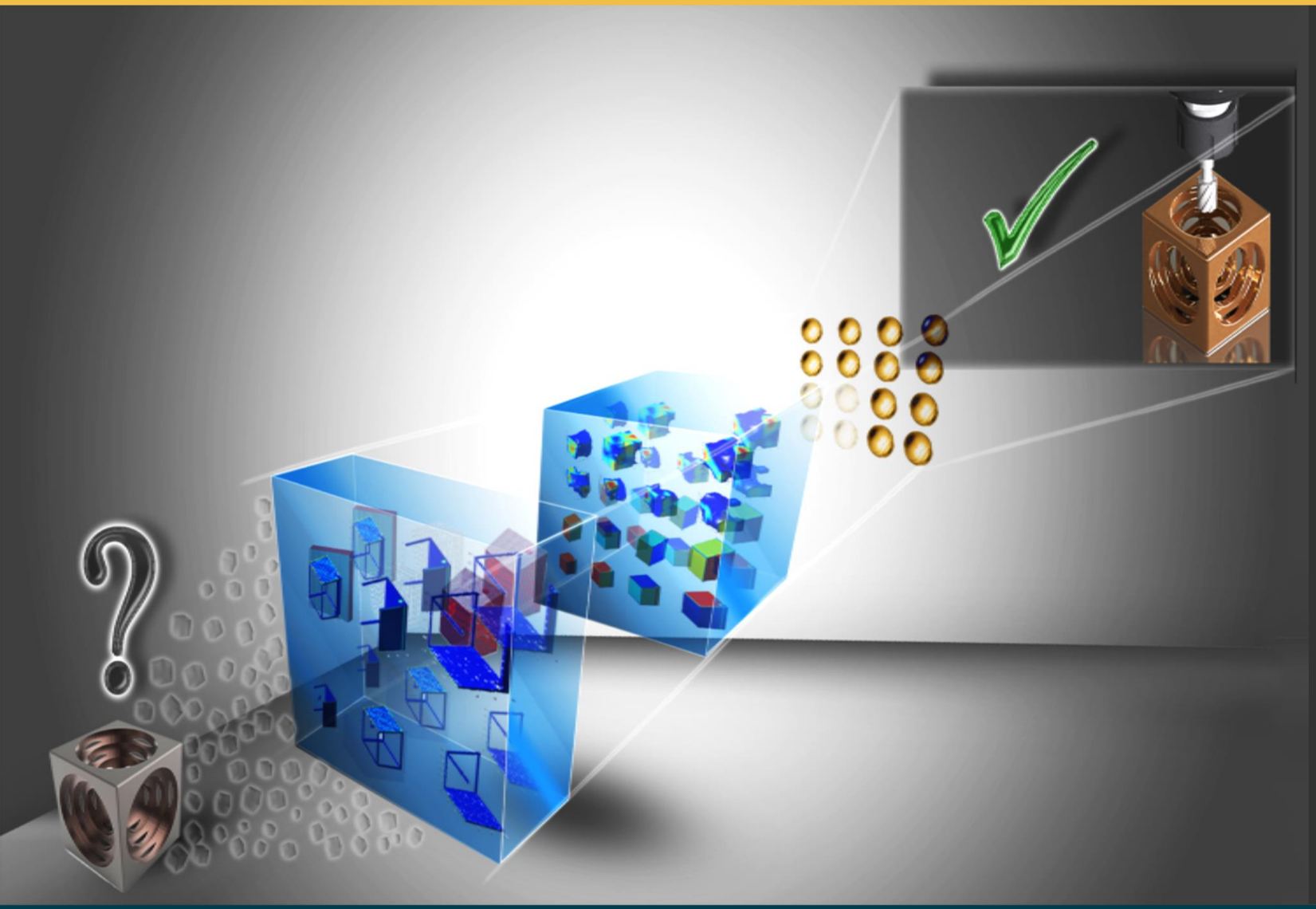
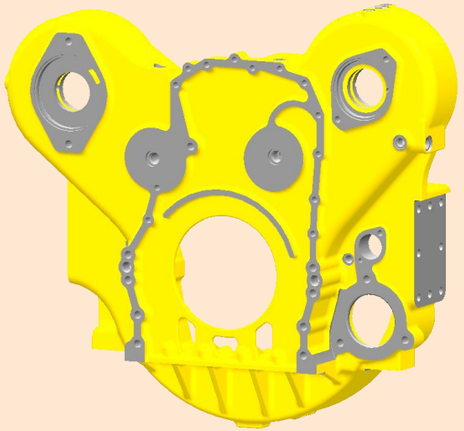
IOWA STATE UNIVERSITY
Department of Mechanical Engineering



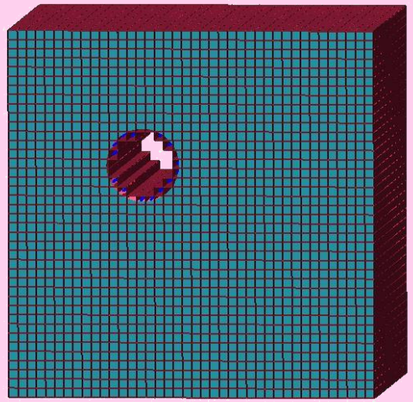
GPU-ACCELERATED DEEP LEARNING FRAMEWORK FOR CYBER-ENABLED MANUFACTURING

ADITYA BALU
SAMBIT GHADAI
SOUMIK SARKAR
ADARSH KRISHNAMURTHY

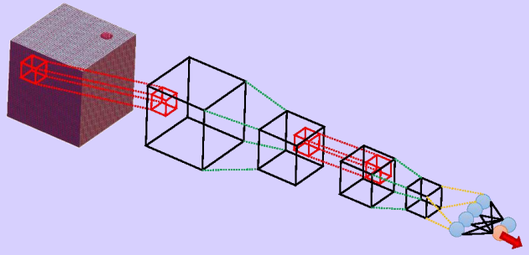
Outline



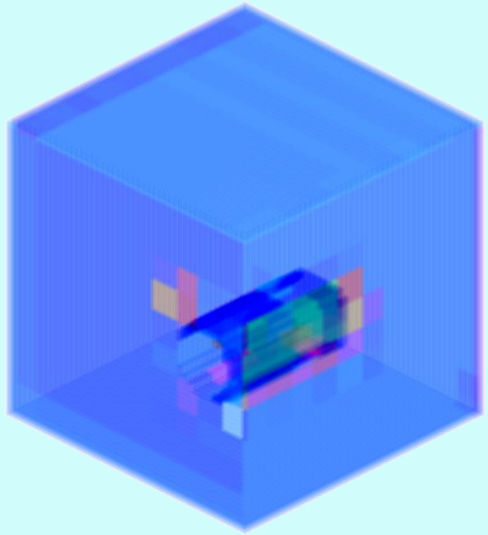
Design for Manufacturing



Volumetric Representations for CAD Models



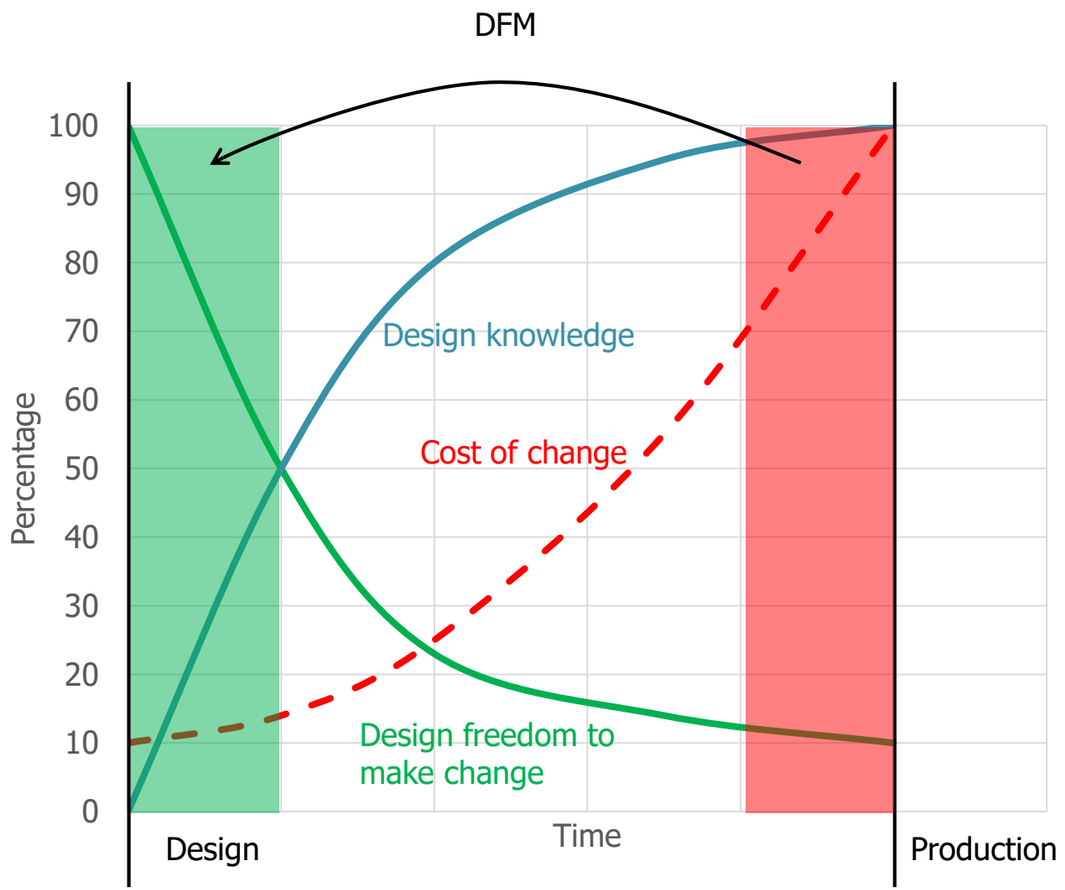
Deep Learning based Design for Manufacturing



Explainable Deep Learning

Reducing Product Cost

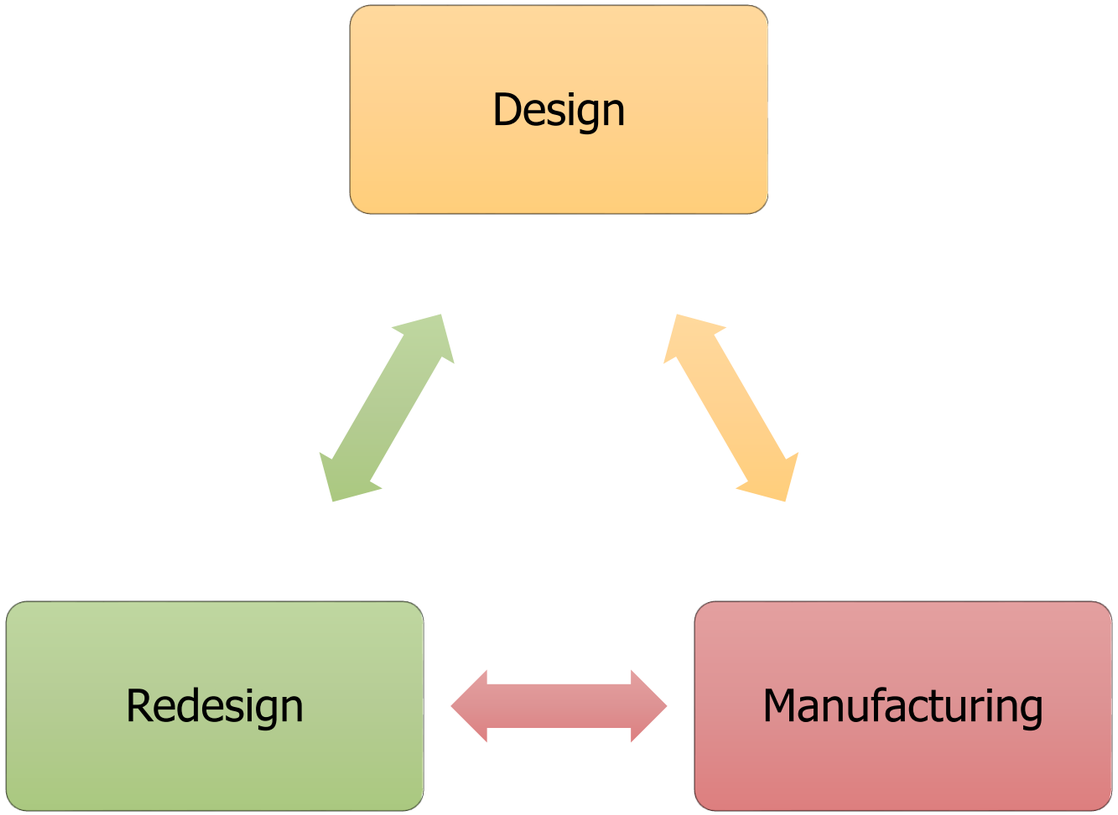
- Design has a large influence on final product cost
- DFM helps identify production issues early



Source: David Stienstra (Rose-Hulman)

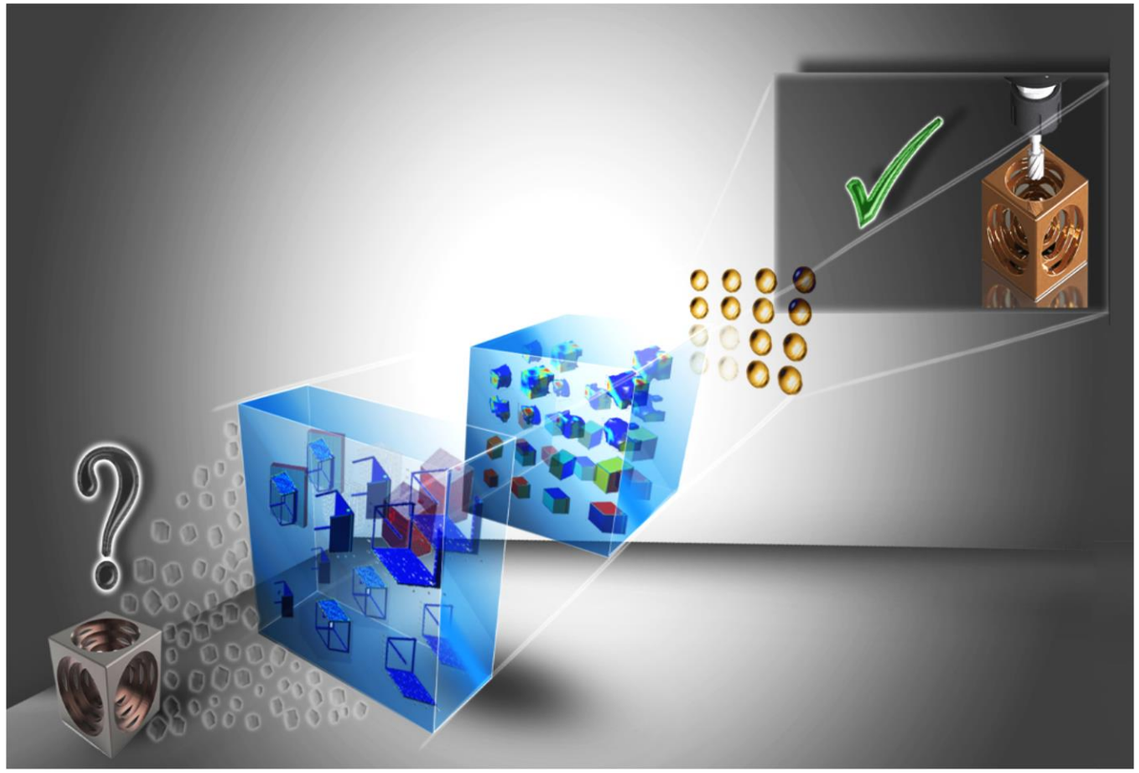
Challenges

- Traditional DFM method involves rule based analysis
- Depends on the experience of the engineers
- Several rules for different processes
  - Example ISO/ASTM 52910:2017(E) Standard Guidelines for Design for Additive Manufacturing



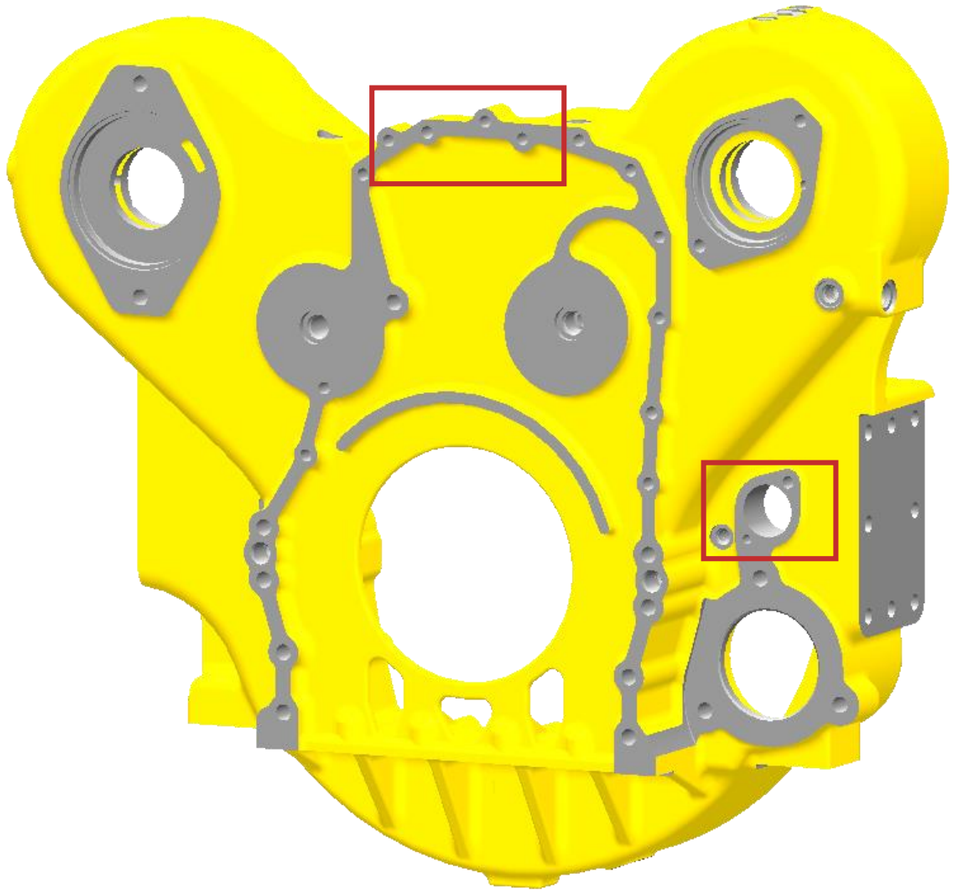
Artificial Intelligence for Design for Manufacturing

- Use deep learning to learn non-manufacturable features in a CAD model
  - Learn from examples of manufacturable and non-manufacturable models
- Advantages
  - No explicit hand-crafting of rules
  - Learn complicated rules that are difficult to codify



Feasibility Demonstration – Drilling Holes

- Common manufacturing operations
- Fewer set of design rules
  - Can manually create ground-truth data
- Complex design rules
  - Depth to diameter ratio
    - Blind vs. through holes
  - Proximity of holes to object boundaries

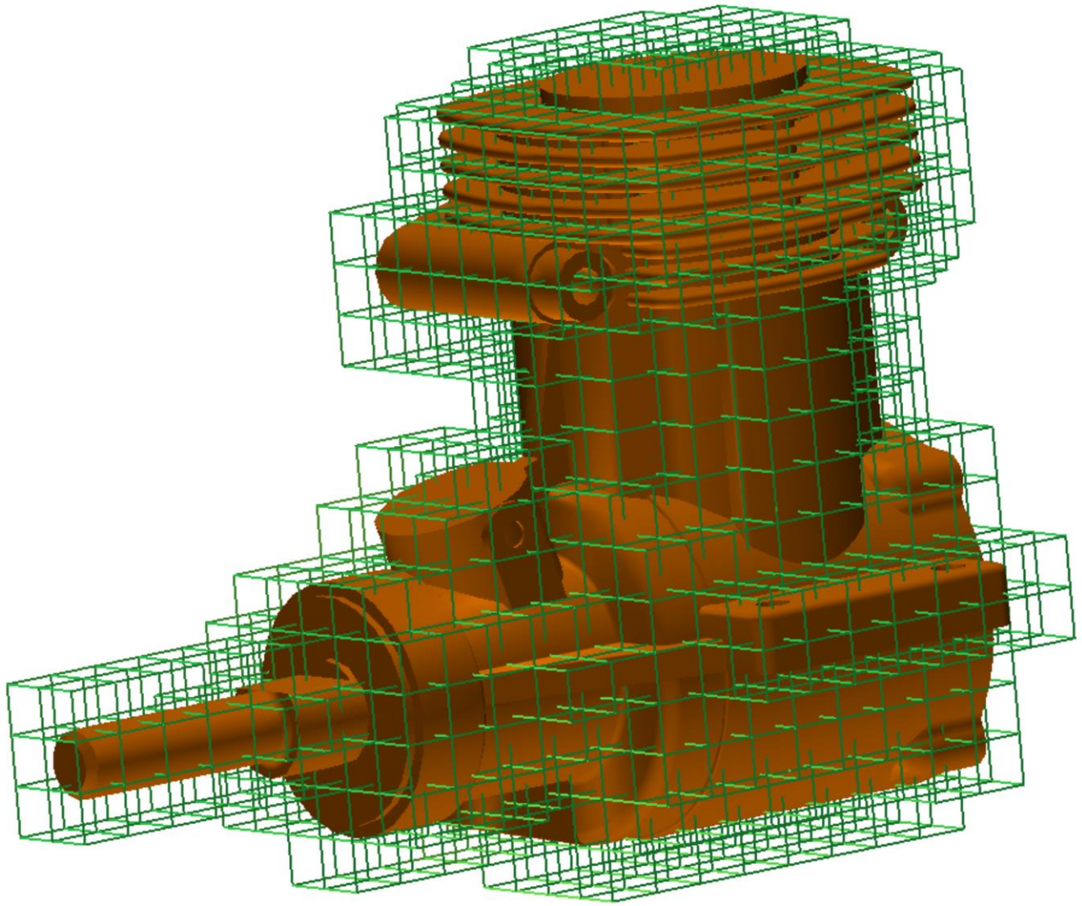


Boundary Representation (B-Rep) CAD Models

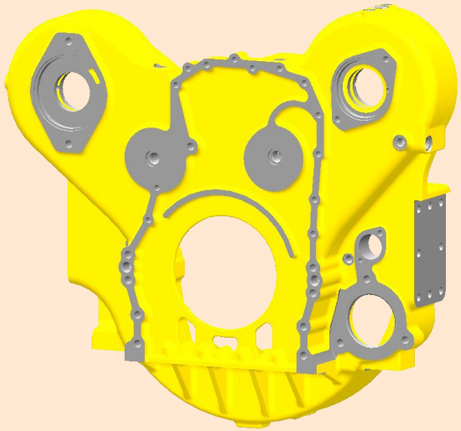
- De-facto representation for CAD models
- Can be easily tessellated into triangles for rendering
- Difficult to interpret volumetric information
  - Size of a feature
  - Internal location of a feature

Voxel Representation

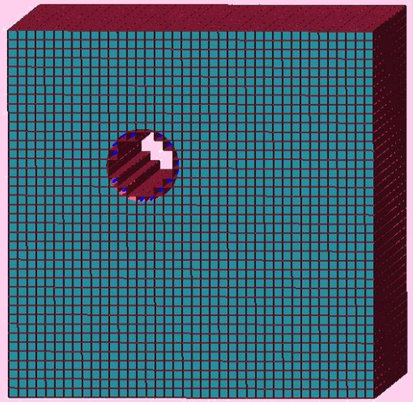
- Binary occupancy information
  - Augmented with extra geometry information
- Can be used as direct input to a convolutional neural network
- Require a fast method to voxelize a large number of CAD models



Outline



Design for Manufacturing



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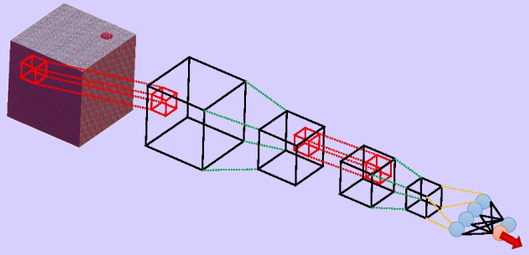
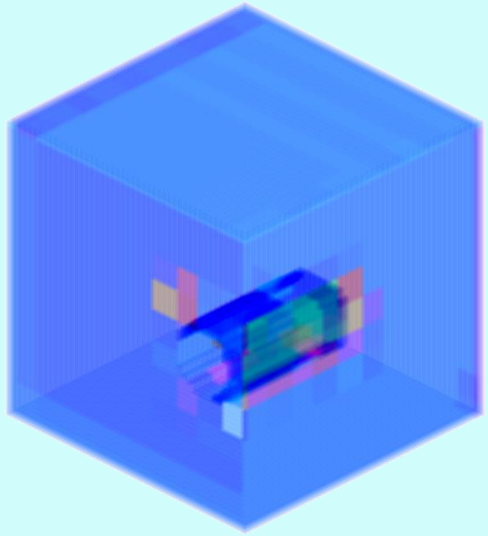


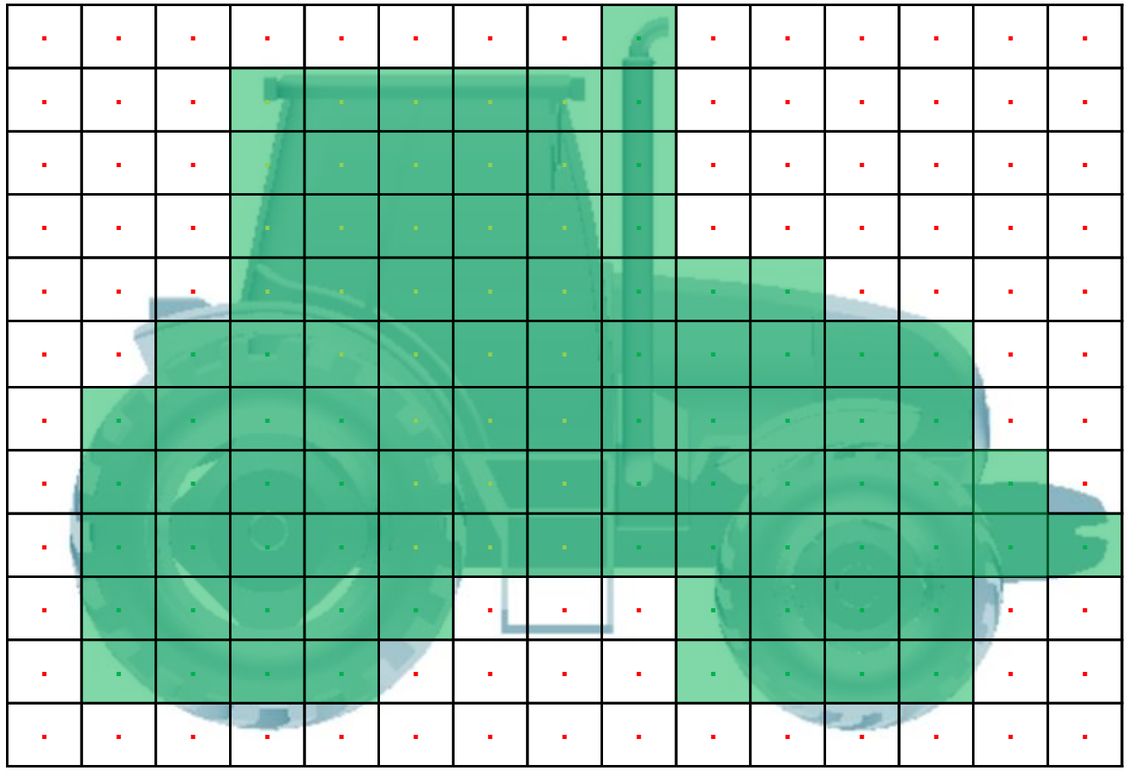
Deep Learning based Design for Manufacturing



Explainable Deep Learning

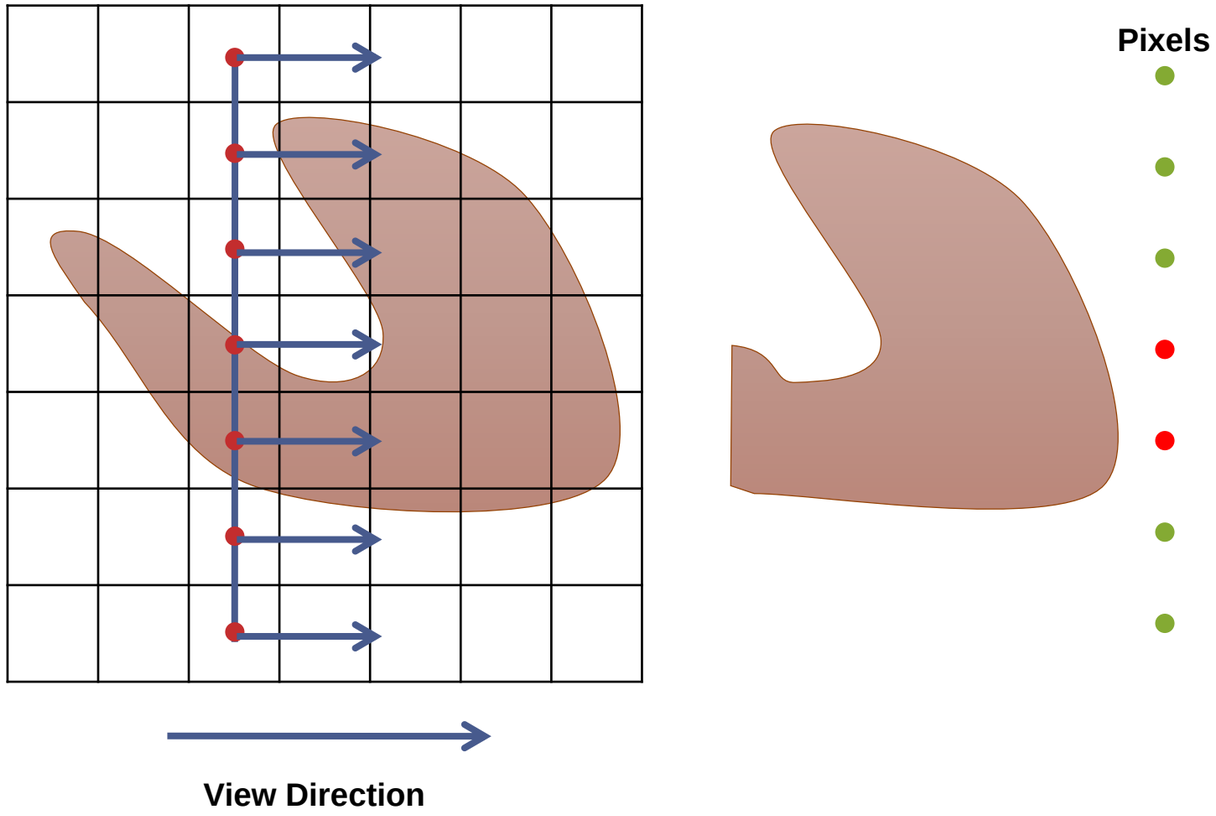
Volumetric Voxelization

- Overlay a regular voxel grid on the object
- Test point membership of the voxel bounding-box center points, classify as *in* or *out*



Point Membership Classification (PMC) Using GPU Slicing

- Use standard PMC using odd ray intersection test
- Slice the object perpendicular to an arbitrary axis
- Render the sliced object and count the number of pixels
- Extend to 3D; Each pixel corresponds to a grid point in a 2D slice



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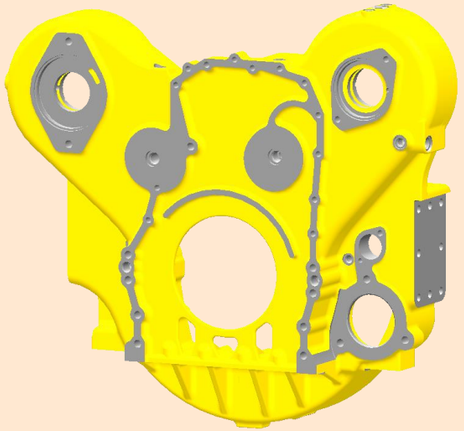

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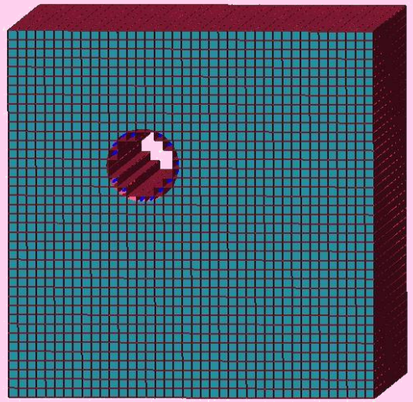

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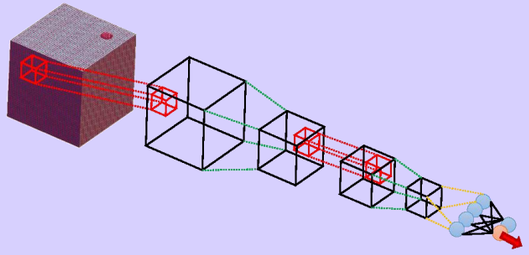
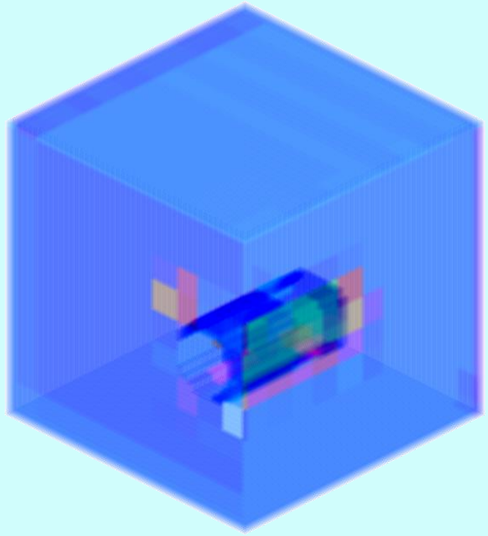


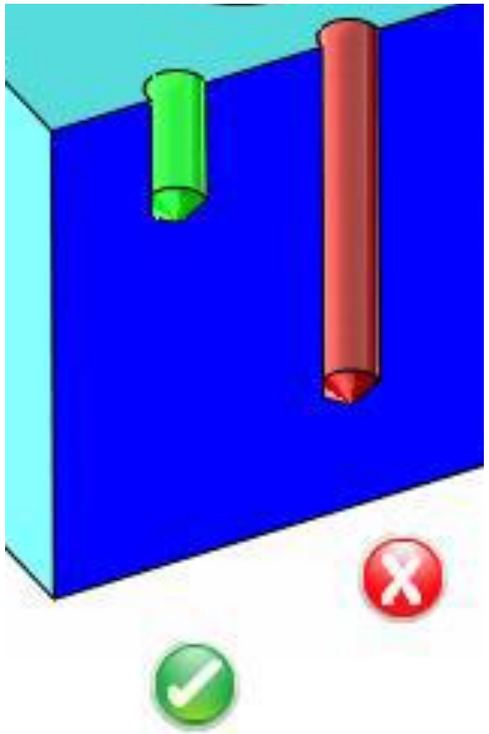
Deep Learning based Design for Manufacturing



Explainable Deep Learning

Learning Local Features

- Local Feature learning is different from object recognition
- Variation in features affect the object classification
- Learning the features by semi-supervised learning



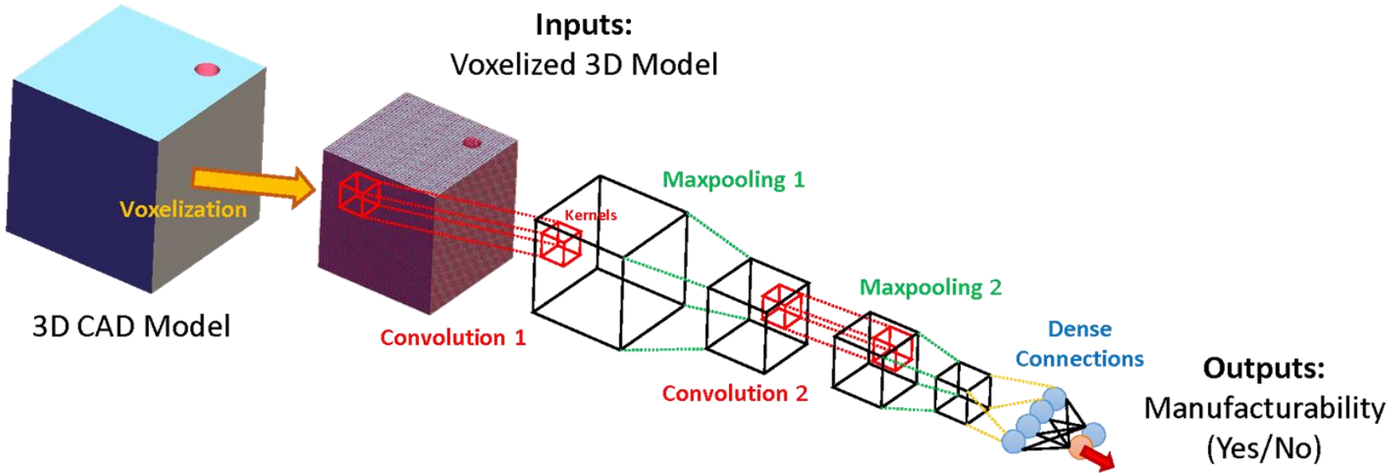
[1]. http://dfmpro.geometricglobal.com/files/2017/04/Whitepaper-A-new-approach-to-design-and-manufacturing-collaboration.pdf

Need for 3D Convolutional Nets

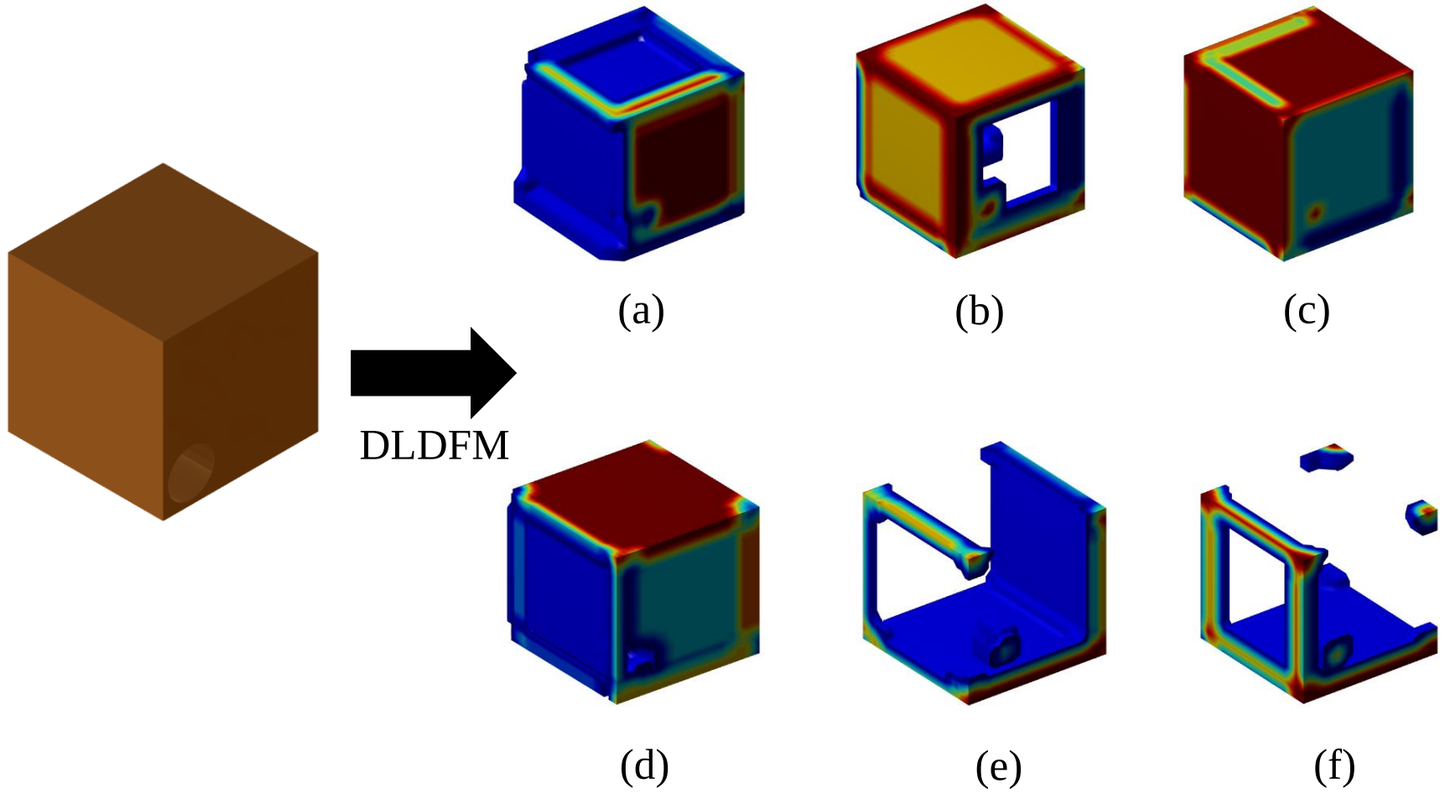
- Hierarchical feature extraction from volumetric representation
- Capability to learn features with object classification
- Amenable to model interpretability due to learning of spatial location

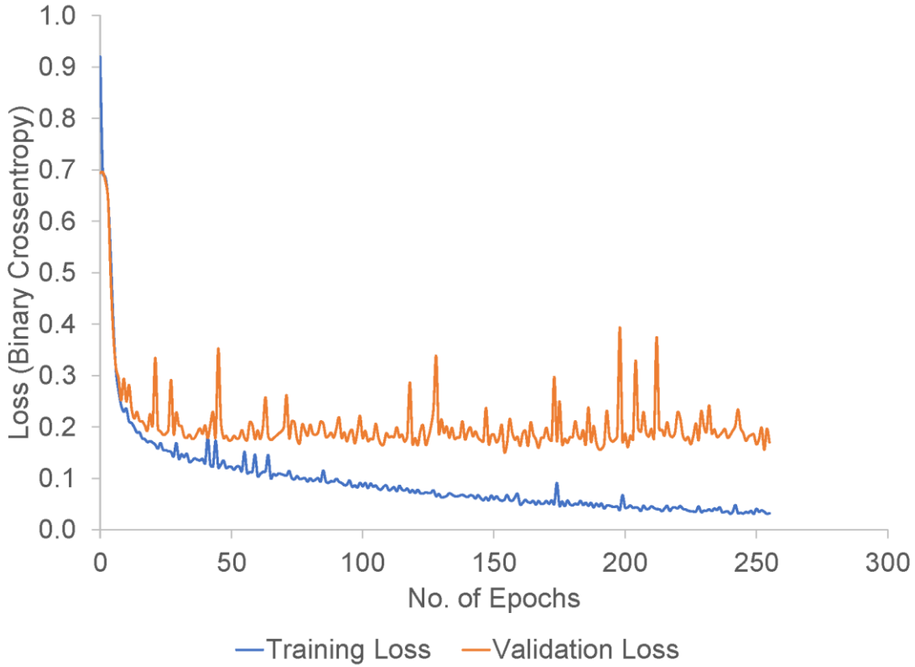
Deep Learning Based Design for Manufacturing

- Binary definition of manufacturability (binary cross-entropy loss)
- Choice of input resolution depending on the GPUs
- Architecture
  - 3D convolutional layer and 3D max. pooling layer
  - ReLU activation with output layer having Sigmoid activation

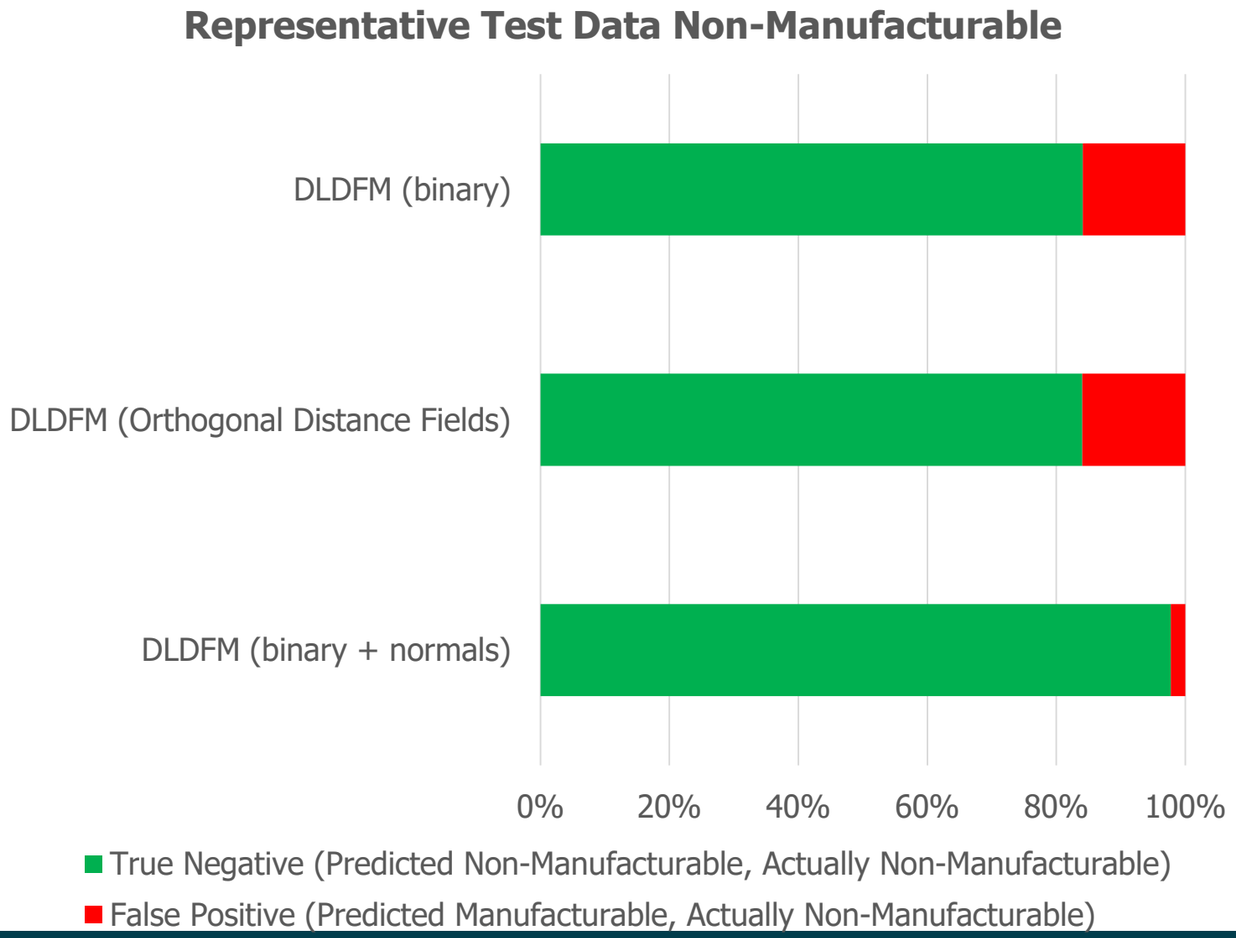


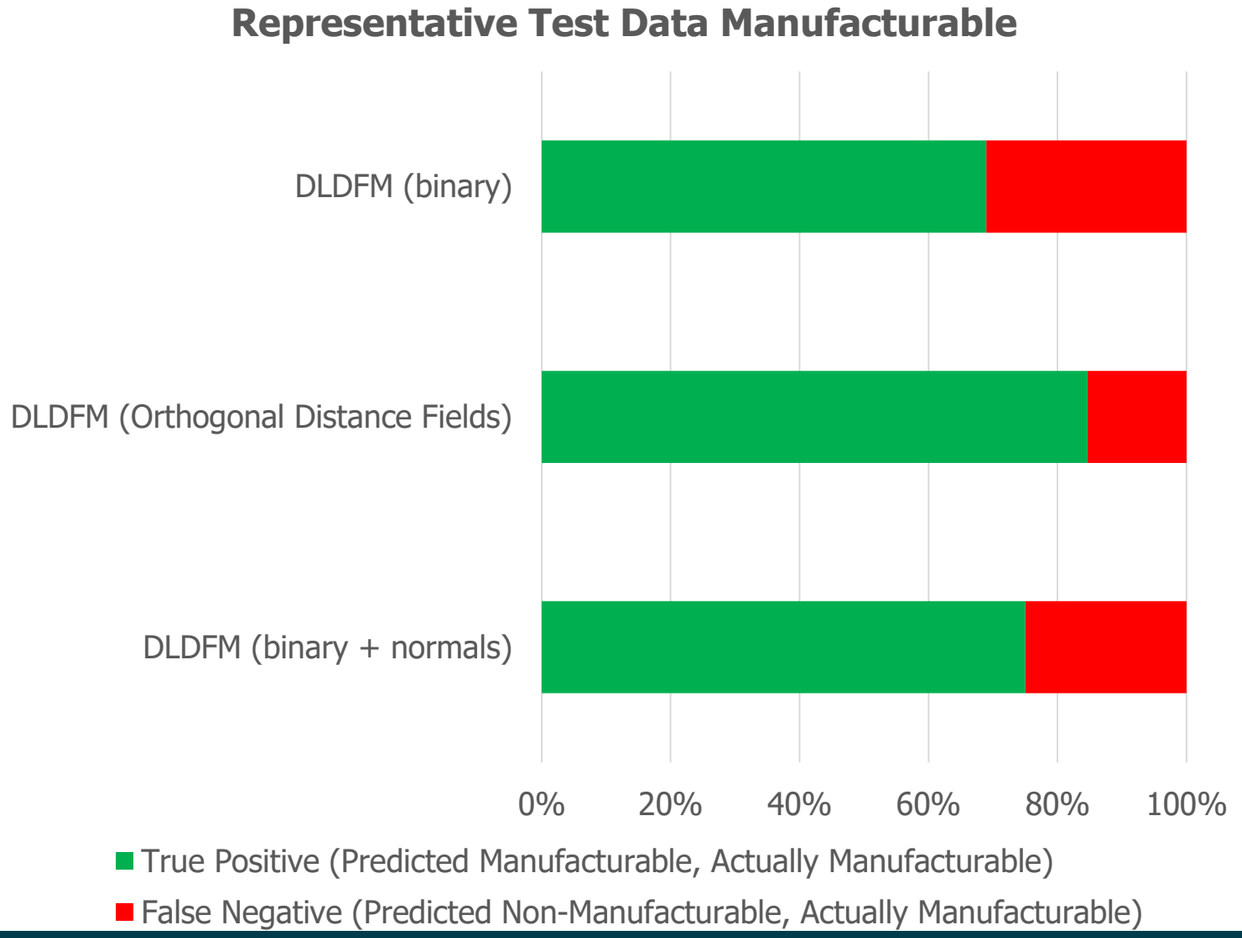
Deep Learning Based Design for Manufacturing





Results


Representative Test Data Non-Manufacturable
DLDFM (binary)
DLDFM (Orthogonal Distance Fields)
DLDFM (binary + normals)
0%
20%
40%
60%
80%
100%
True Negative (Predicted Non-Manufacturable, Actually Non-Manufacturable)
False Positive (Predicted Manufacturable, Actually Non-Manufacturable)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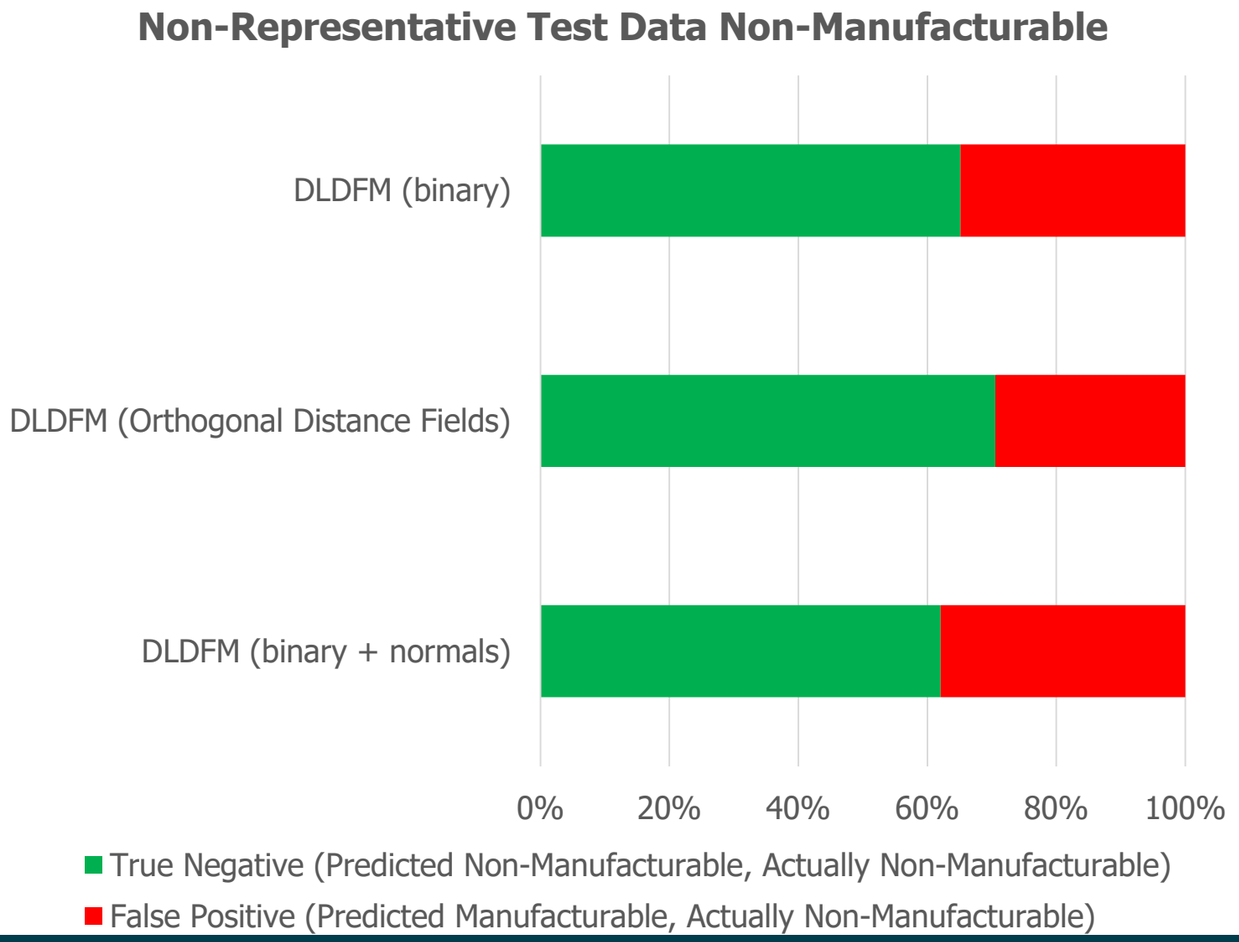
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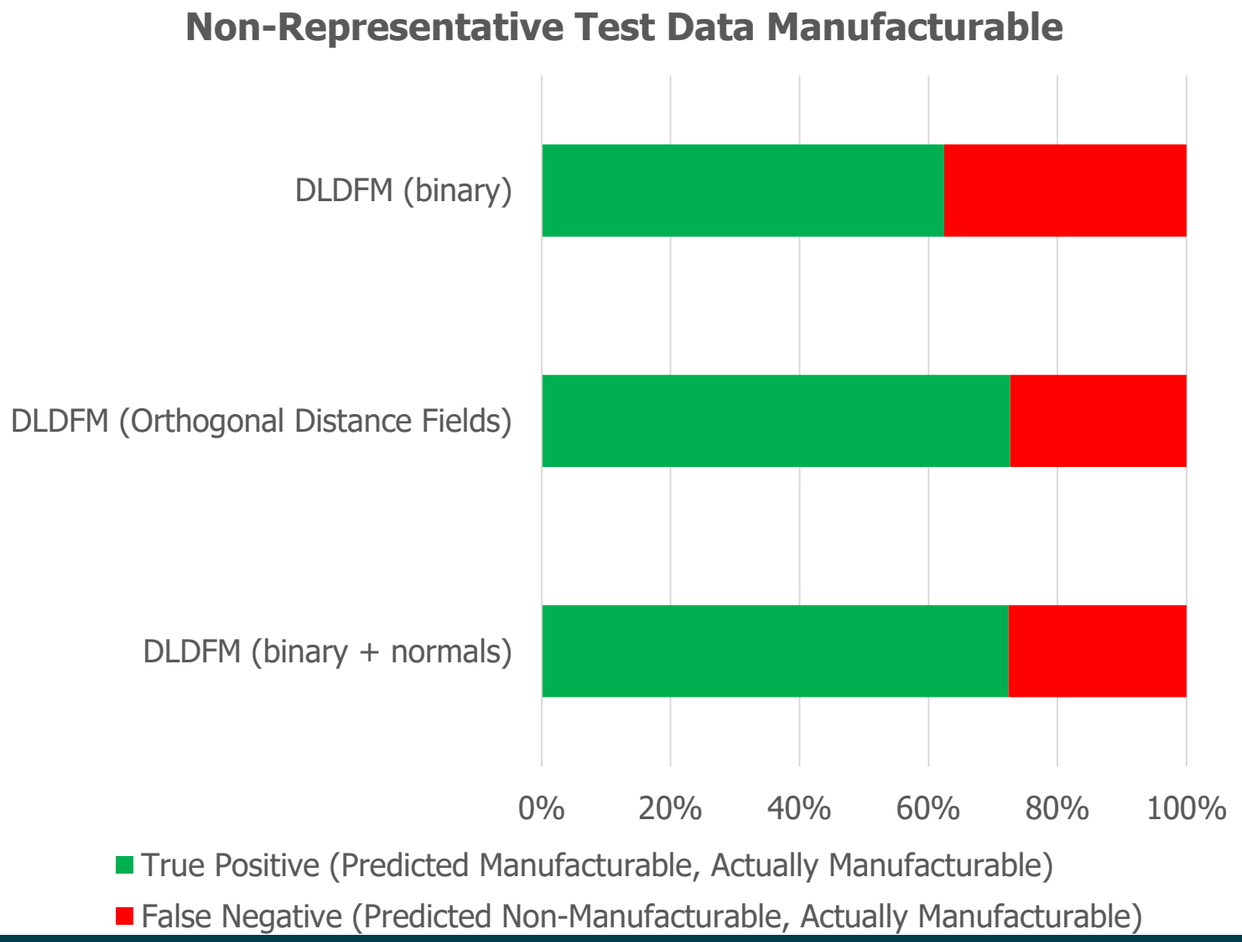
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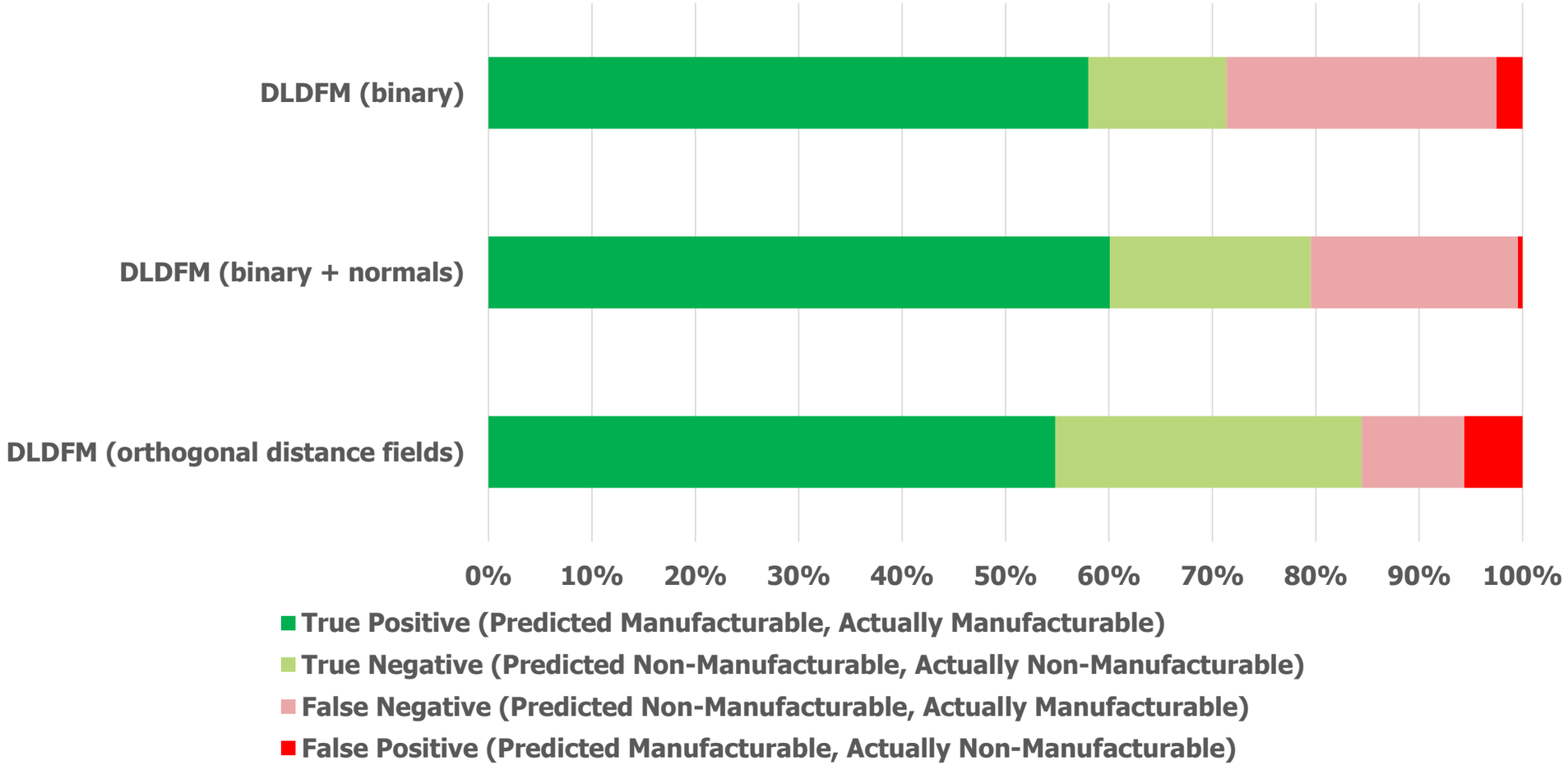
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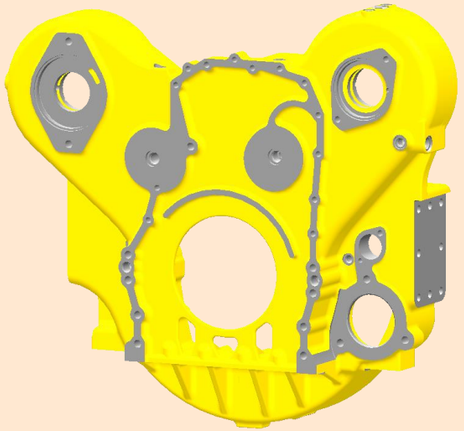
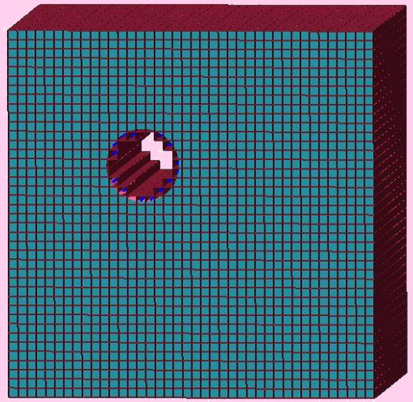


Design for Manufacturing



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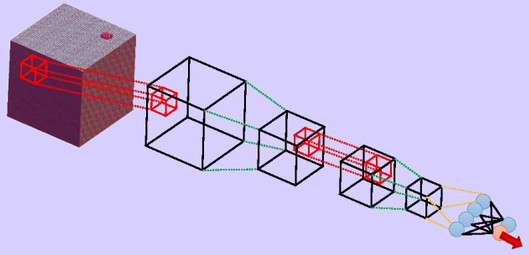
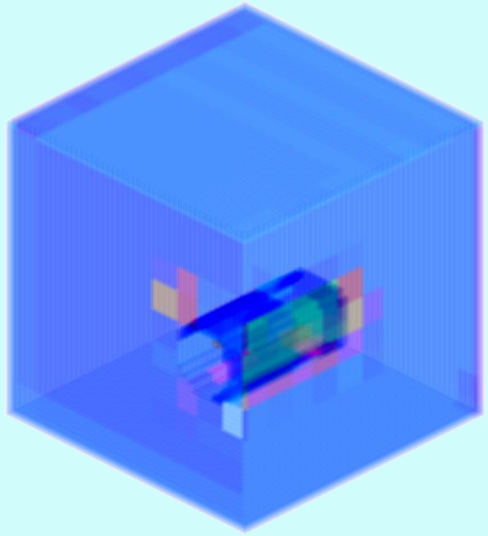


Deep Learning based Design for Manufacturing



Explainable Deep Learning

Model Interpretability

- Possible methods
  - Back-propagation
  - Guided back-propagation, saliency map, etc.

  Disadvantage: Not class discriminative
  - Grad-CAM
    - Class discriminative

References:

[1]. Zeiler, Matthew D., and Rob Fergus. "Visualizing and understanding convolutional networks." *European conference on computer vision*. Springer International Publishing, 2014.

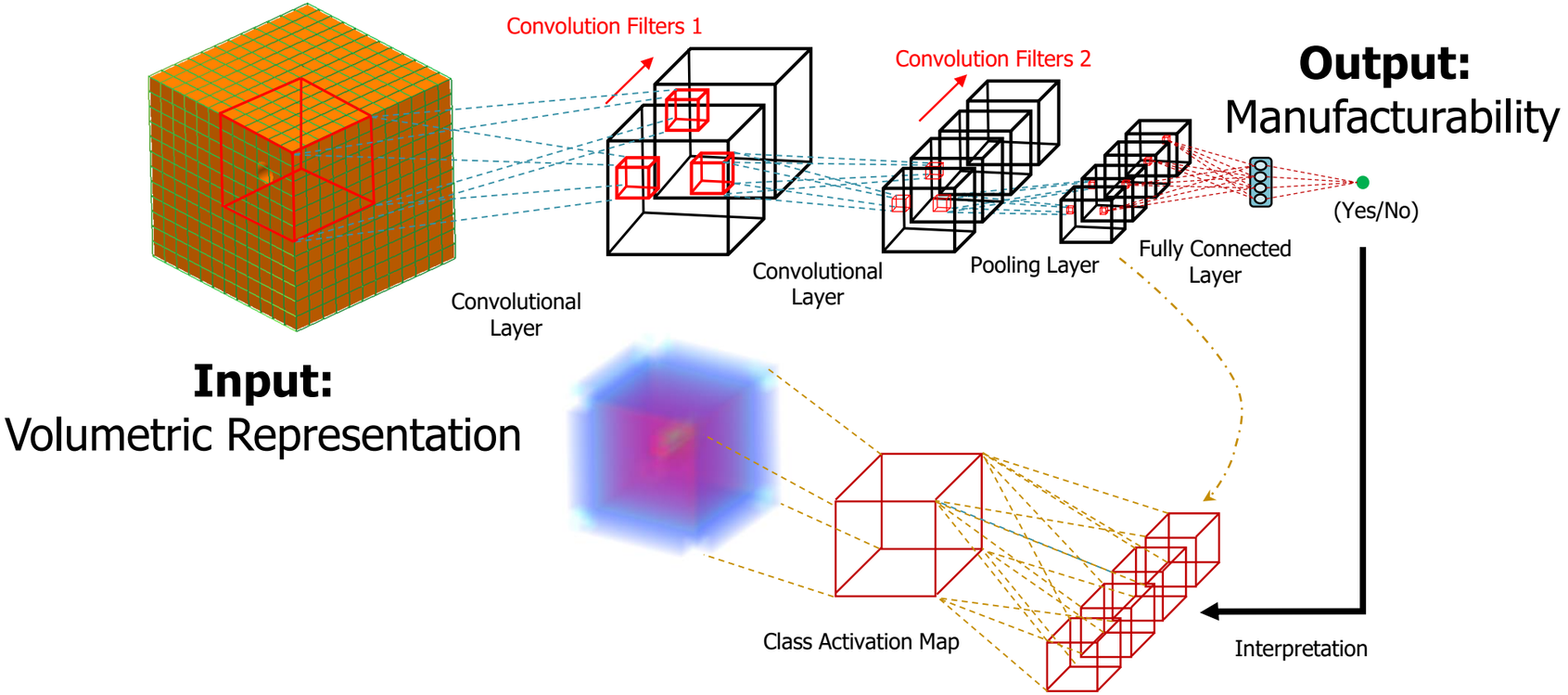
[2]. Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." *arXiv preprint arXiv:1409.1556* (2014).

[3]. Zhou, Bolei, et al. "Learning deep features for discriminative localization." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2016.

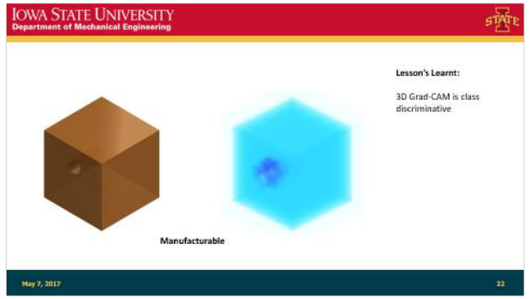
[4]. Selvaraju, Ramprasaath R., et al. "Grad-CAM: Why did you say that?." arXiv preprint arXiv:1611.07450 (2016).

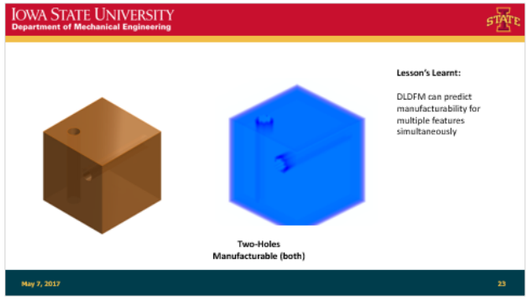
3D Grad-CAM

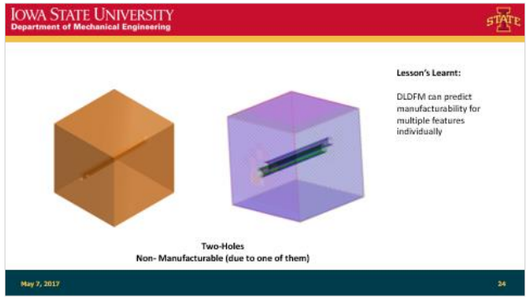
- Perform global average pooling and back-propagate the activations

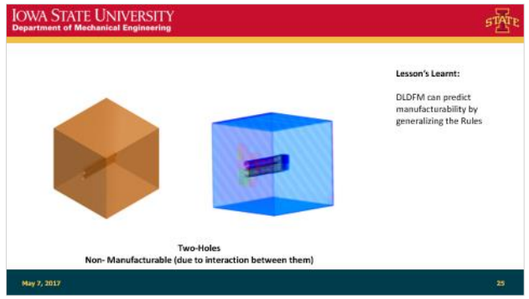


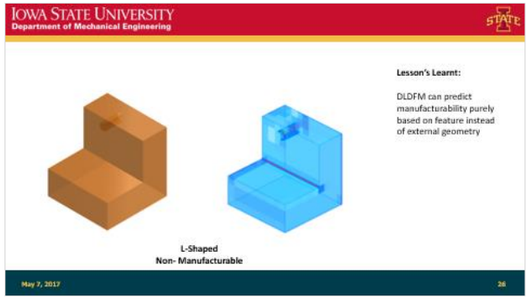
Insights from GradCAM

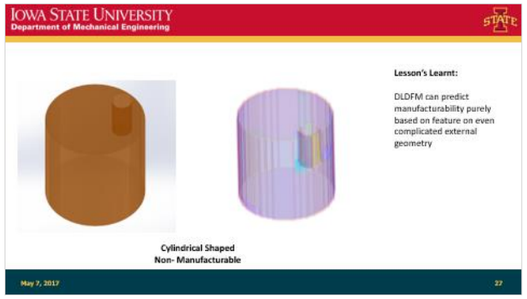


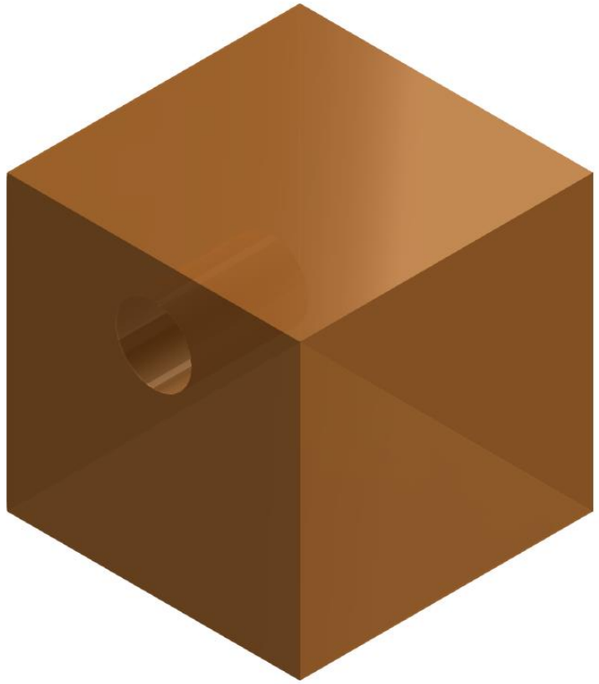


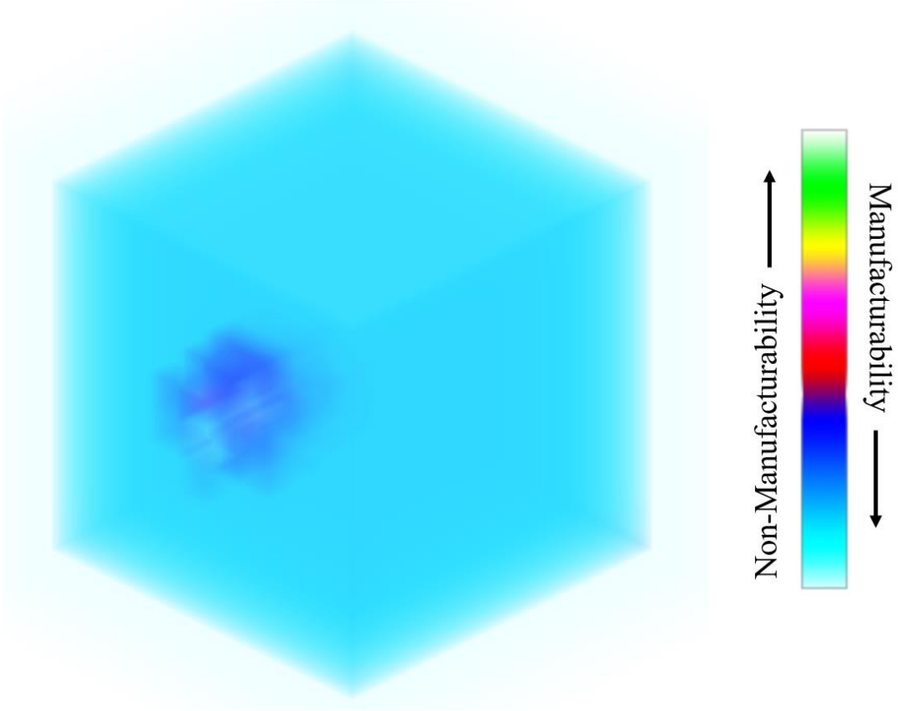








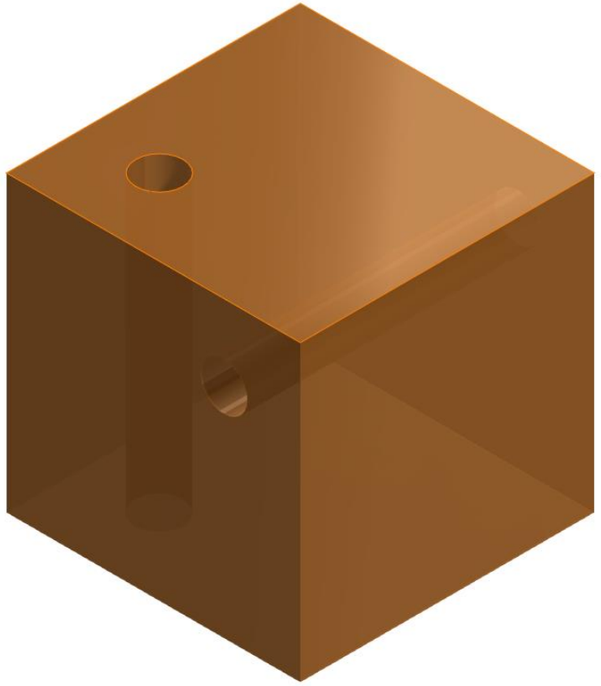


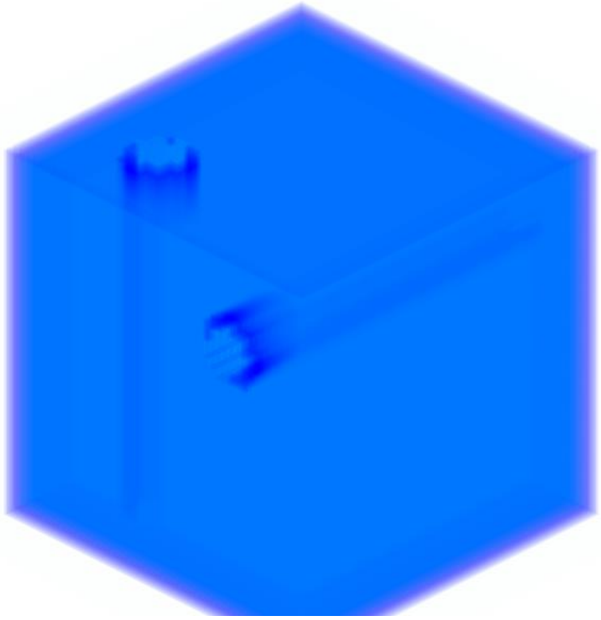


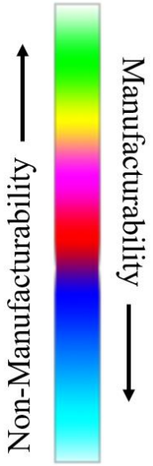
One Hole Manufacturable

Insight:

3D Grad-CAM is class discriminative



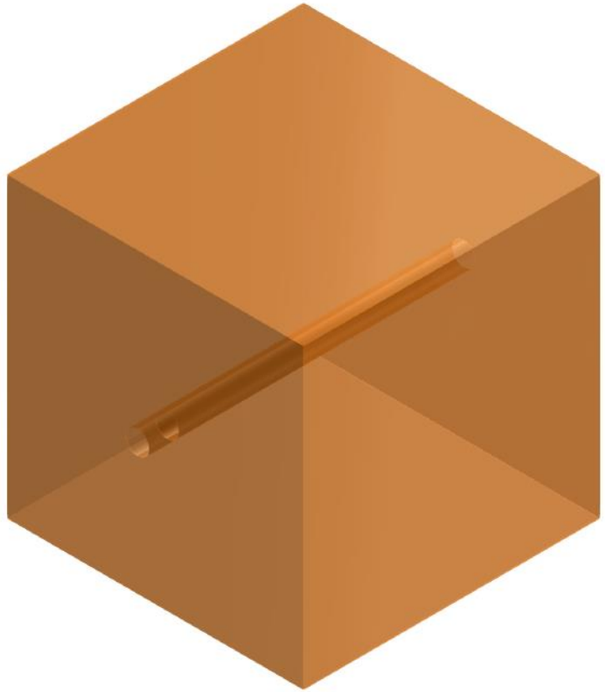


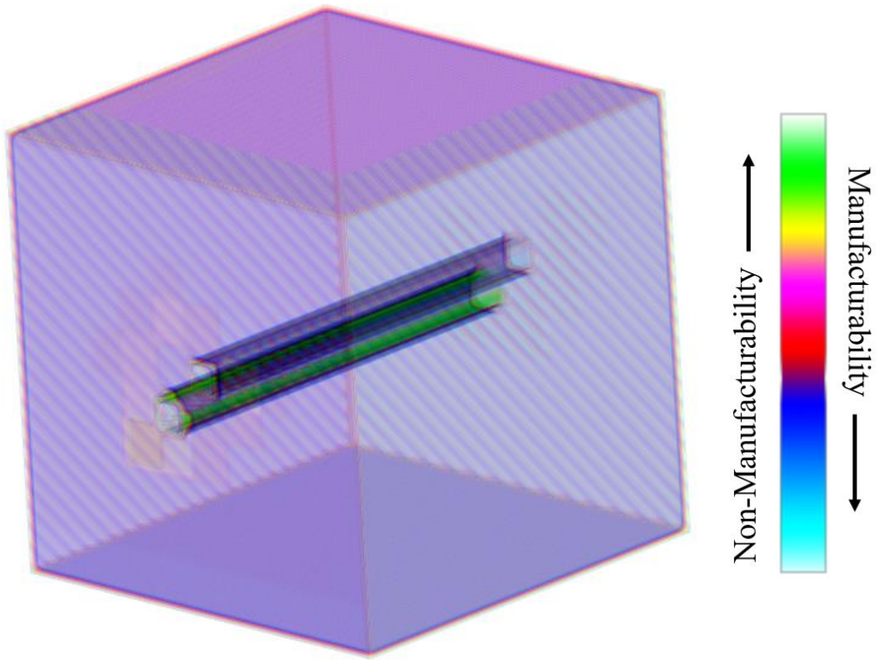


Two Holes
Manufacturable (both)

Insight:

DLDFM can predict manufacturability of multiple features simultaneously

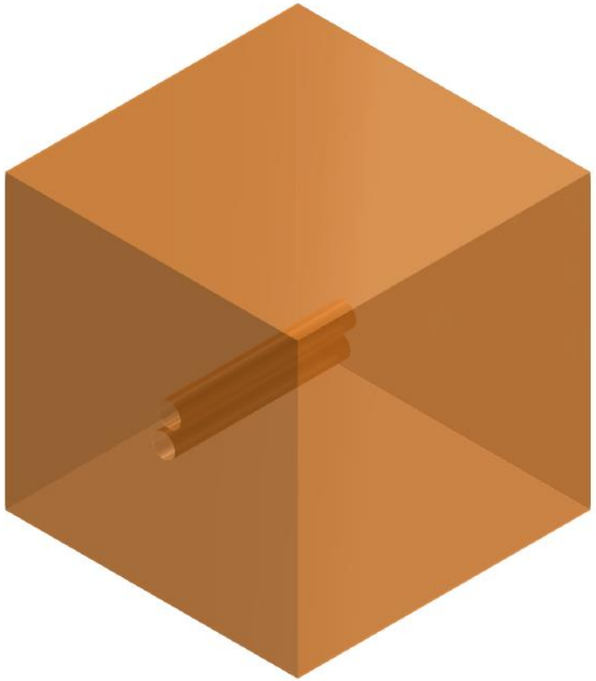


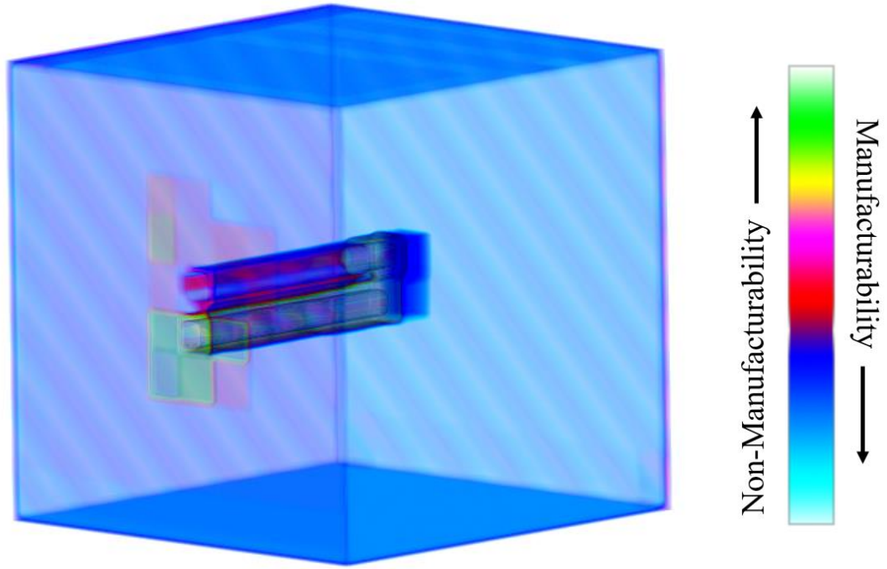


Two Holes
Non-Manufacturable (due to one of them)

Insight:

DLDFM can predict manufacturability of individual features

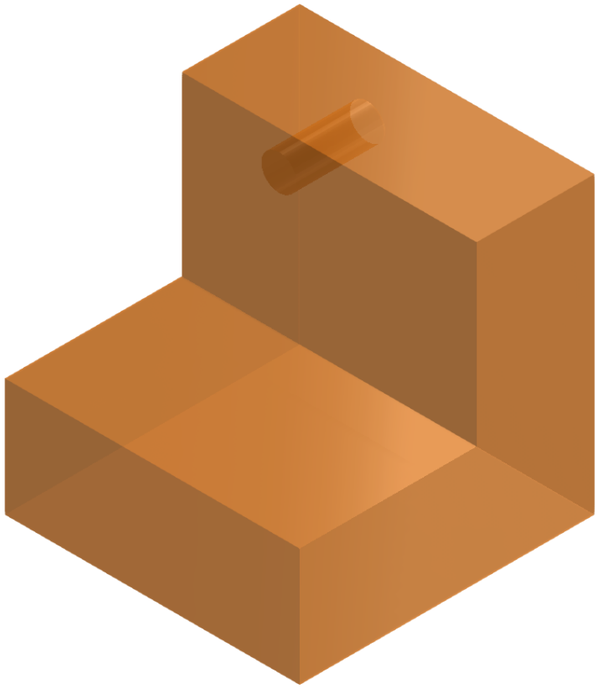


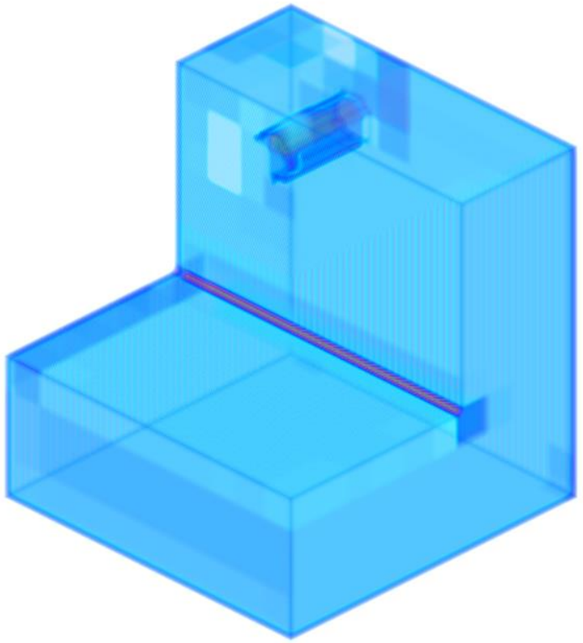


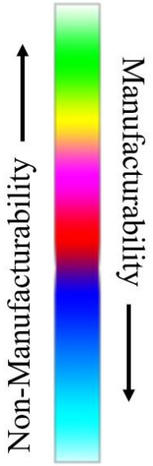
Two Holes
Non-Manufacturable (due to interaction between them)

Insight:

DLDFM can predict manufacturability of interacting features by generalizing the rules



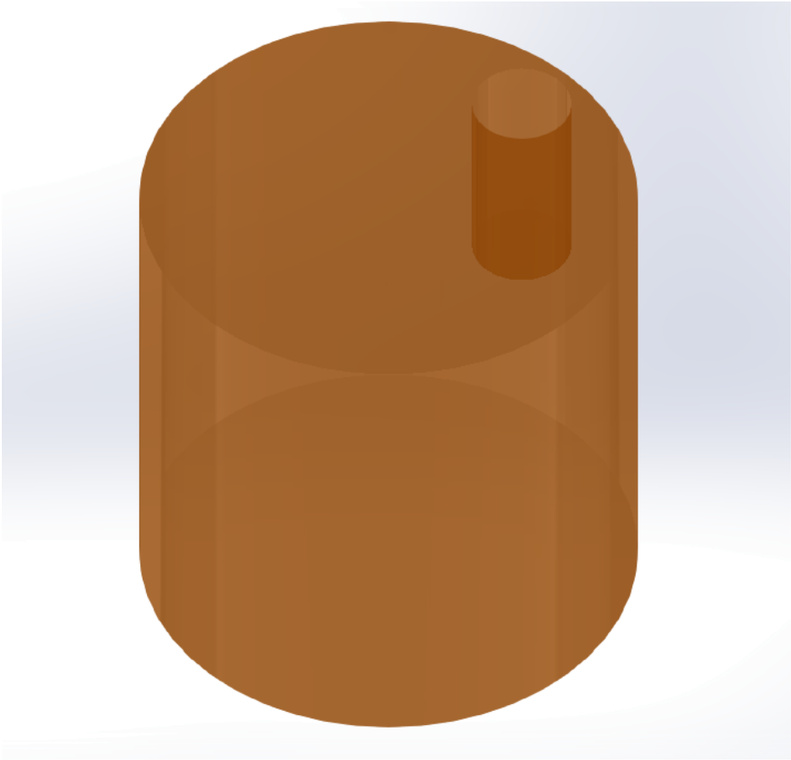


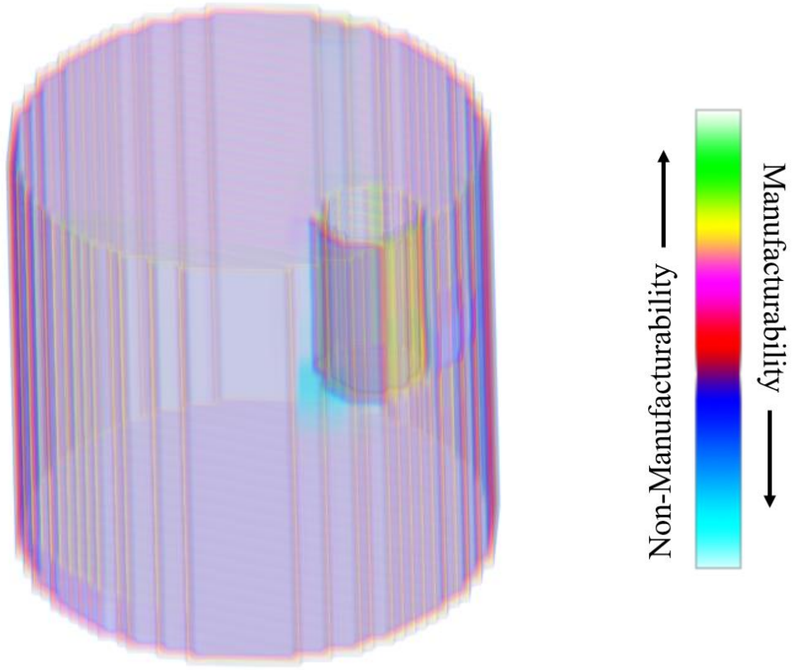


L-Shaped Block with Hole
Non-Manufacturable (close to external face)

Insight:

DLDFM can predict manufacturability based on a local feature instead of external geometry



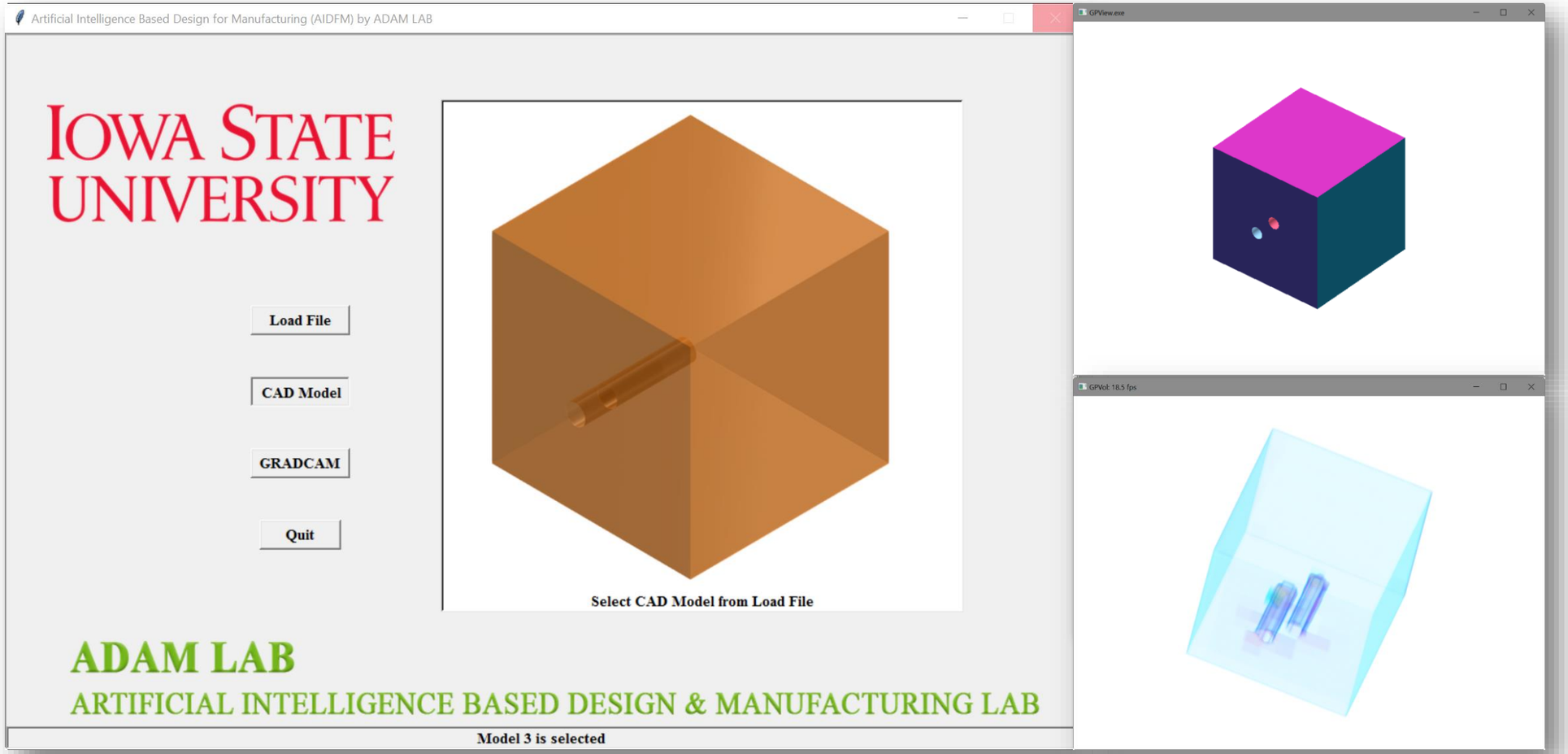


Insight:

DLDFM can predict manufacturability based on a local feature even with complicated external geometry

Cylindrical-Shaped Block with Hole
Non- Manufacturable (close to external cylindrical face)

Demo


Artificial Intelligence Based Design for Manufacturing (AIDFM) by ADAM LAB
IOWA STATE UNIVERSITY
Load File
CAD Model
GRADCAM
Quit
Select CAD Model from Load File
ADAM LAB
ARTIFICIAL INTELLIGENCE BASED DESIGN & MANUFACTURING LAB
Model 3 is selected
GPView.exe
GPVol: 18.5 fps

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  - Kin Gwn Lore

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    - CMMI:1644441 – CM: Machine-Learning Driven Decision Support in Design for Manufacturability
  - nVIDIA
    - Titan X GPU for Academic Research

Thank You!

Questions?