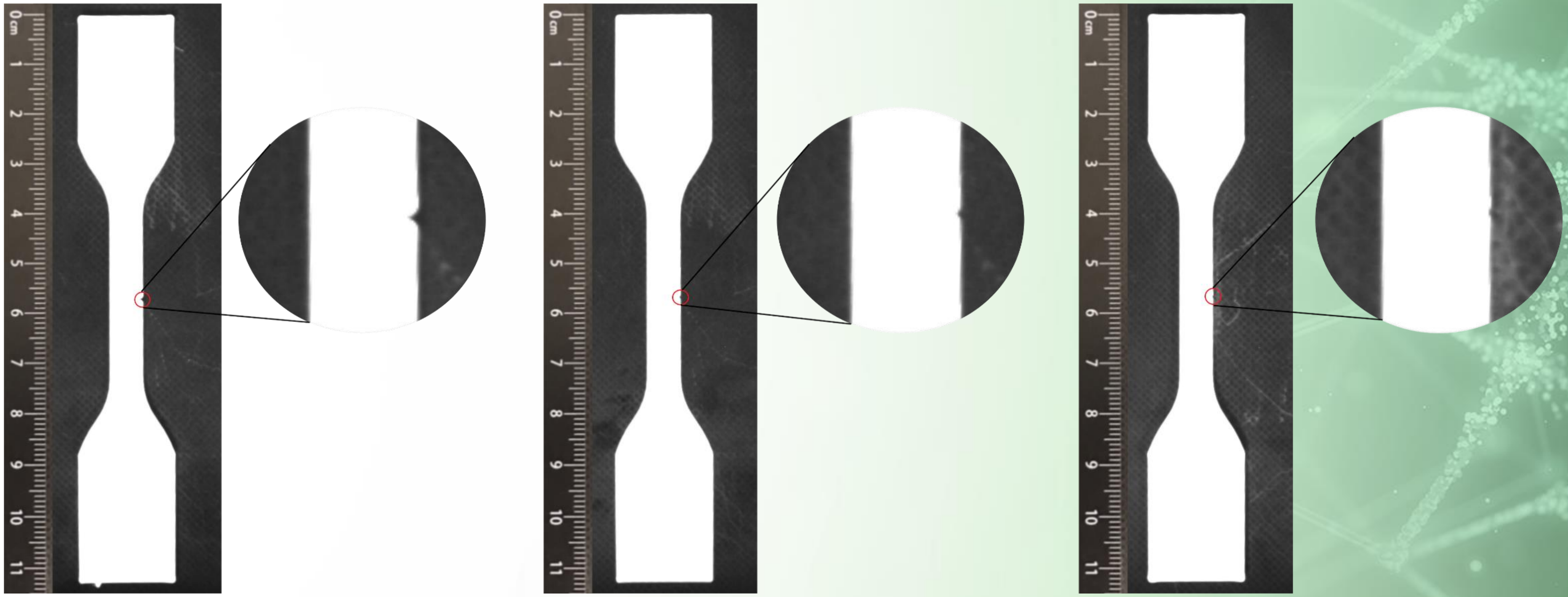
Defects impact on structural quality

Decision boundary for different defect sizes impacting on structural quality

- algorithm = SVM
- kernel = polynomial
- degree = 3

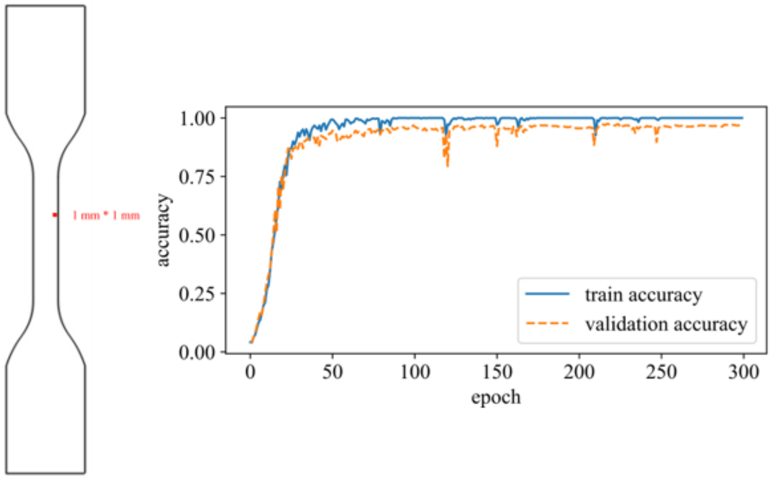


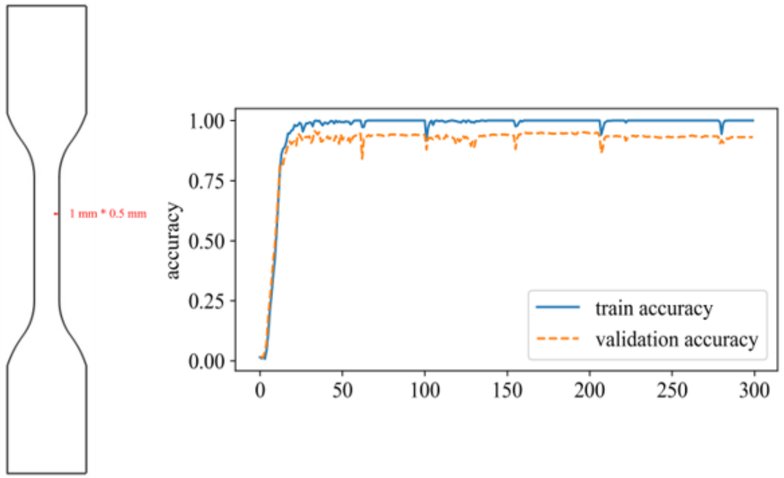
Final defects

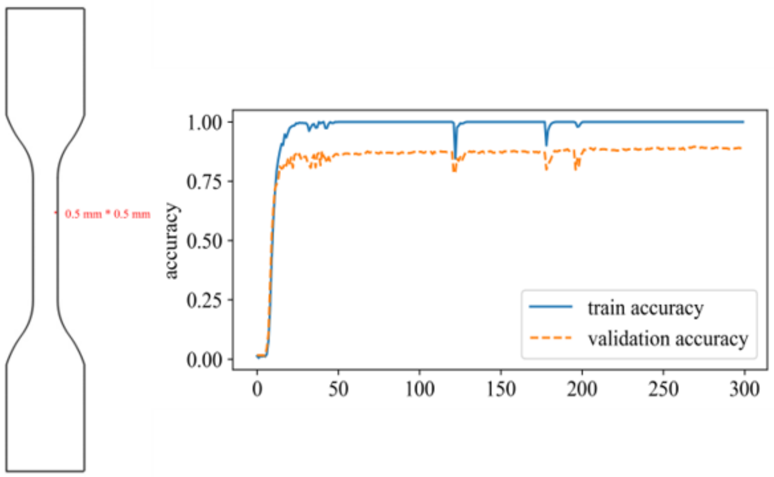


Final defect sizes (1 mm x 1 mm, 1 mm x 0.5 mm, 0.5 mm x 0.5 mm) for defect detection accuracy test.

Results: training processes







- training accuracy: 100%
- validation accuracy: 96.11%

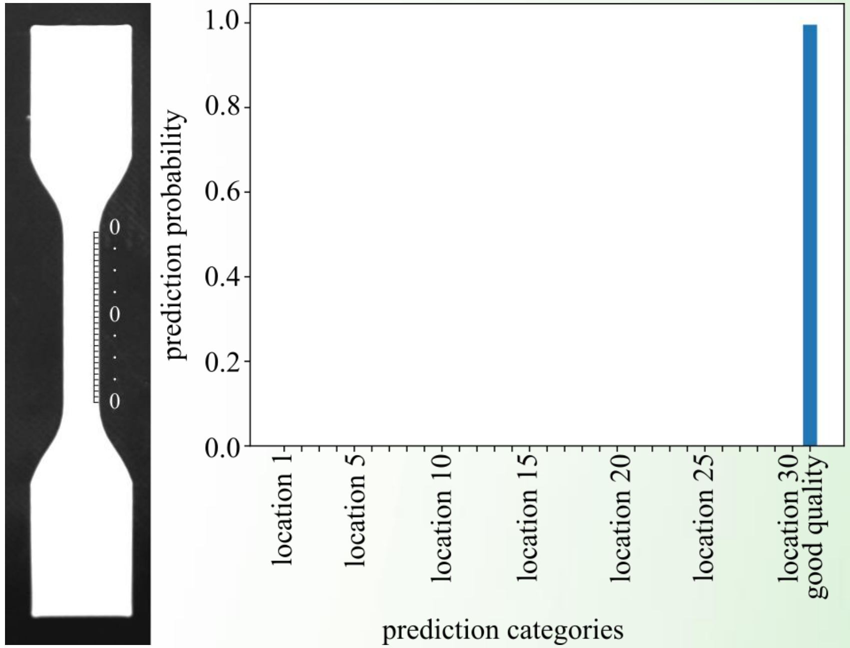
- training accuracy: 100%
- validation accuracy: 93.07%

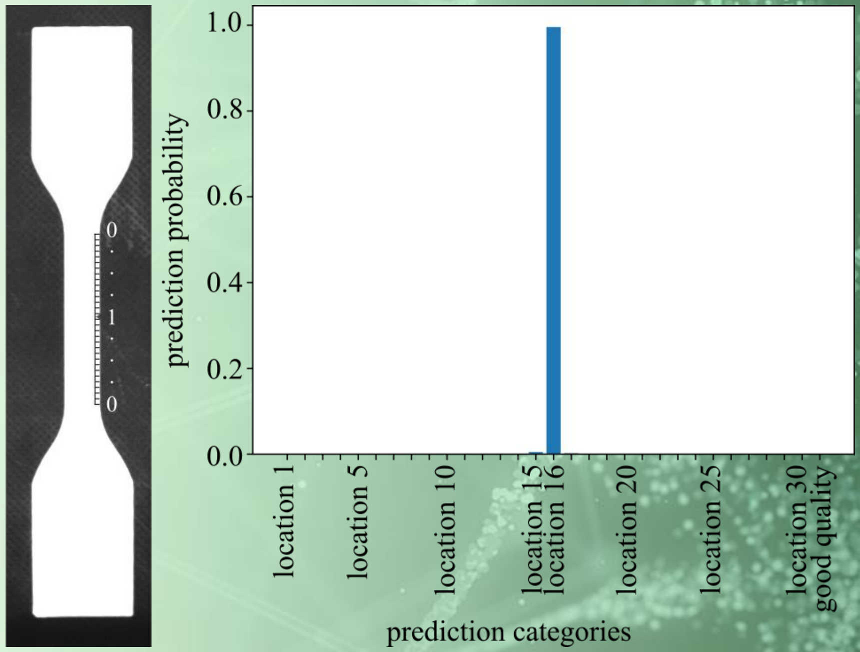
- training accuracy: 99.42%
- validation accuracy: 88.50%

Results: failure prediction

Specimen quality prediction result

- prediction result for good quality with 100% accuracy
- prediction result for failure at location 16 with 99.31% accuracy





Conclusion

1. This paper presented an online methodology of detecting structural defects for FFF.
2. The approach studies defect size vs. model detection accuracy and integrates the product structure validation into the online defect detection rather than just focusing on surface defects.
3. The designed FFF printer integrates an optical camera that can capture the product's printing process images used to train a CNN model. After training, this method can detect structural defects online.
4. Result shows the proposed defect detection approach has a promising accuracy, even for the minimal structural quality impacting defect size (here is 0.5 mm x 0.5 mm), which is verified to be a feasible method for FFF product defect detection.

Acknowledgements

This material is based upon work supported by the South Carolina Research Authority under grant 30228 and the South Carolina Space Grant Consortium under grant 521179-RP-SC007. The support of these agencies is gratefully acknowledged. Any opinions, findings, and conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the South Carolina Research Authority or the South Carolina Space Grant Consortium. Distribution Statement A. Approved for public release: distribution unlimited.

NASA SC Space Grant Consortium

SCRA South Carolina Research Authority

UofSC South Carolina

Thanks!

Presenter: Yanzhou Fu
Correspondence: yanzhouf@email.sc.edu

NASA SC Space Grant Consortium

SCRA South Carolina Research Authority

UofSC South Carolina