Geometrical Deep Learning on 3D Models: Classification for Additive Manufacturing

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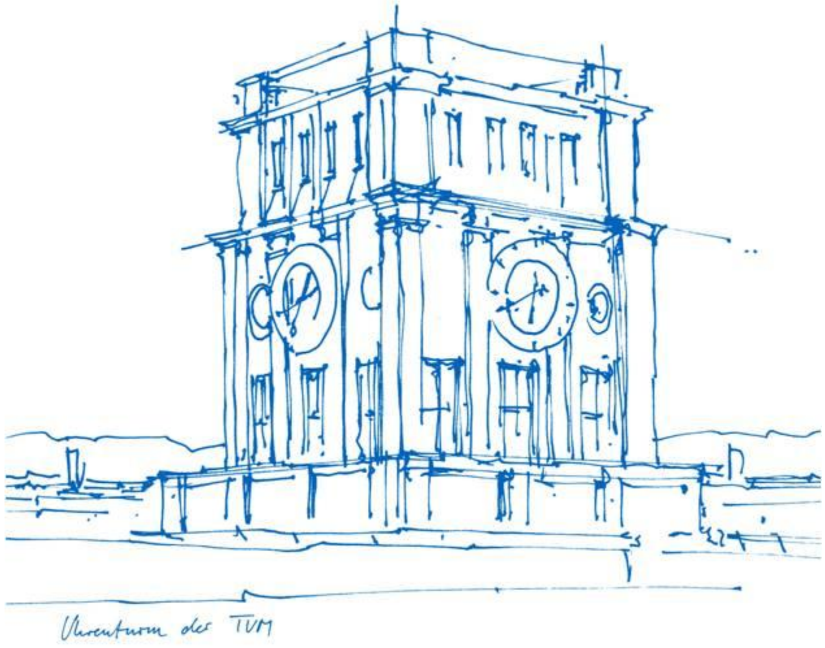


Motivation

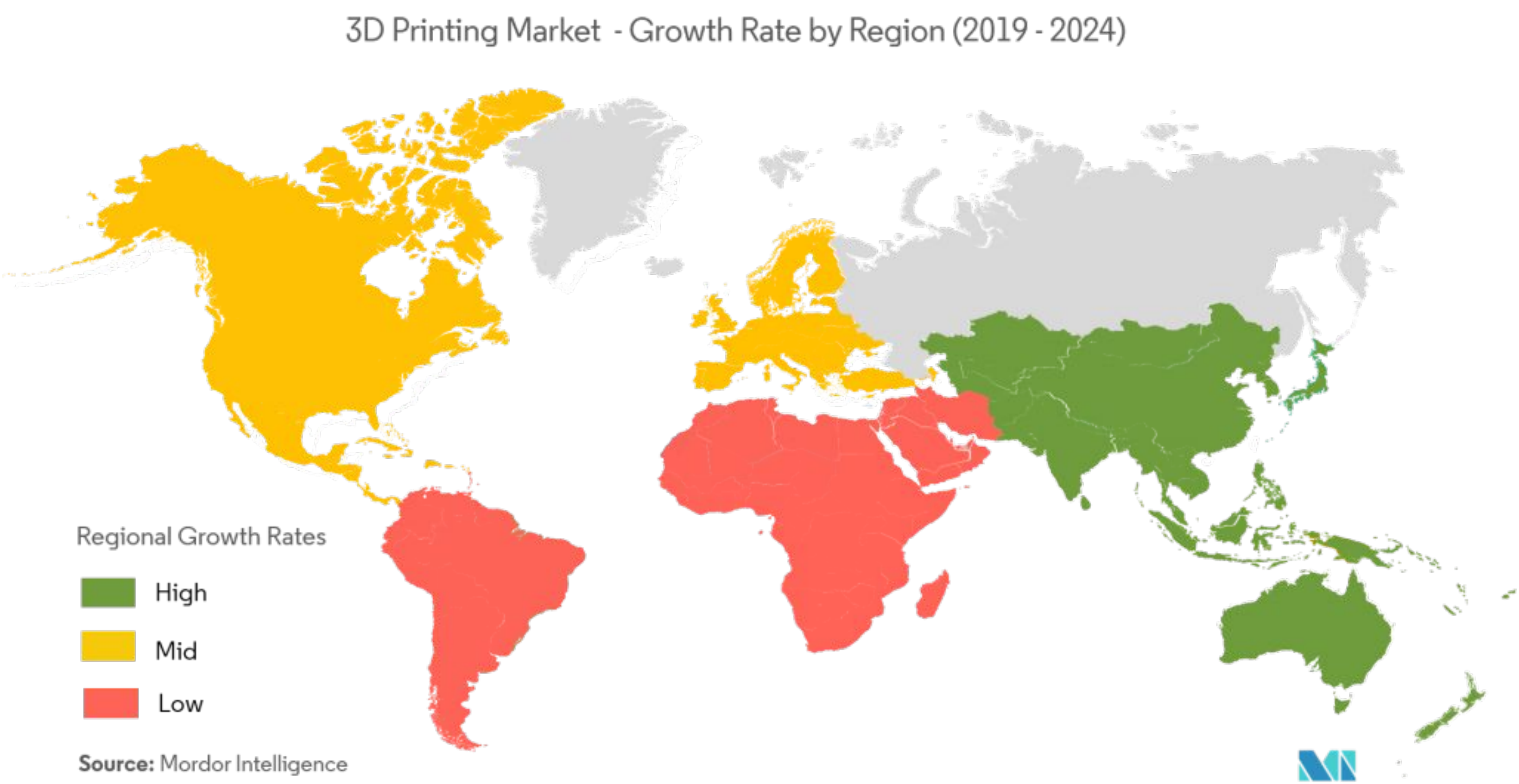
Hard to achieve the right balance:

Quality ⟷ Speed ⟷ Cost

Additive manufacturing here to transform production processes:

- create design iterations
- enhance quality through cost-effective prototyping
- create specific tooling parts

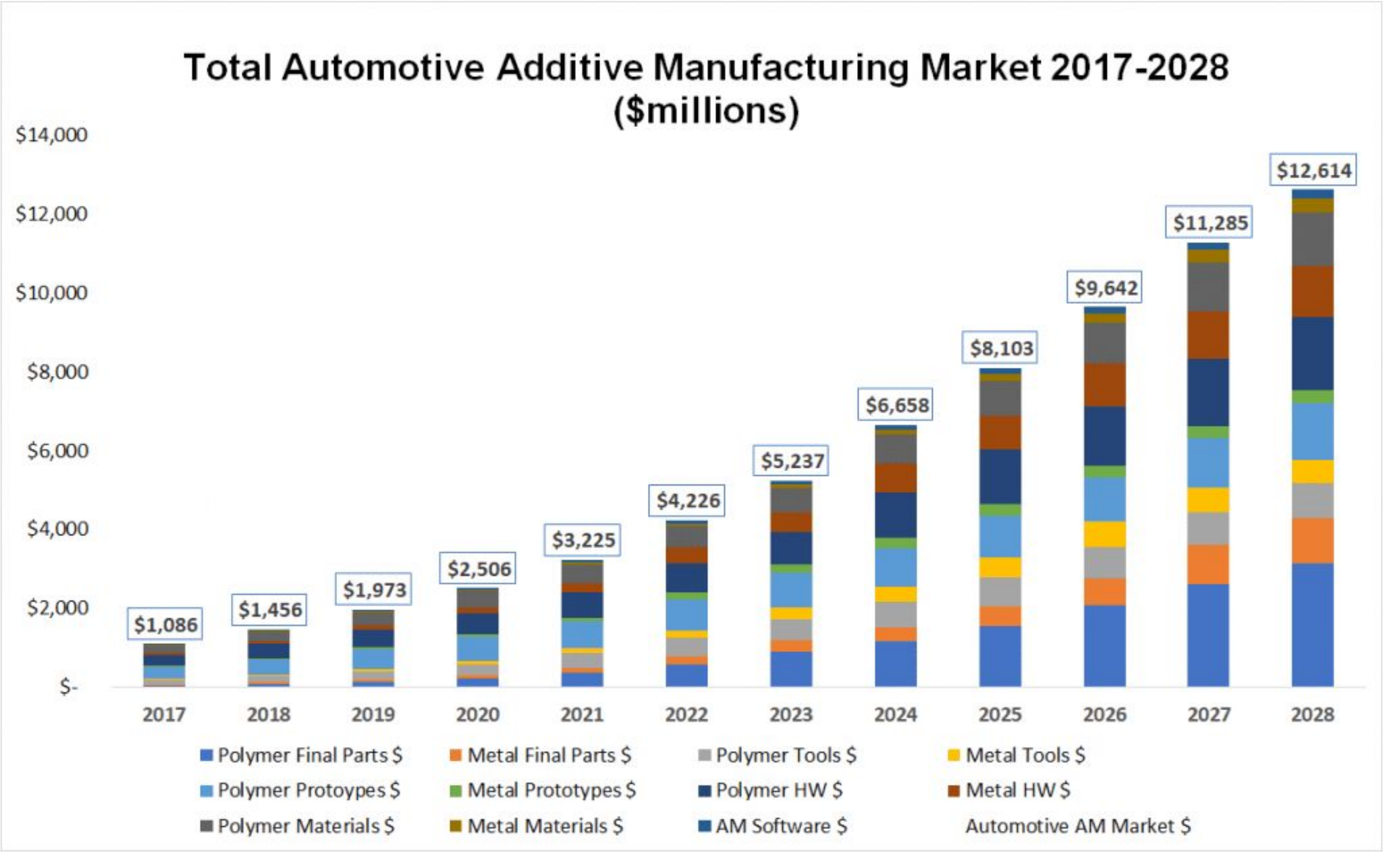
Motivation



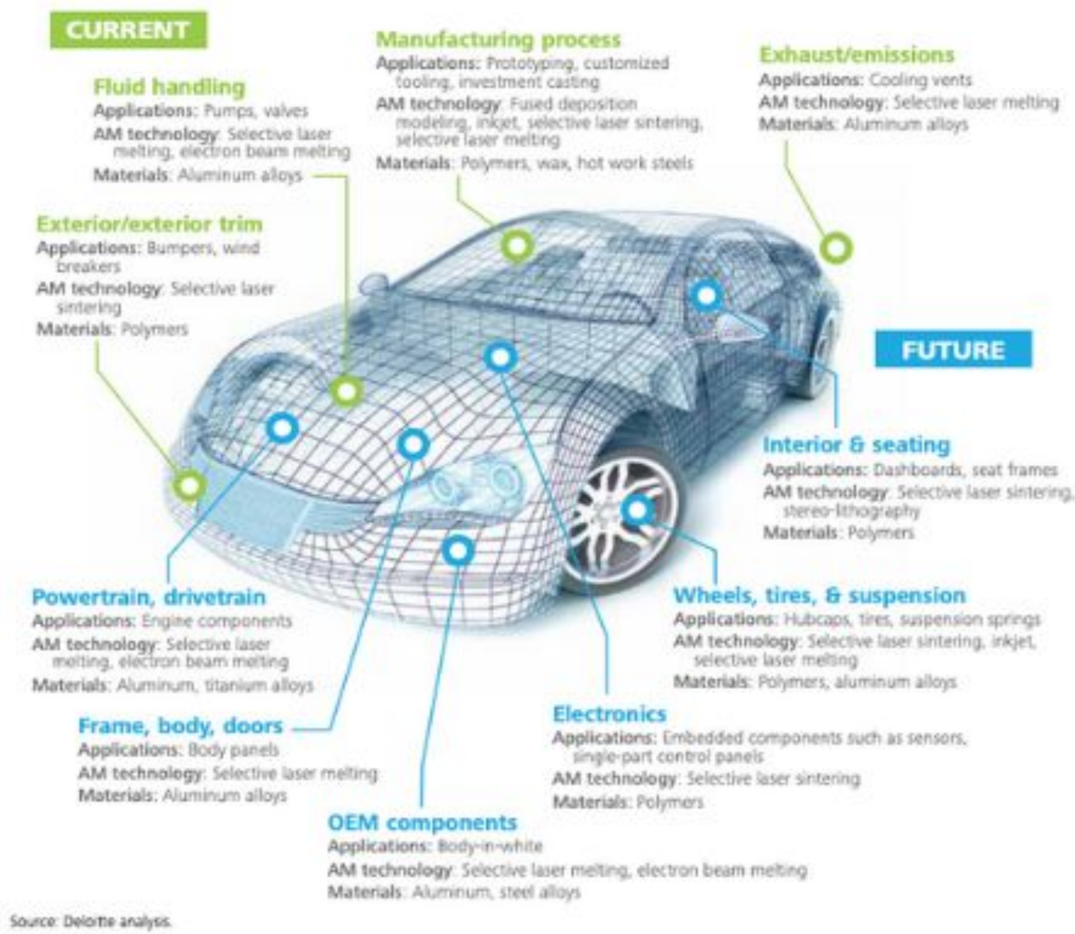
3D Printing Market - Growth Rate by Region (2019 - 2024)
Regional Growth Rates
High
Mid
Low
Source: Mordor Intelligence

Motivation

By 2028 AM industry revenues would hit **$12.6** Billion in the automotive Industry



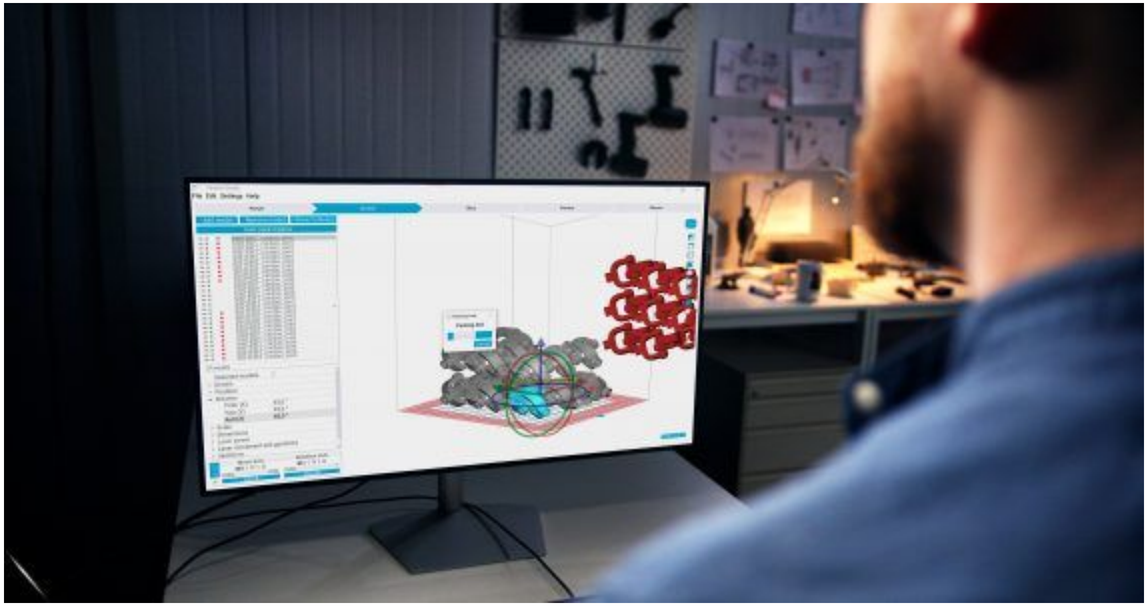
Motivation



Applications of AM in the automotive industry

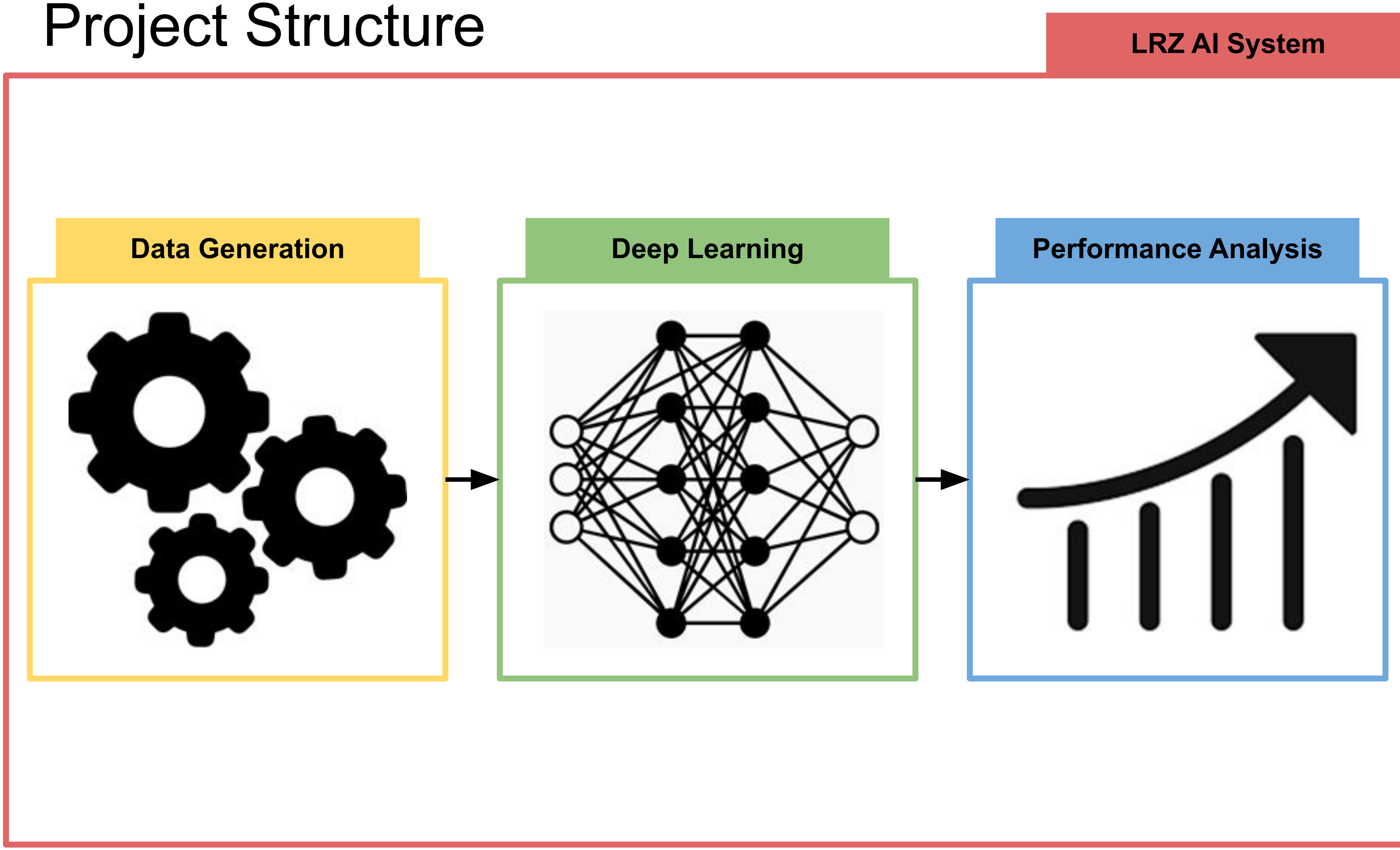
Problem Definition & Project Goal

Requires a lot of human expertise and supervision.
In particular, the process of **identifying whether a 3D model is manufacturable by a given 3D printer** is a **very time-consuming** and **complex task.**

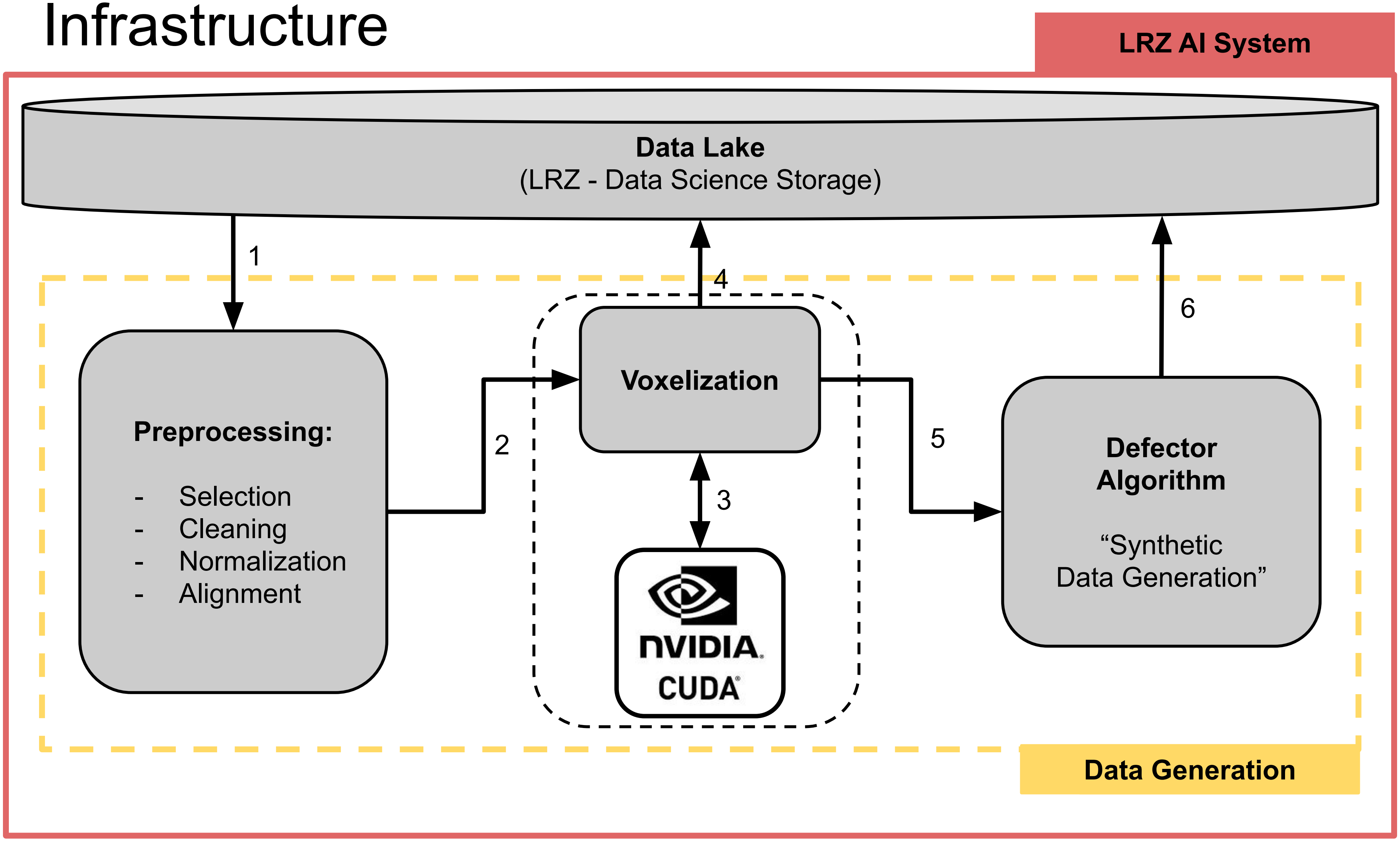


Automate this process using advanced **convolutional neural networks** (CNNs)

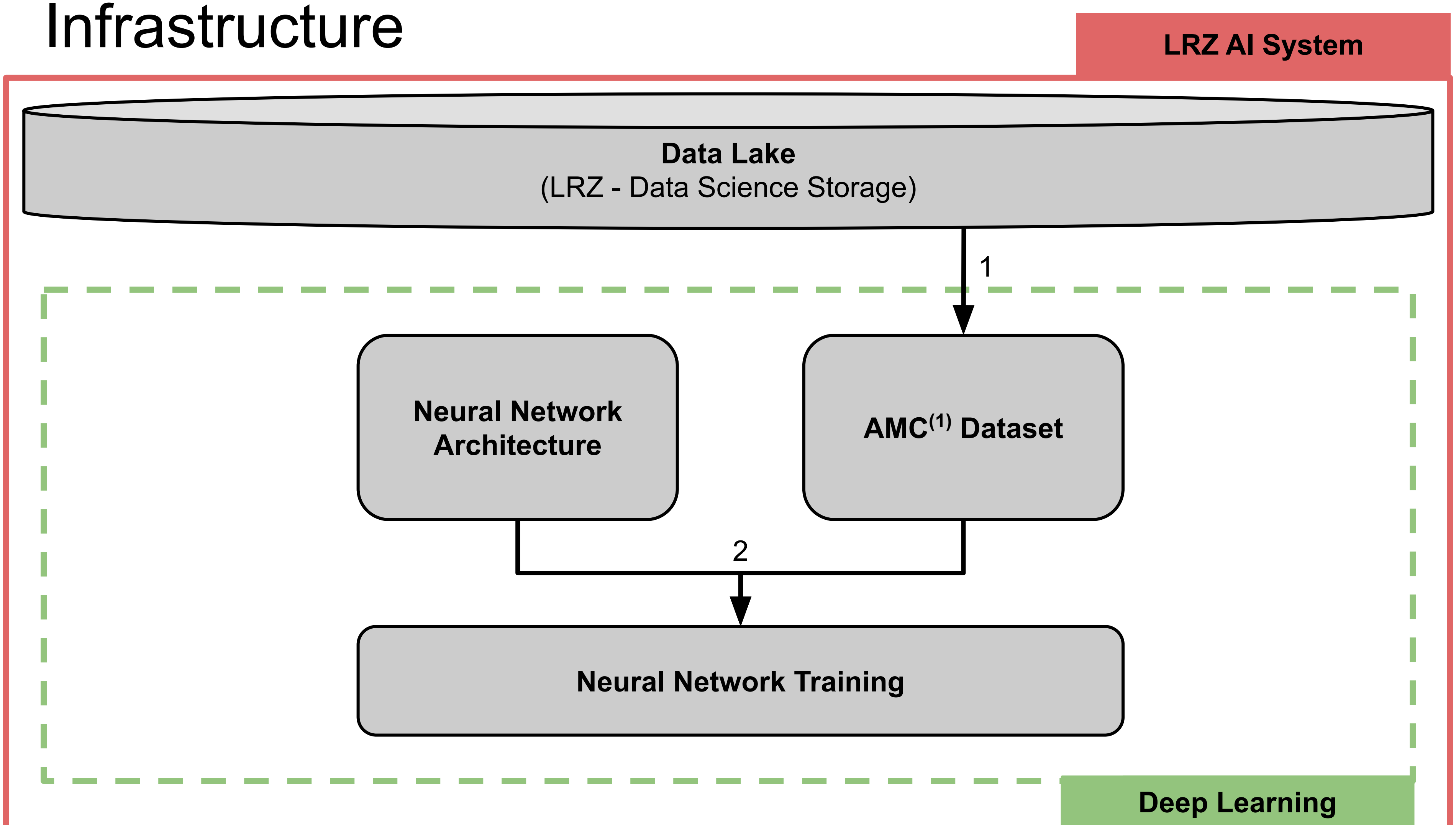
Project Structure



Infrastructure

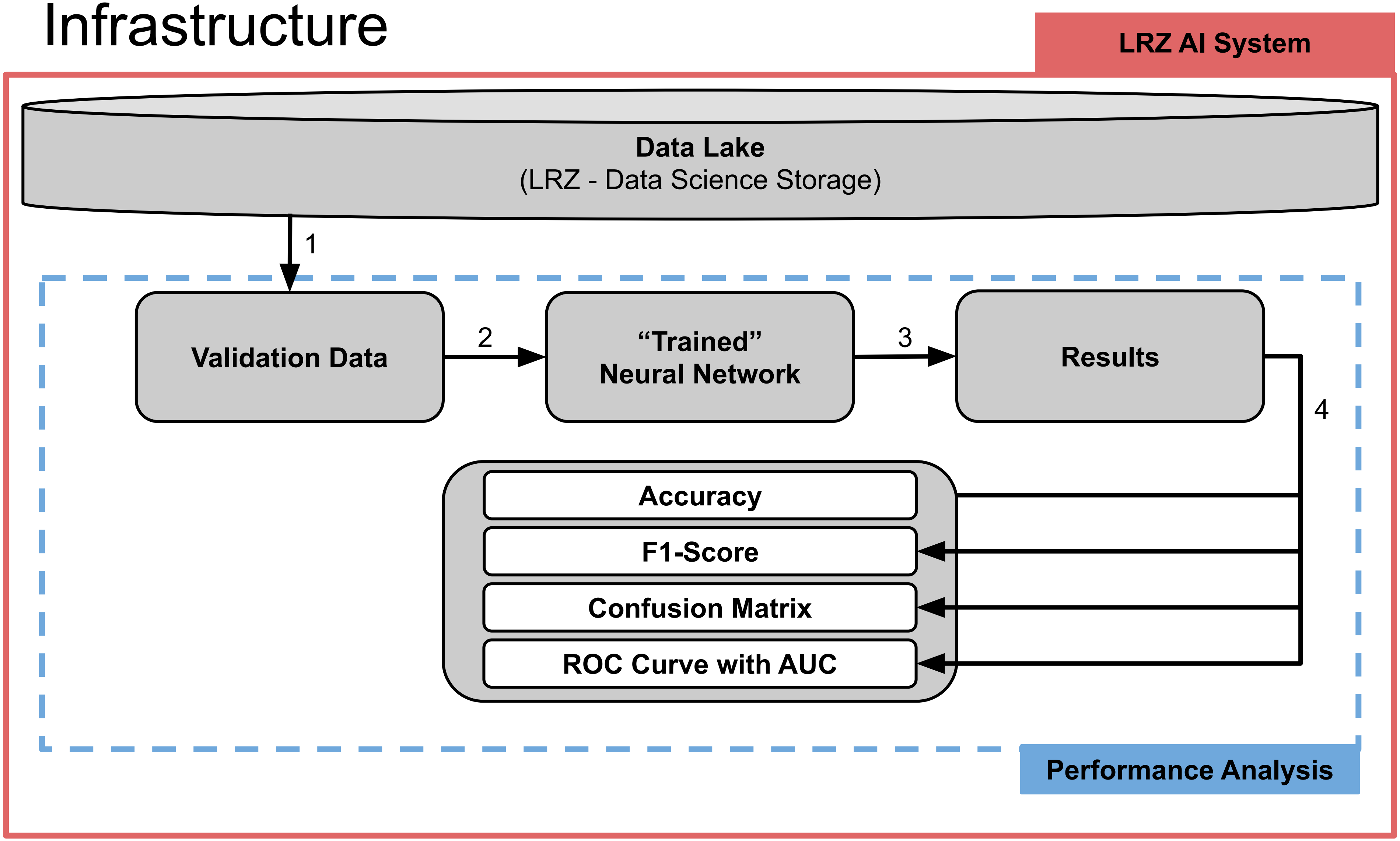


Infrastructure

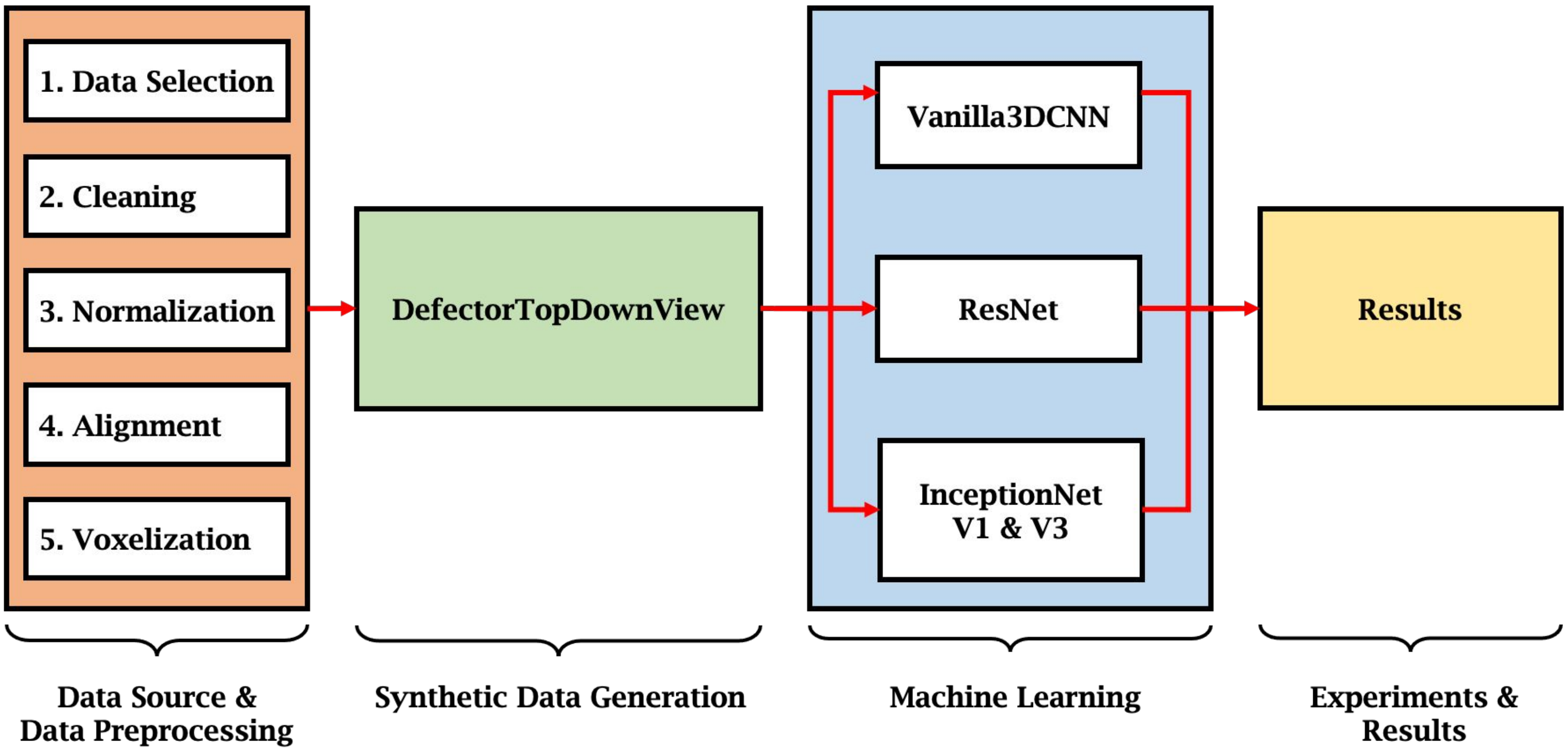


(1) AMC: Additive Manufacturing Classification

Infrastructure

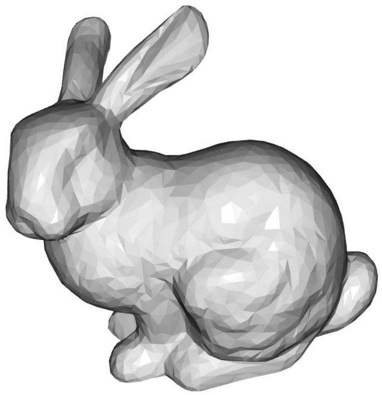


Holistic Project Overview

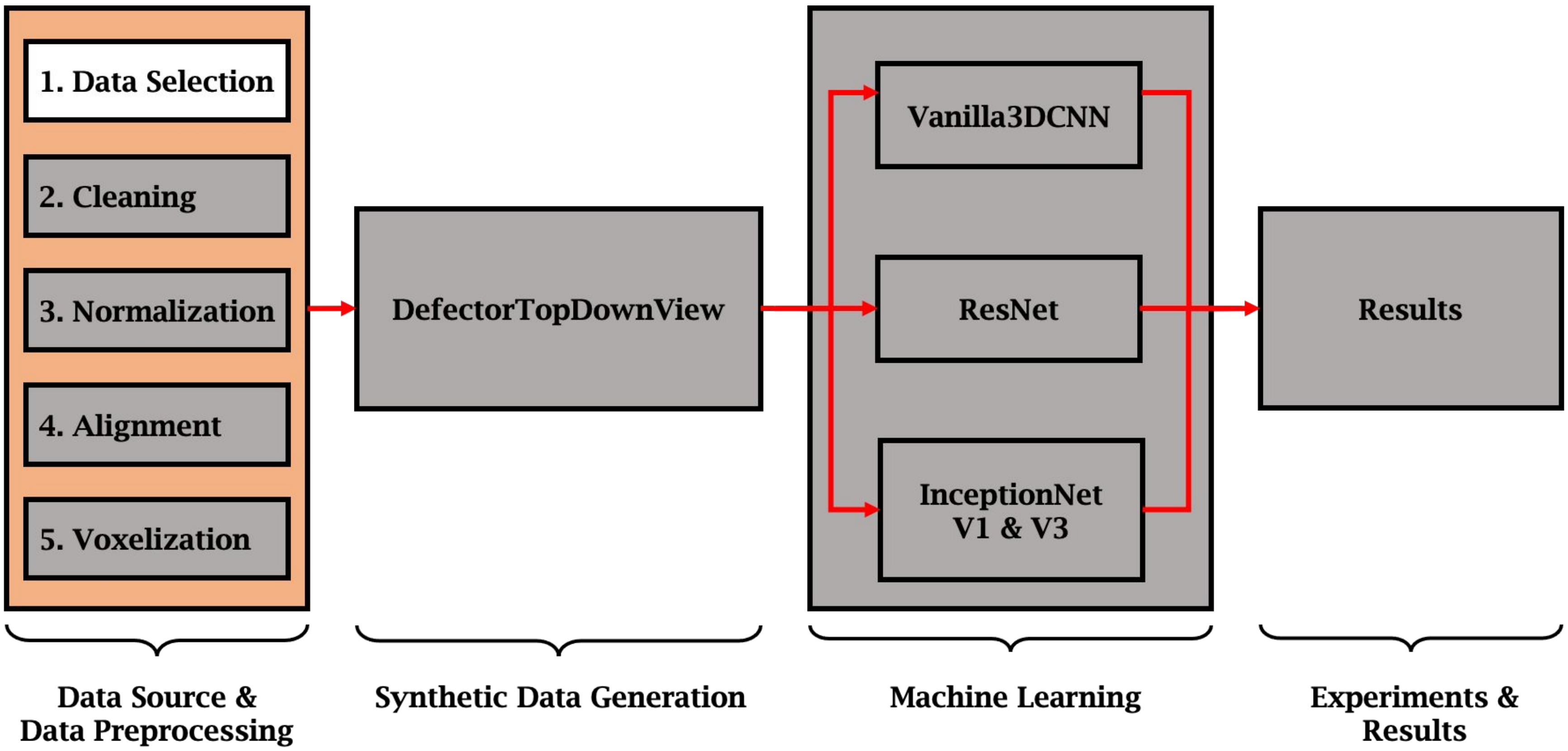


Data Format: Triangular Mesh

- A triangular mesh is a data representation of 3D objects.
- It consists of two main data structures: **Vertices** and **Triangles**.
- **Vertices** is a list of 3D points.
- **Triangles** is a list of triangles, where a triangle connects 3 vertices.



Triangular Mesh Representation


1. Data Selection
2. Cleaning
3. Normalization
4. Alignment
5. Voxelization
DefectorTopDownView
Vanilla3DCNN
ResNet
InceptionNet V1 & V3
Results
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Synthetic Data Generation
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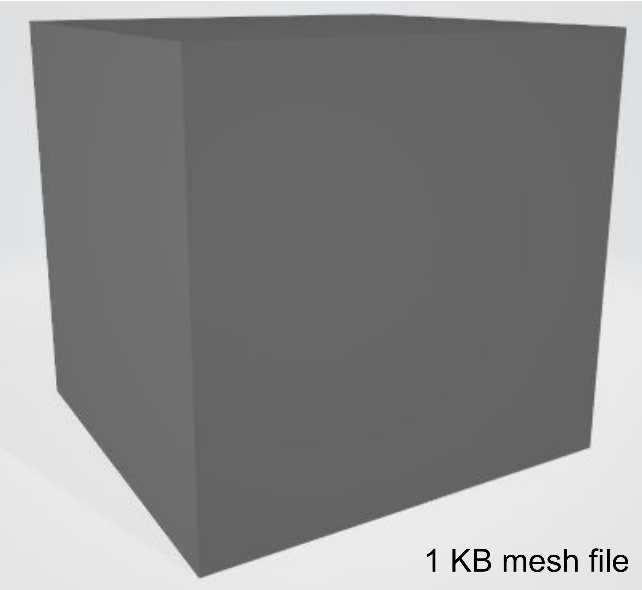
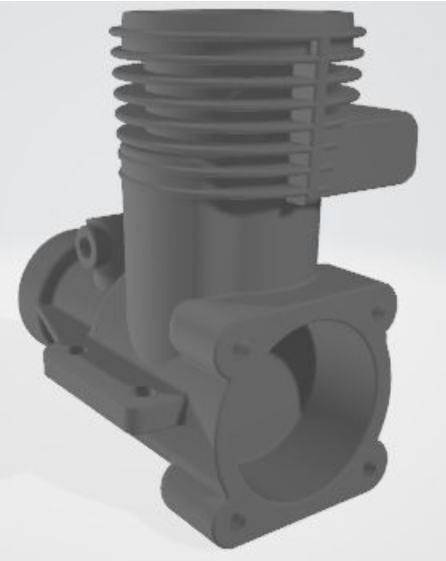
Data Selection

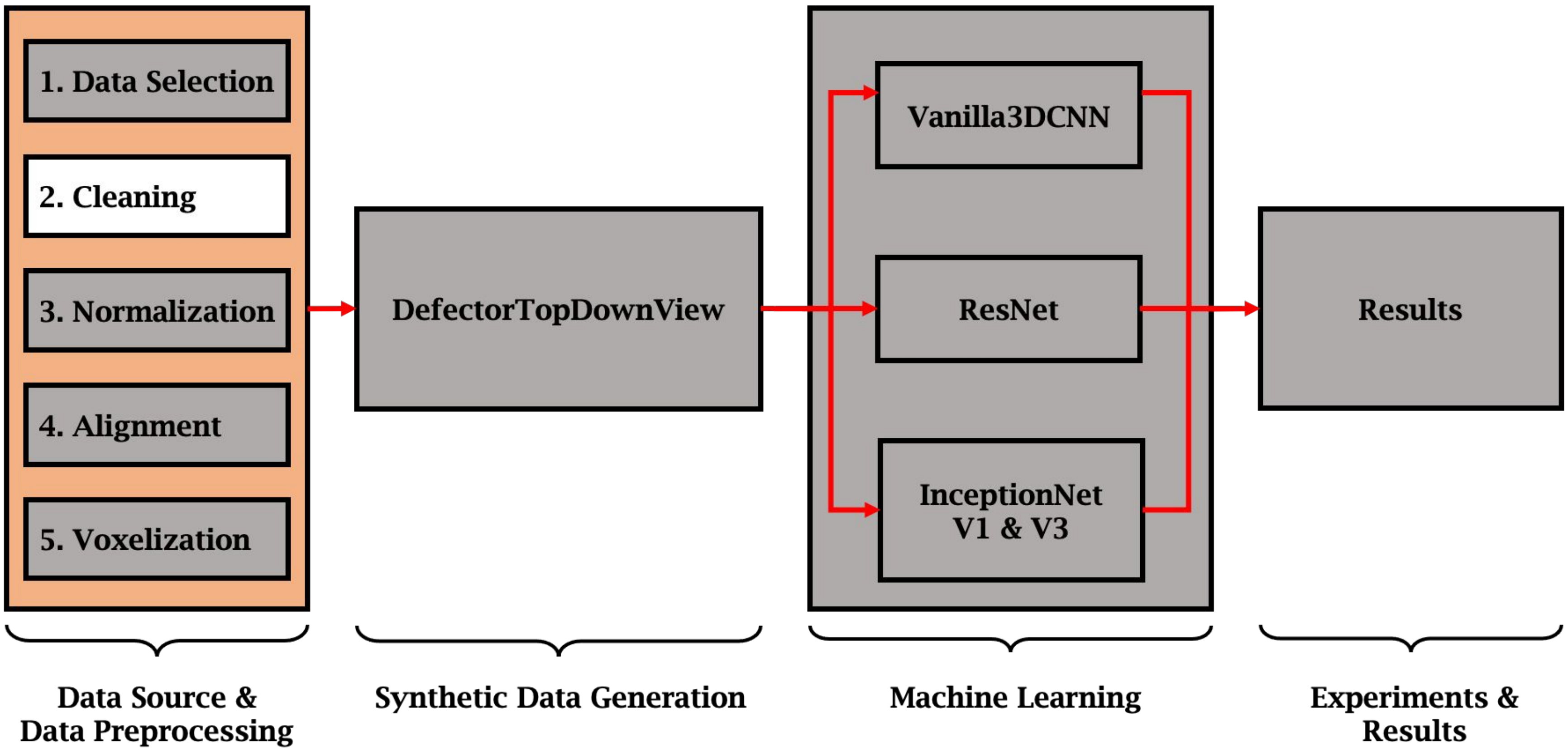
- dataset contains models of varying complexity
- more triangles are needed in meshes of higher complexity
- more triangles translated to bigger file size
- we applied a cutoff value of 25 KB to select models considered for further preprocessing steps



1 KB mesh file



32 MB mesh file



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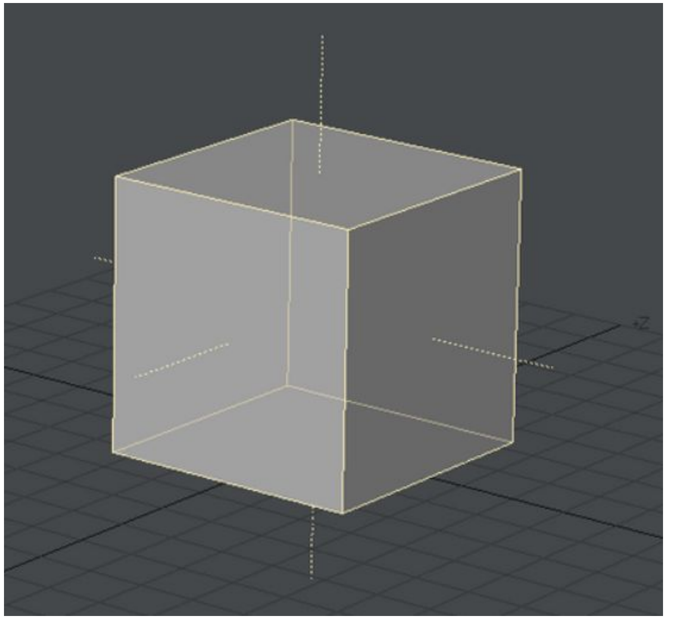
Cleaning

- For a 3D mesh to be 3D-printable, 2 main properties should be satisfied:
  - 1. **Watertightness**: mesh has no holes + normals are facing outwards

Stanford Bunny Model Bottom View
Invalid: has holes

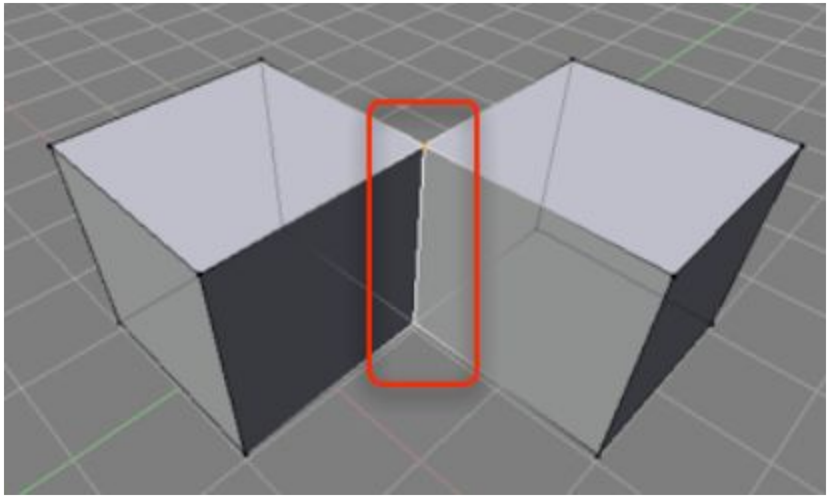


Valid: normals are facing outwards

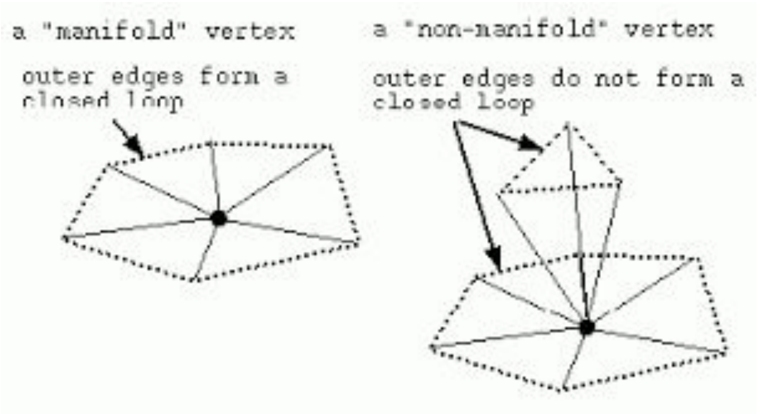
https://support.shapeways.com/hc/en-us/articles/360007107674-Tips-for-successful-modeling

Cleaning

- For a 3D mesh to be 3D-printable, 2 main properties should be satisfied
  - 2. **Manifold geometry**: mesh has no edges shared by more than two faces



Invalid: edge shared by 4 faces

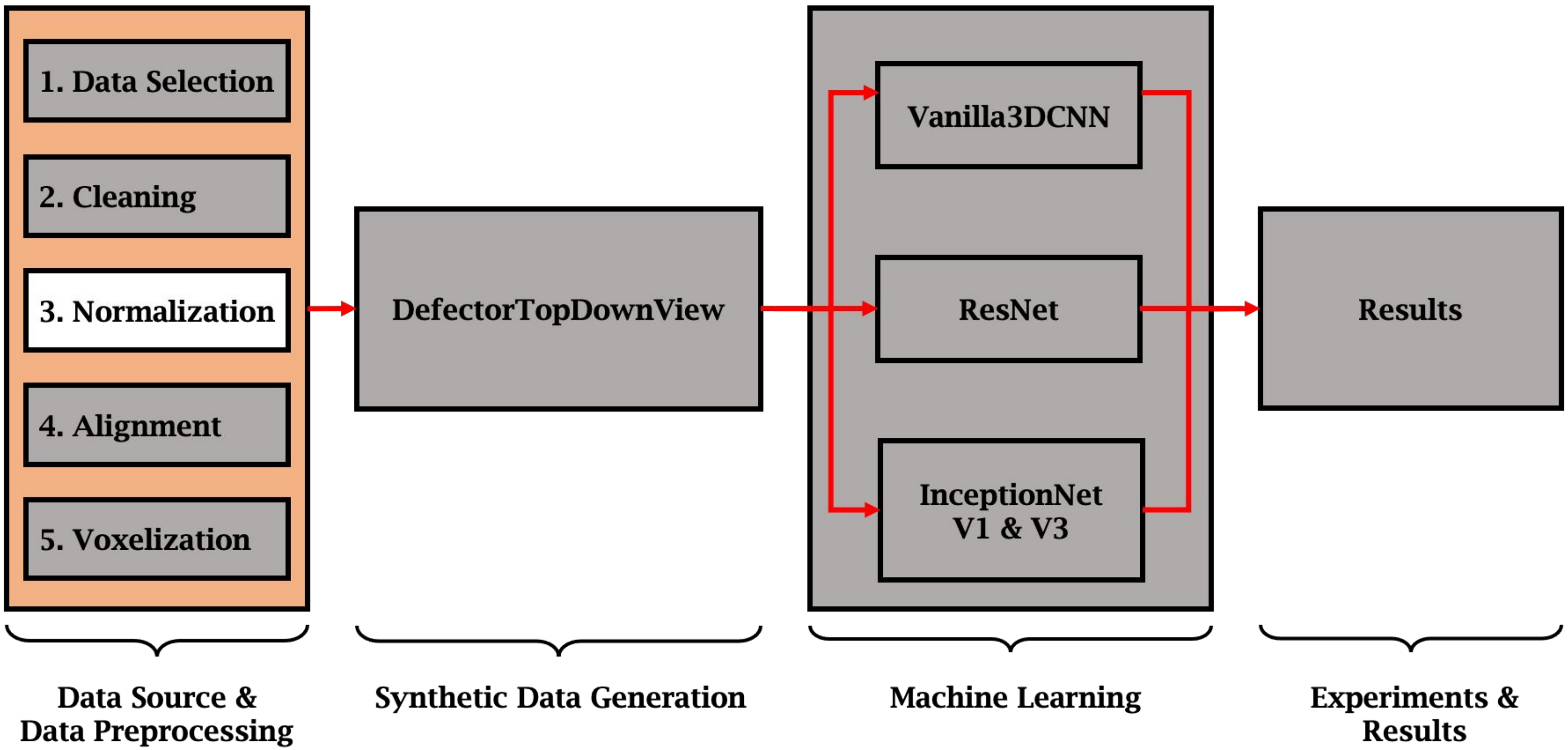


https://www.sculpteo.com/en/3d-learning-hub/create-3d-file/fix-non-manifold-geometry/

Cleaning

- Mesh cleaning functions were utilized from O3D. [1]
  - **Vertices fixes**
    - Remove vertices that have identical coordinates ([*x1*, *y1*, *z1*], [*x1*, *y1*, *z1*])
    - Remove vertices that are not referenced in any triangle
  - **Edges fixes**
    - Remove non-manifold edges
  - **Triangles fixes**
    - Remove triangles that reference the same three vertices ([*v1*, *v2*, *v3*], [*v2*, *v1*, *v3*])
    - Remove triangles that reference a single vertex multiple times in a single triangle ([*v1*, *v2*, *v2*])

[1] http://www.open3d.org/docs/release/index.html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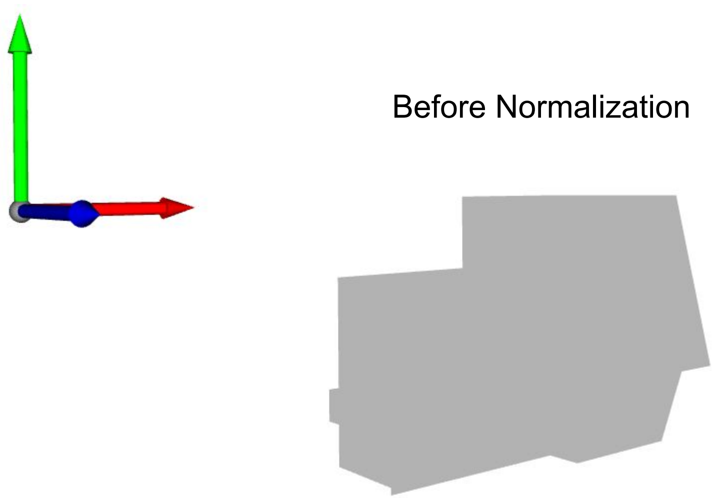
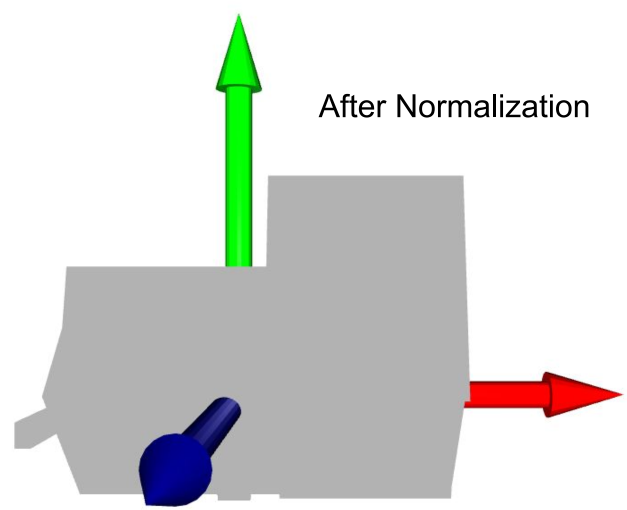
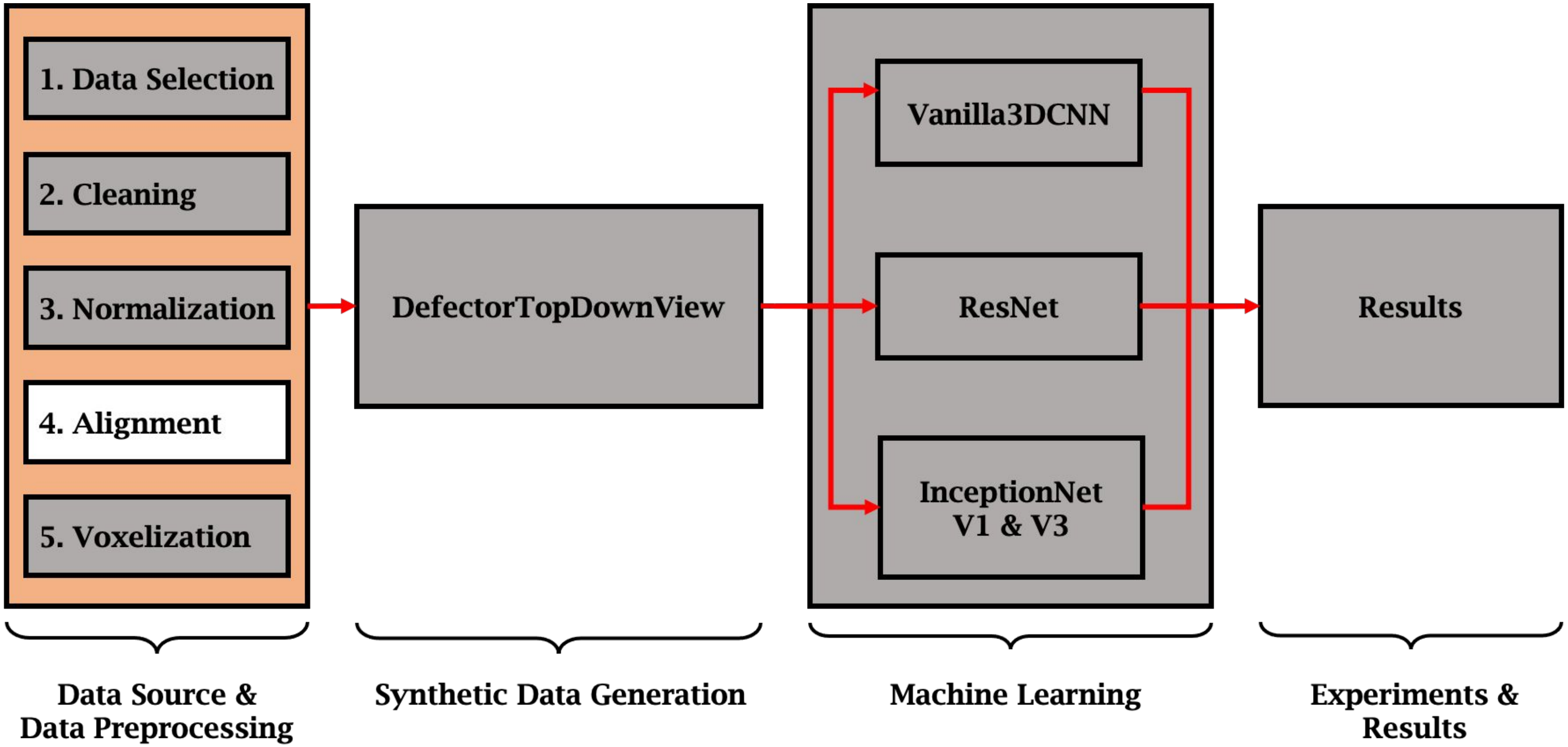
Normalization

- Performed to make sure all vertices of different objects lie in the same range
- **Step 1**: Center the mesh around the origin
  - Find the center of the mesh vertices
  - Translate the mesh vertices to the origin by subtracting the center from all vertices
- **Step 2**: Scale the vertices so that they lie in a [-1, 1] range
  - Divide the mesh vertices by the difference between the maximum bounding point and the minimum bounding point.


Before Normalization


After Normalization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Alignment

- Performed to make sure all meshes are presented in the same orientation.
- The axis of the minimum Moment Of Inertia (MOI) of a mesh represents the axis around which most of the mass of the object is wrapped. [1]
- Aligning the axis of the minimum MOI with one of the coordinate axes will allow meshes to be presented in the same orientation
- How its done [2] & [3]:
    - **Step 1**: Find the axis of the minimum MOI
    - **Step 2**: Compute a rotation matrix that aligns the axis of the minimum MOI with a coordinate axis
    - **Step 3**: Apply the rotation matrix on the mesh vertices

[1] James Dann and James J. Dann. The People's Physics Book. third edition, 2006.
[2] https://physics.stackexchange.com/questions/426273/how-to-find-the-axis-with-minimum-moment-of-inertia
[3] https://stackoverflow.com/questions/67017134/find-rotation-matrix-to-align-two-vectors

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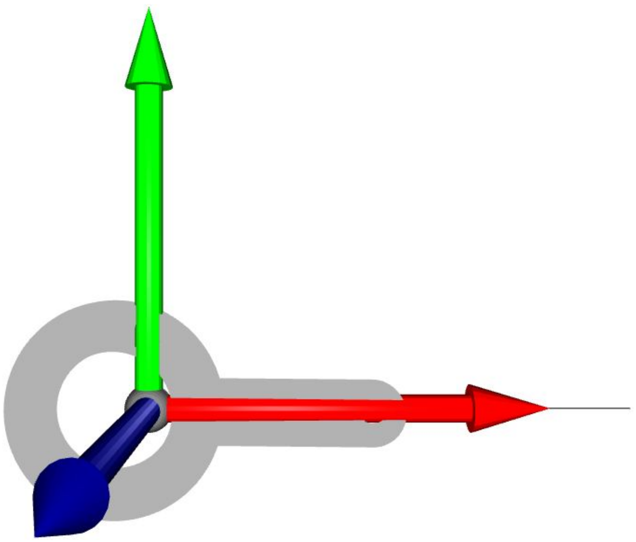
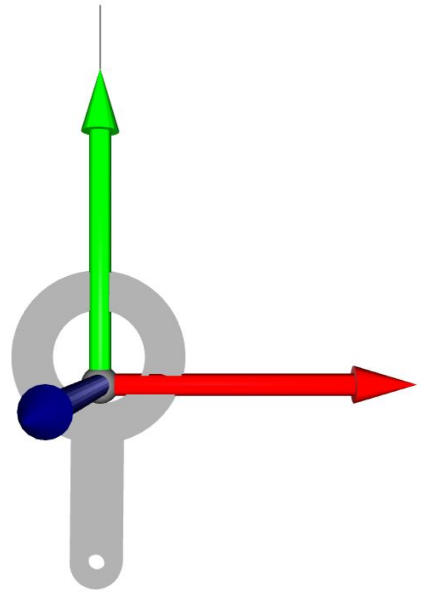
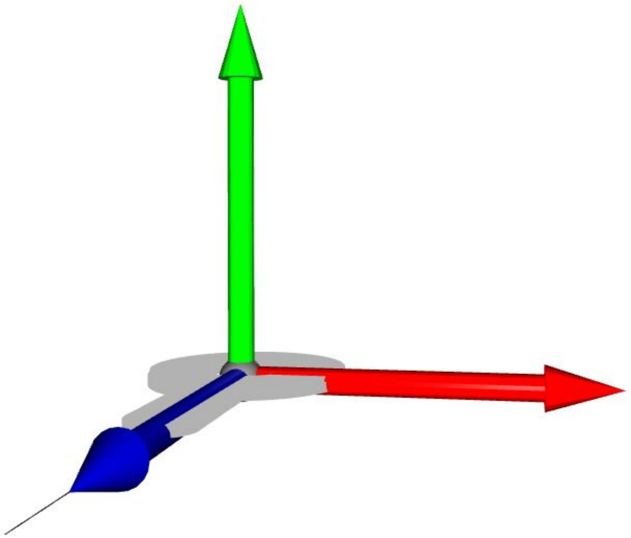
Alignment



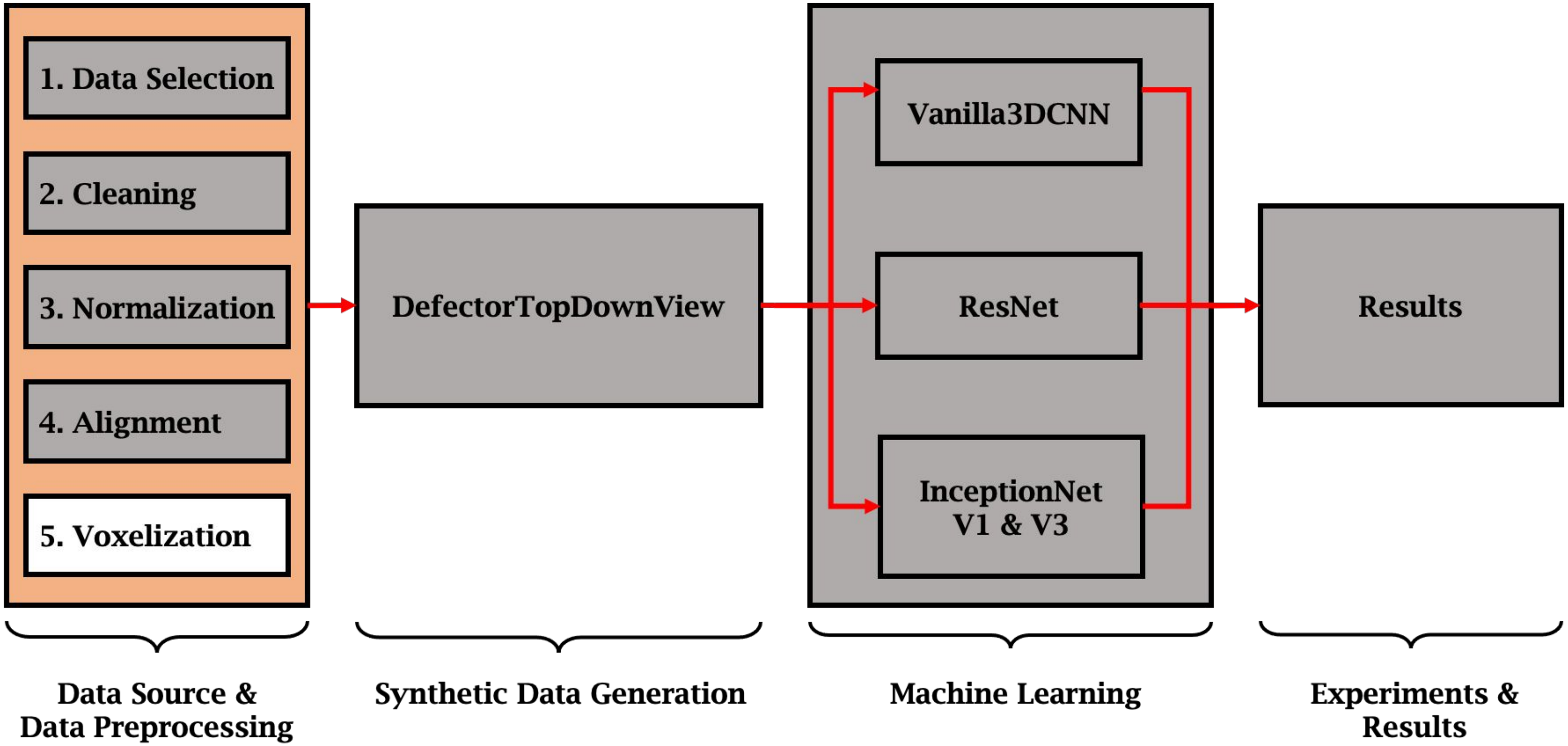
Alignment of min MOI axis and X-axis



Alignment of min MOI axis and Y-axis



Alignment of min MOI axis and Z-axis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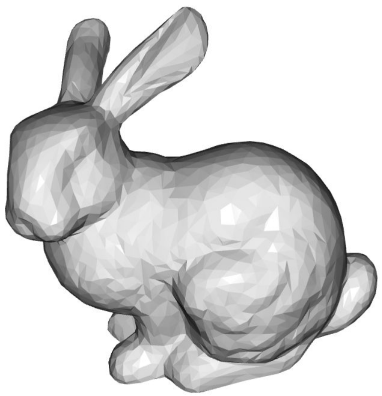
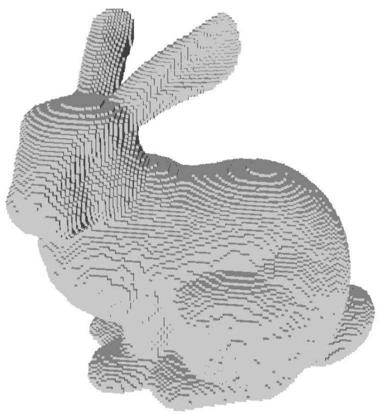
Voxelization

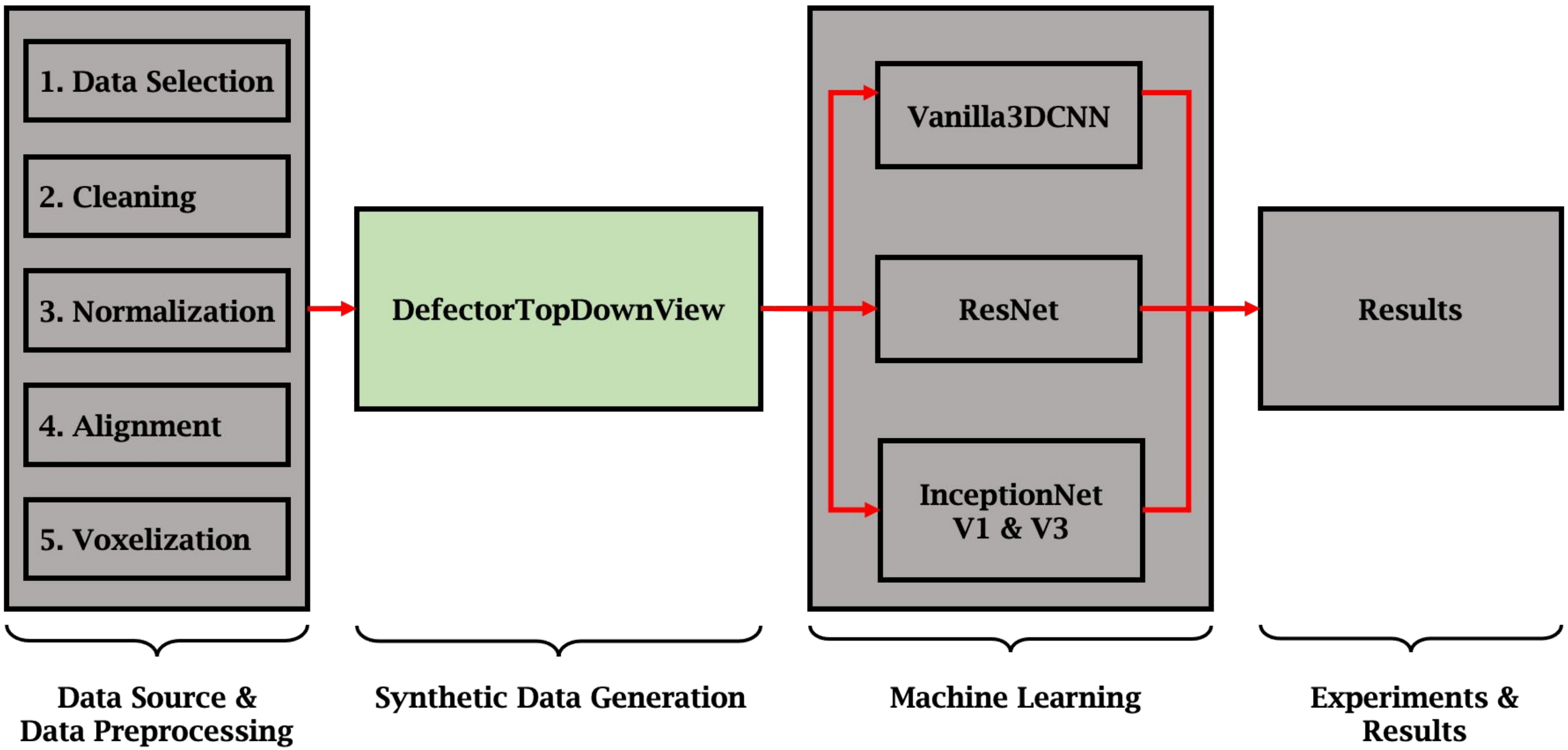
- All previous transformations were applied on the triangular mesh representation
- Final preprocessing step is converting the model to a voxelized representation
- What is a voxel representation?
  - A data representation that uses voxels. A voxel can be regarded as a pixel in a three-dimensional space.
- Why use voxel representation?
  - We hypothesized that SOTA CNNs will offer good performance after replacing 2D convolutions with 3D convolutions
  - It allows for an easy introduction of defects



Triangular Mesh Representation



Voxelized Representation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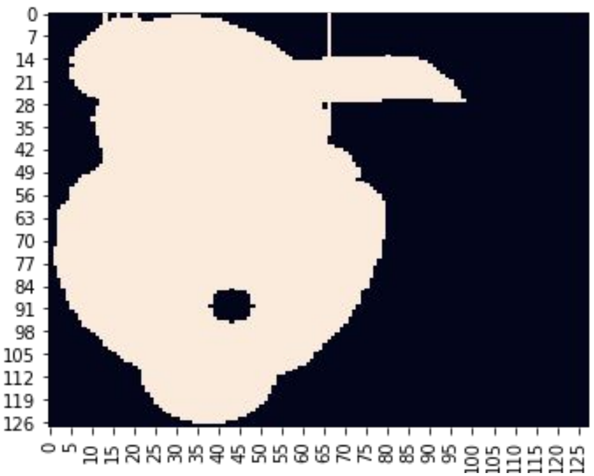
Assumptions & Definitions 1/2

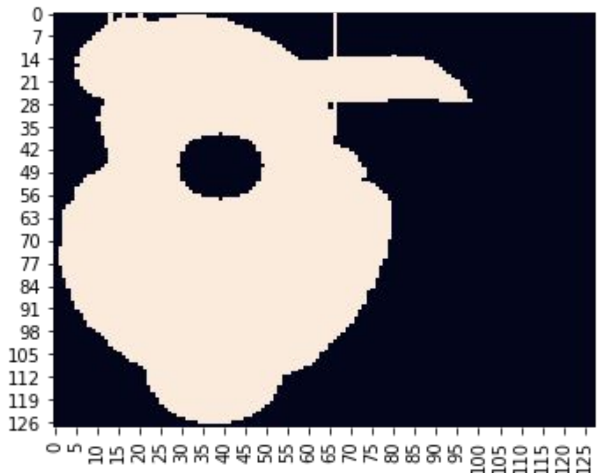
- **Problem:** Limited labeled data
- **Goal**: Synthetically add defects to 3D models in order to generate non-printable models
- **Assumption**:
  - All previous selected models are printable
  - Defects are here **holes aligned with the z-axis** that are added to the 3D model
  - Deciding parameters:
    - **Radius**
      - radius printable (10 voxels)
      - radius non-printable (5 voxels)
    - **Border**
      - Border printable (5 voxels)
      - Border non-printable (3 voxels)

Assumptions & Definitions 2/2

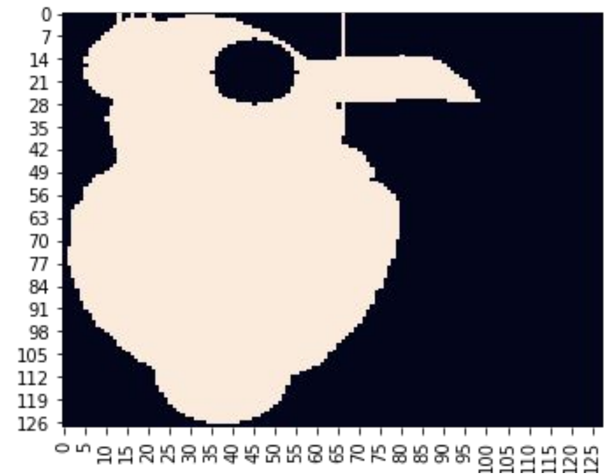
Resulting models:



Model **non-printable** defect in middle



Model **printable** defect in middle



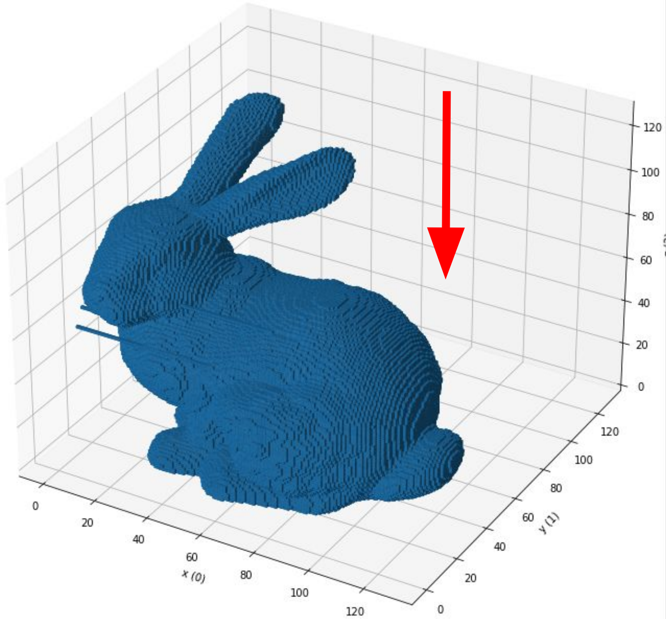
Model **non-printable** defect at border

Idea

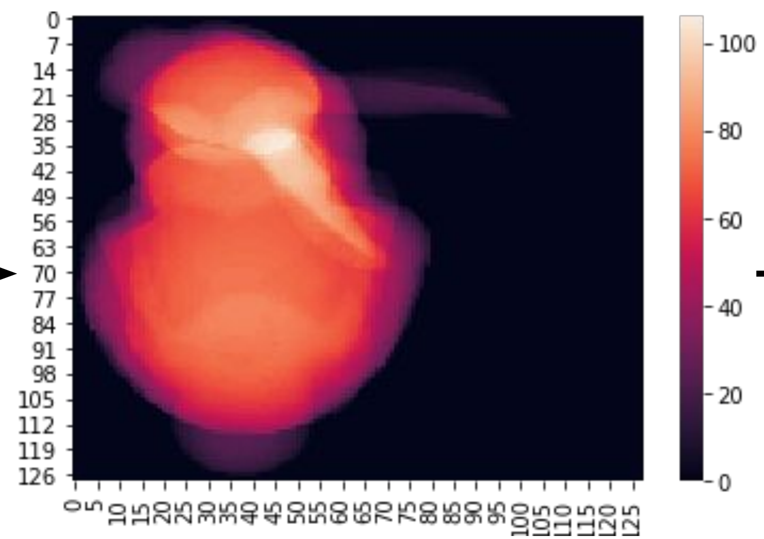
- **Main Idea: Transform 3D model data** s.t. it can be used to find right offset

→ **TopDownView**:

- Inspiration: **Heatmaps** (visualizing 3D data in 2D), **common sense**
- **Project 3D model data onto the (x, y)-grid**

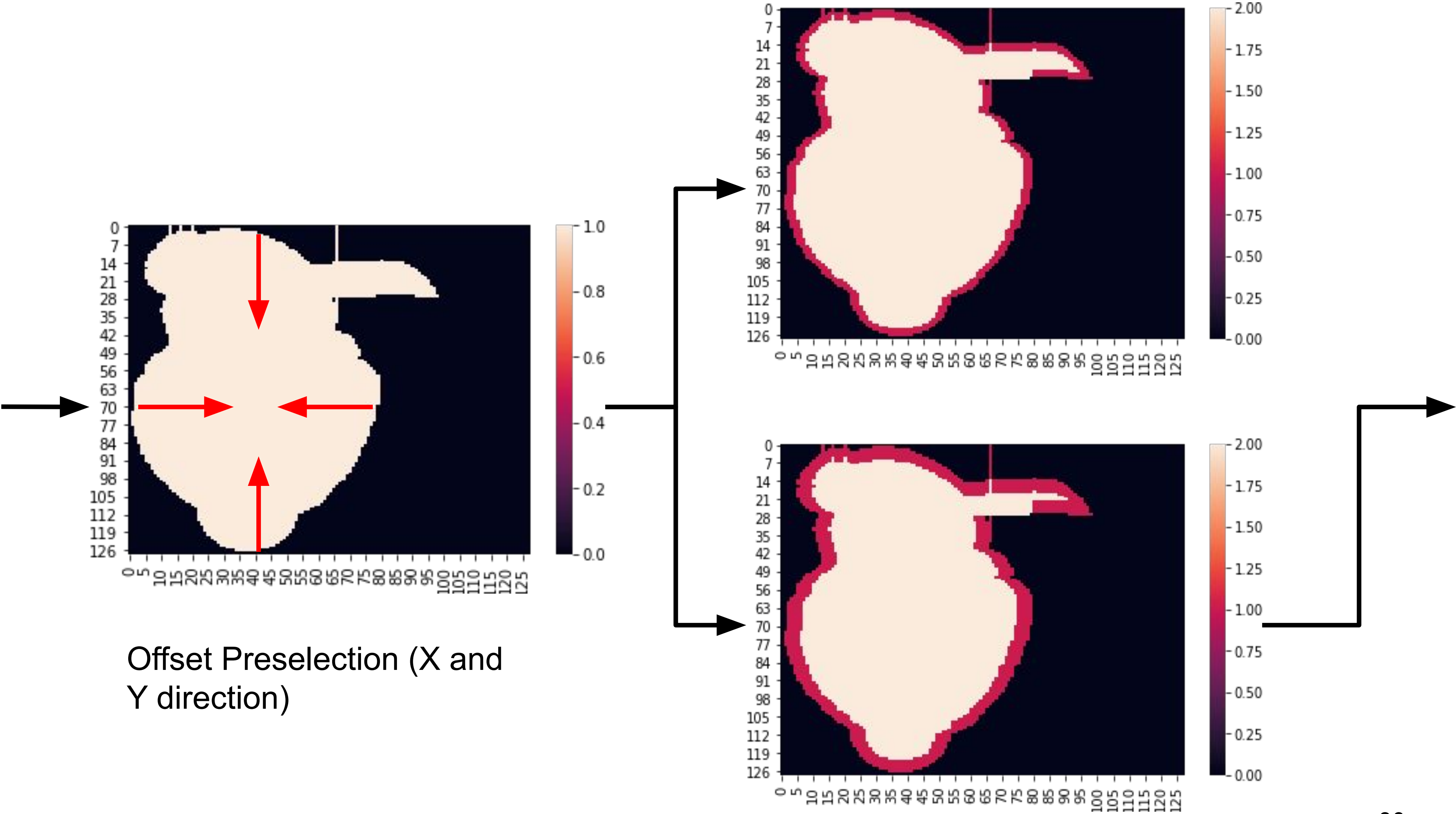


Summation over the z-axis



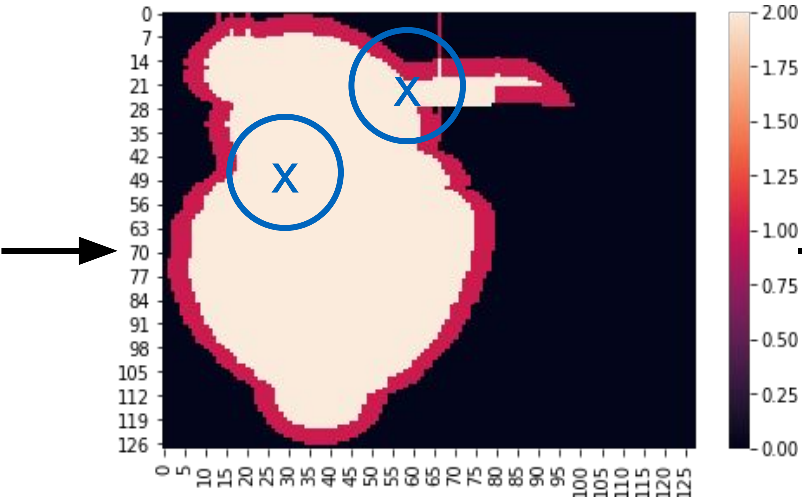
TopDownView

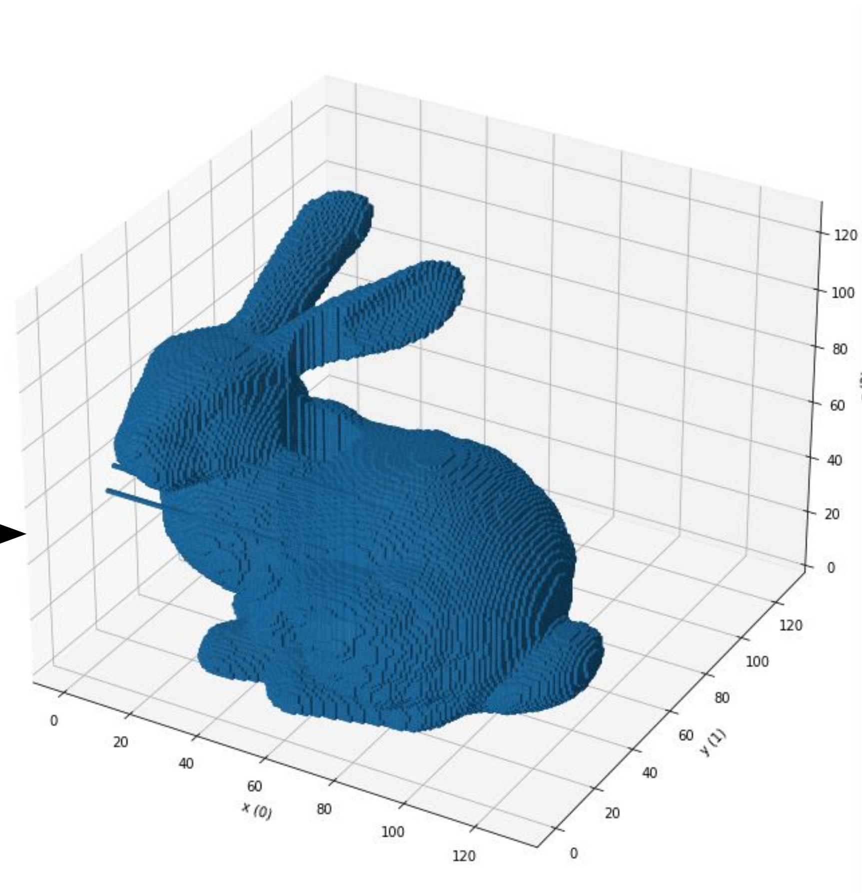
Defects in the middle 1/2



Offset Preselection (X and Y direction)

Defects in the middle 2/2





Non-axis direction check

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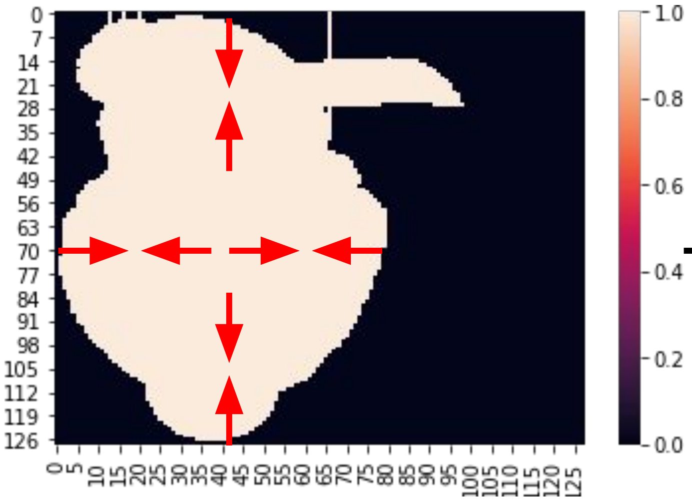
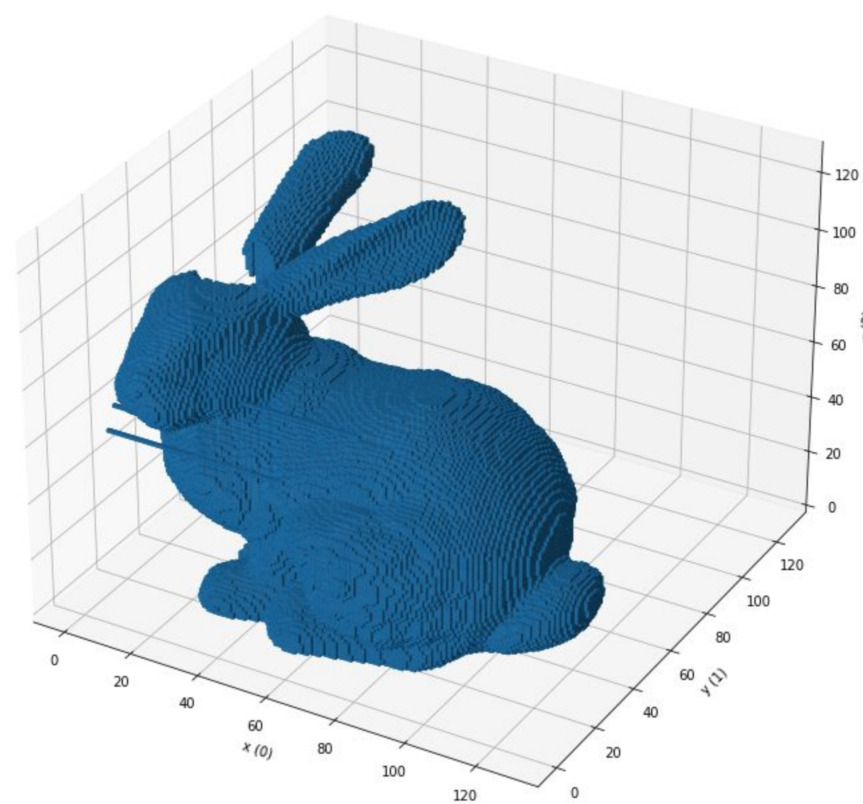
Defects at the border 1/2



Offset Preselection (X and Y direction)

Defects at the border 2/2

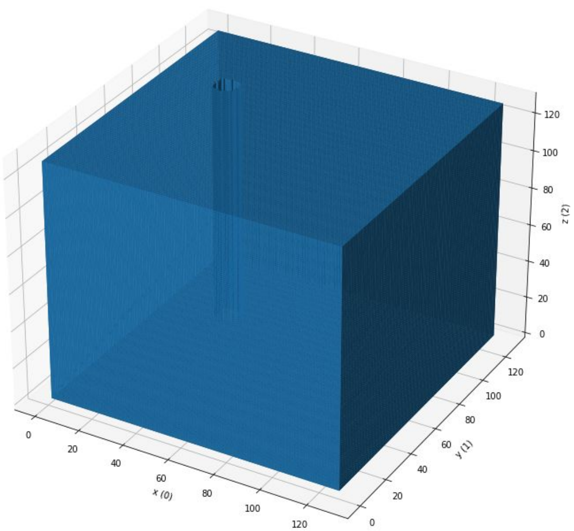


Non-axis direction check

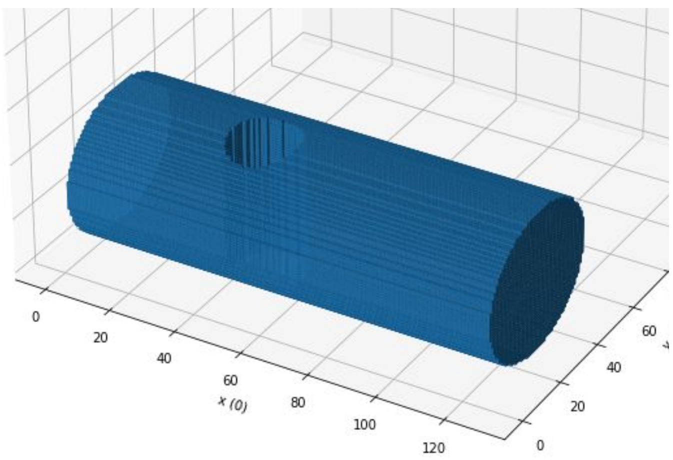
AMC Dataset

→ **Additive Manufacturing Classification (AMC) Dataset:**

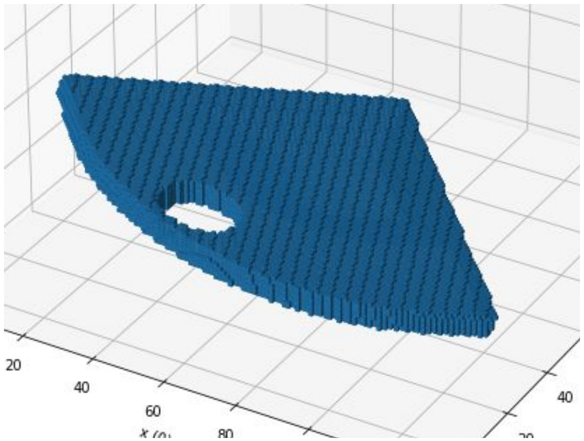
- **7430** 3D models
- **Balanced in terms of labels (printable / non-printable)**
- But: **Defects not equally distributed**



Non-printable defect middle



Printable defect middle

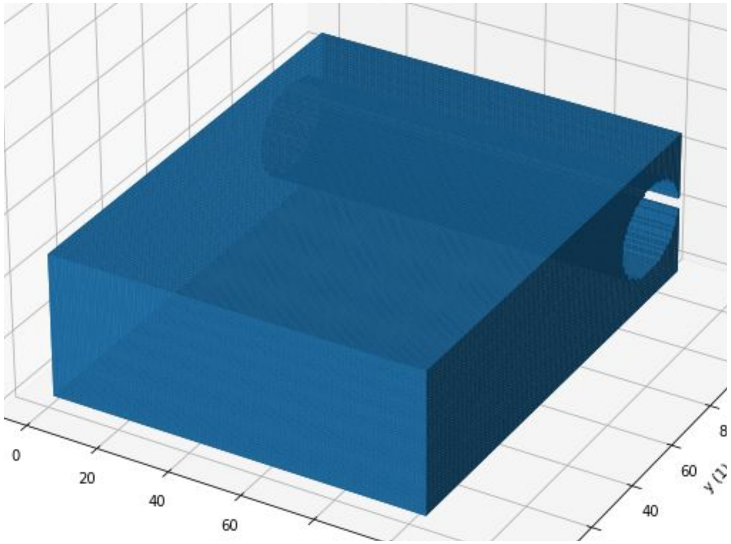


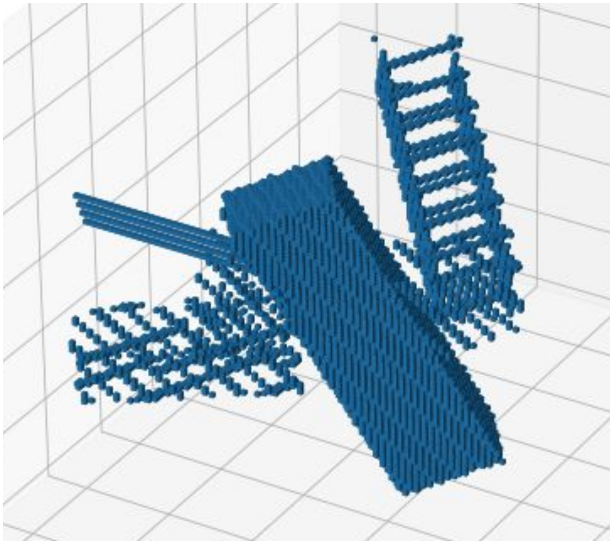
Non-printable defect border

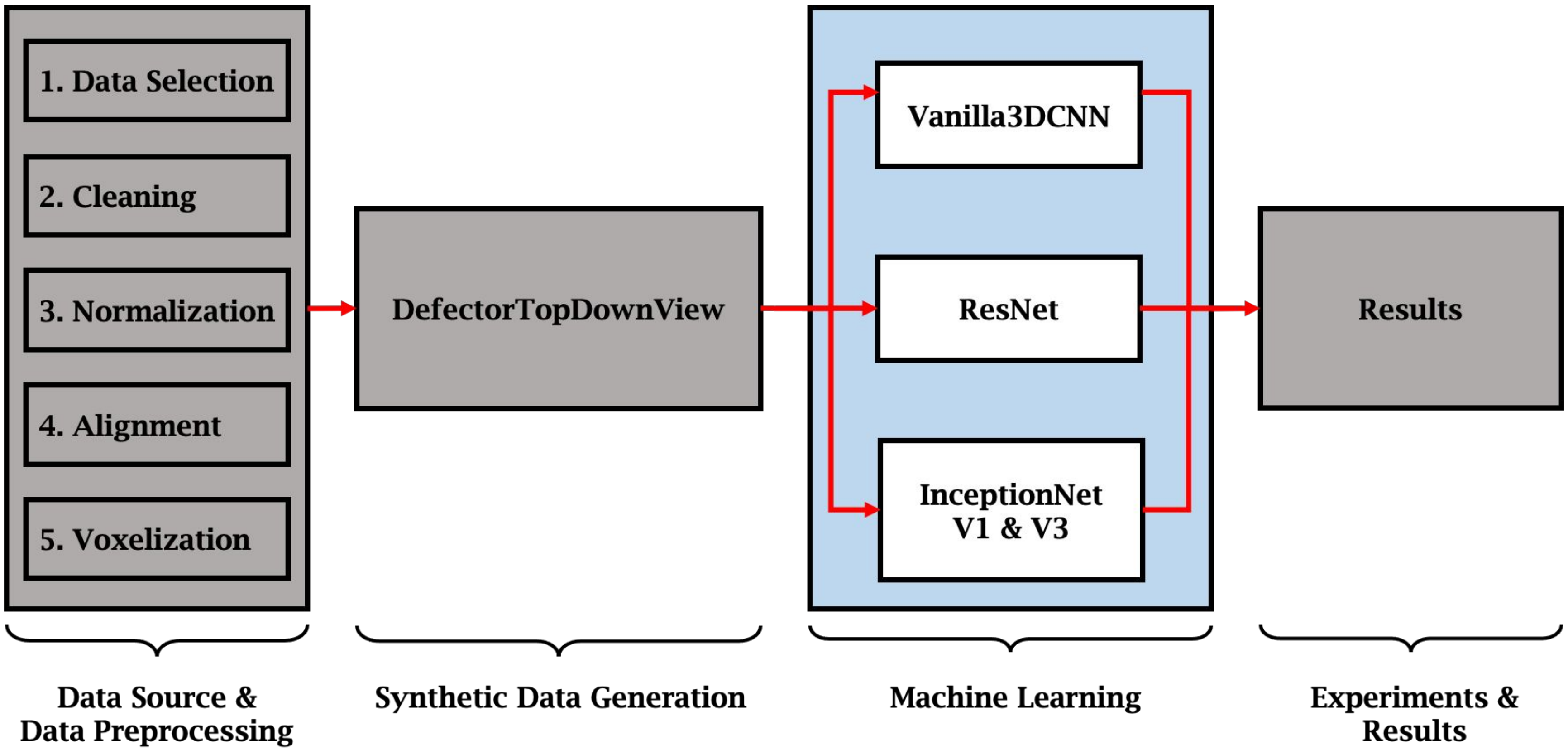
Limitations

- **Strong assumptions** on the input models

  → **Selected models already contain holes or are too complex**
- **Artificial defined defects**, i.e. too far away from the real given problem, strong abstraction
- If models and the defects gets more complex, this approach **quickly reaches its limitations**



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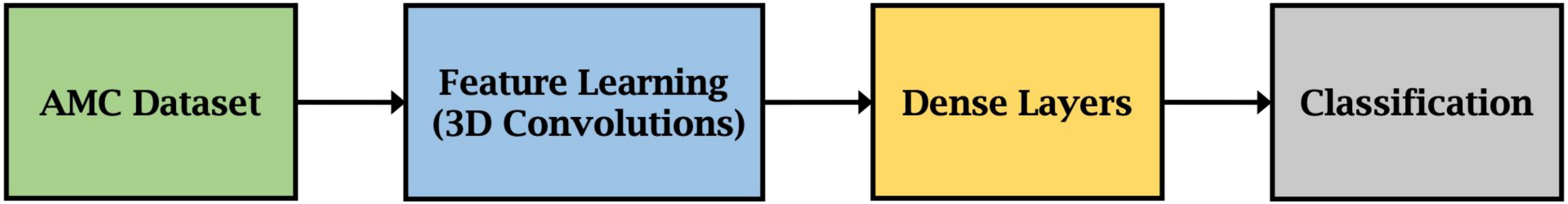
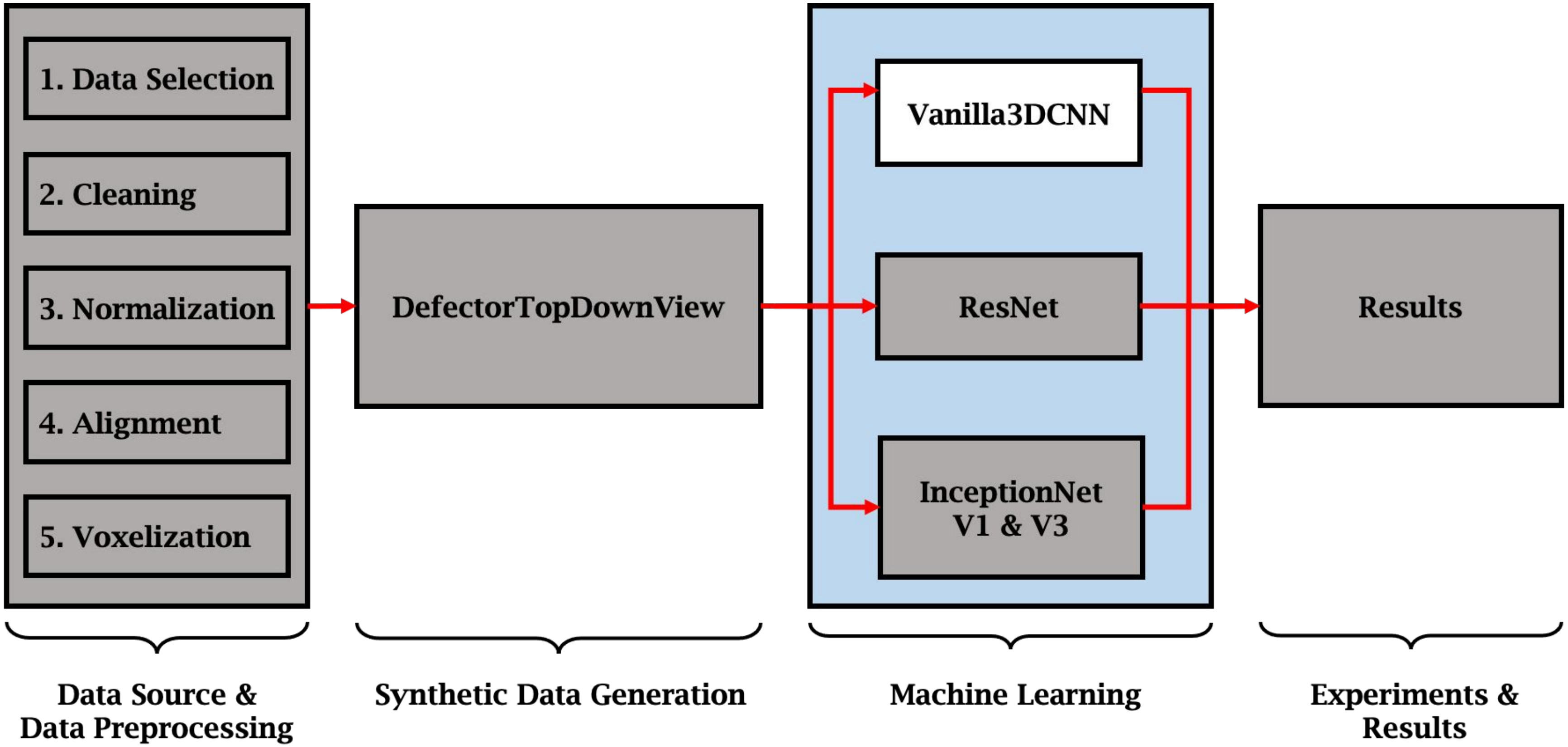
Deep Learning Workflow



- Type of problem to be solved: Binary Classification
- Architectures examined for feature extraction:
  - Vanilla3DCNN
  - ResNet
  - InceptionNet V1
  - InceptionNet V3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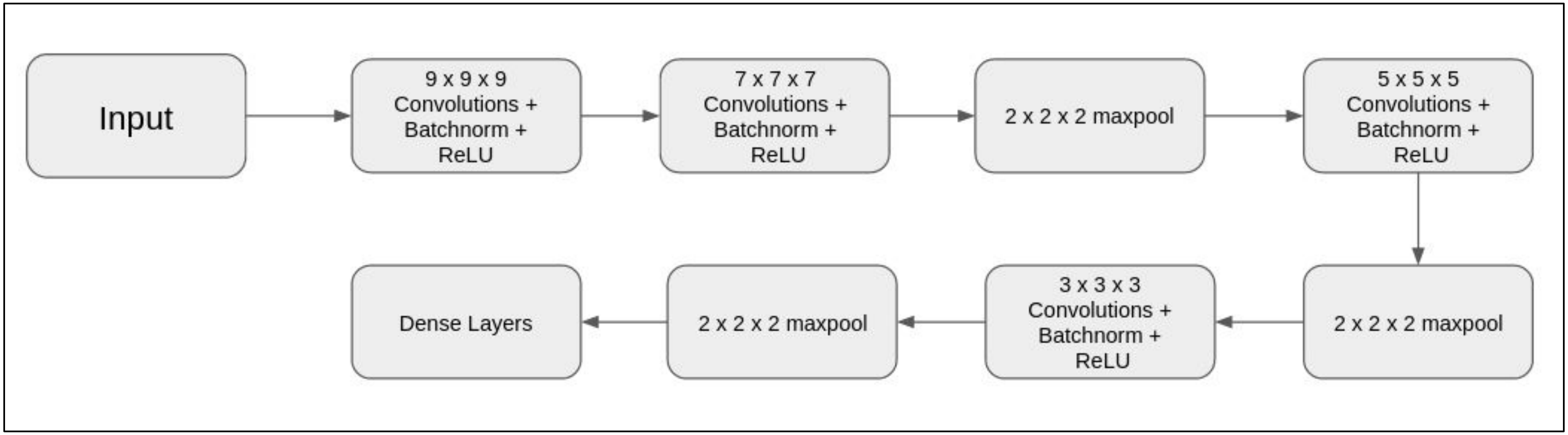
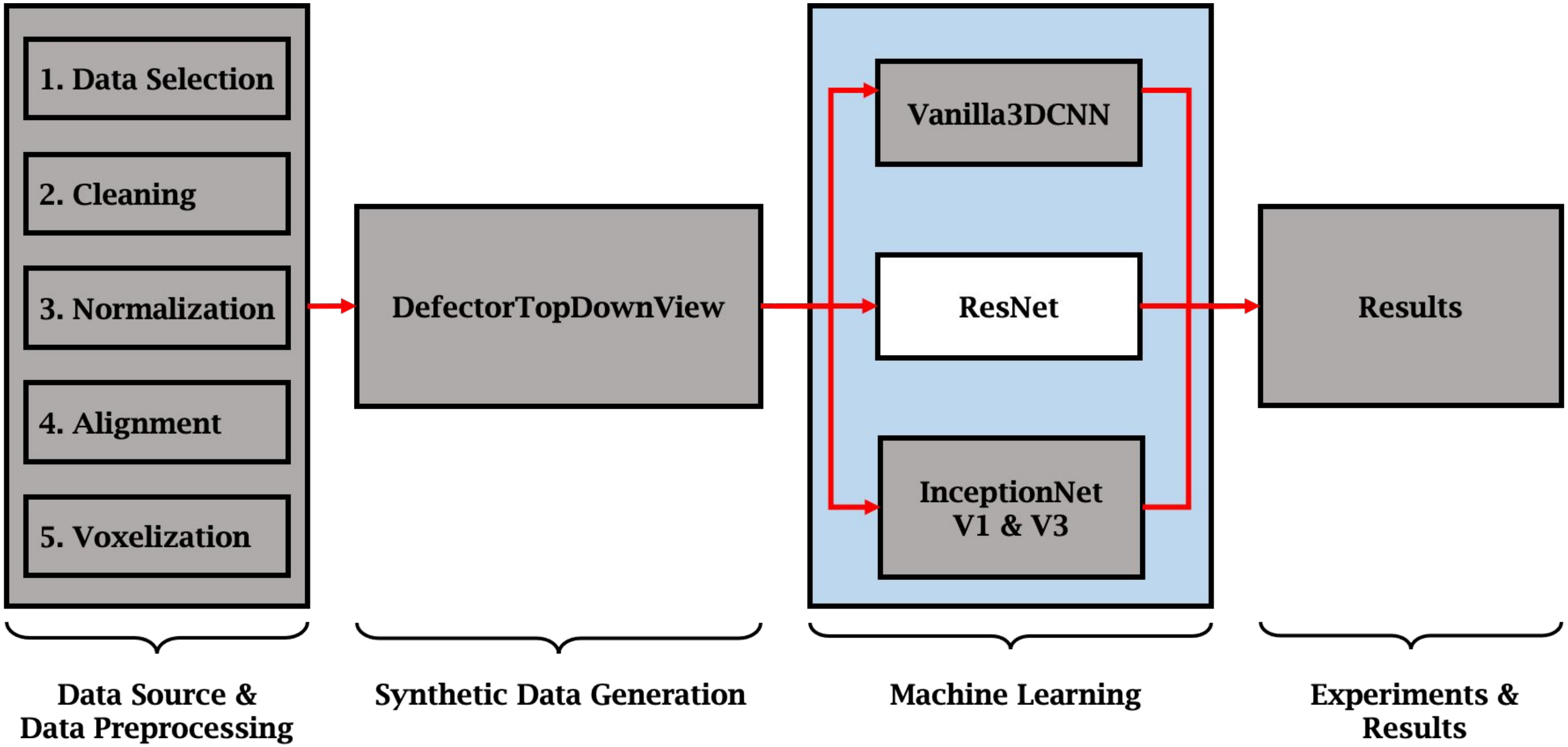
Vanilla3DCNN Architecture



- Number of trainable parameters: **1.8M**
- 4 convolution layers with kernel sizes 9, 7, 5 and 3 were used.
- Maxpooling layer to **reduce spatial size.**
- Batch normalization layers to **stabilize the training process**.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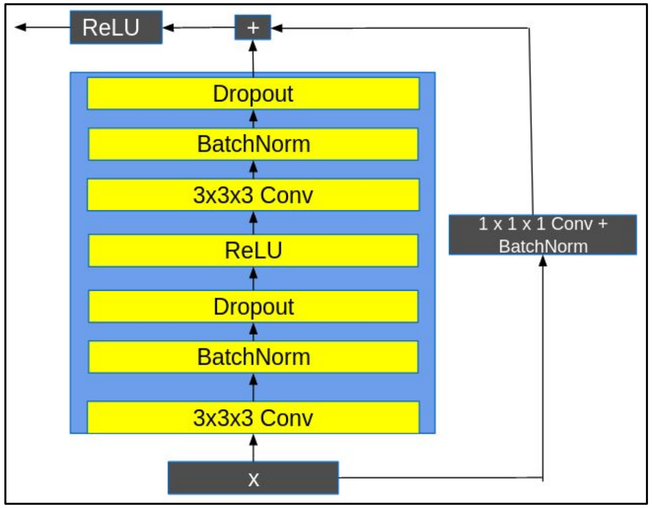
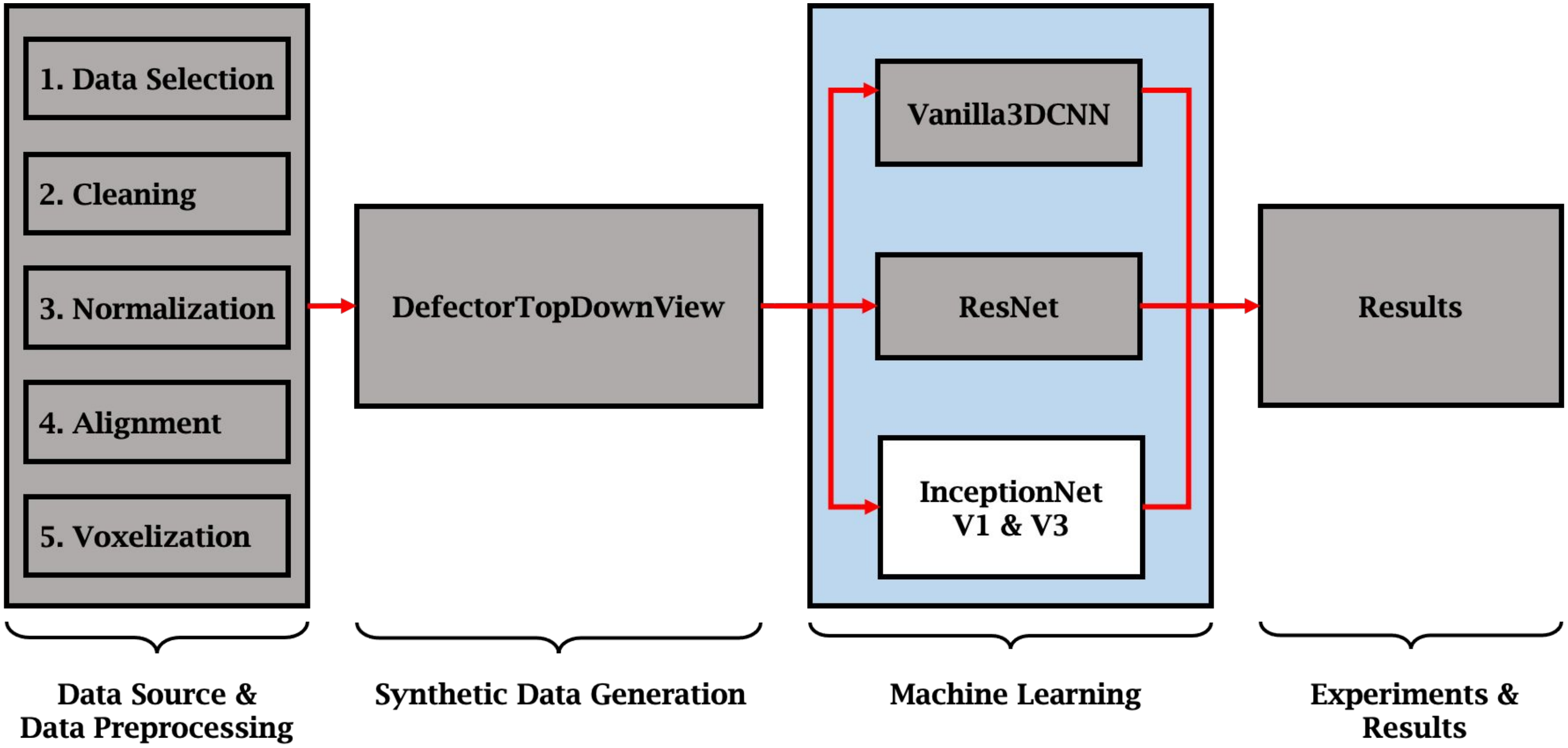
ResNet Architecture



- Number of trainable parameters: **9.1M**
- Basic residual block contains two 3 x 3 x 3 layers with batch norm layers and dropout layers.
- Basic residual block repeated twice.
- To **avoid sudden reduction of input spatial dimensions**, two pooling layers used at the end.


1. Data Selection
2. Cleaning
3. Normalization
4. Alignment
5. Voxelization
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ResNet
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V1 & V3
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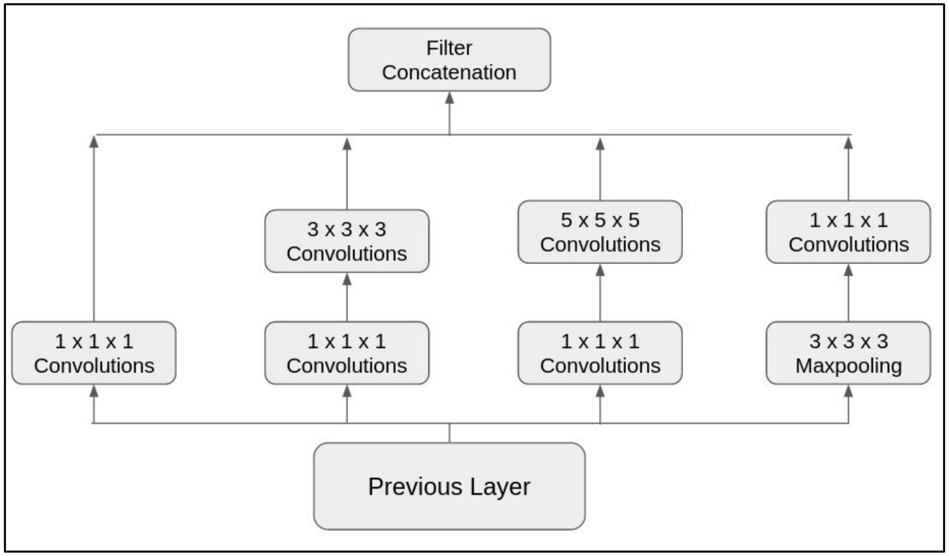
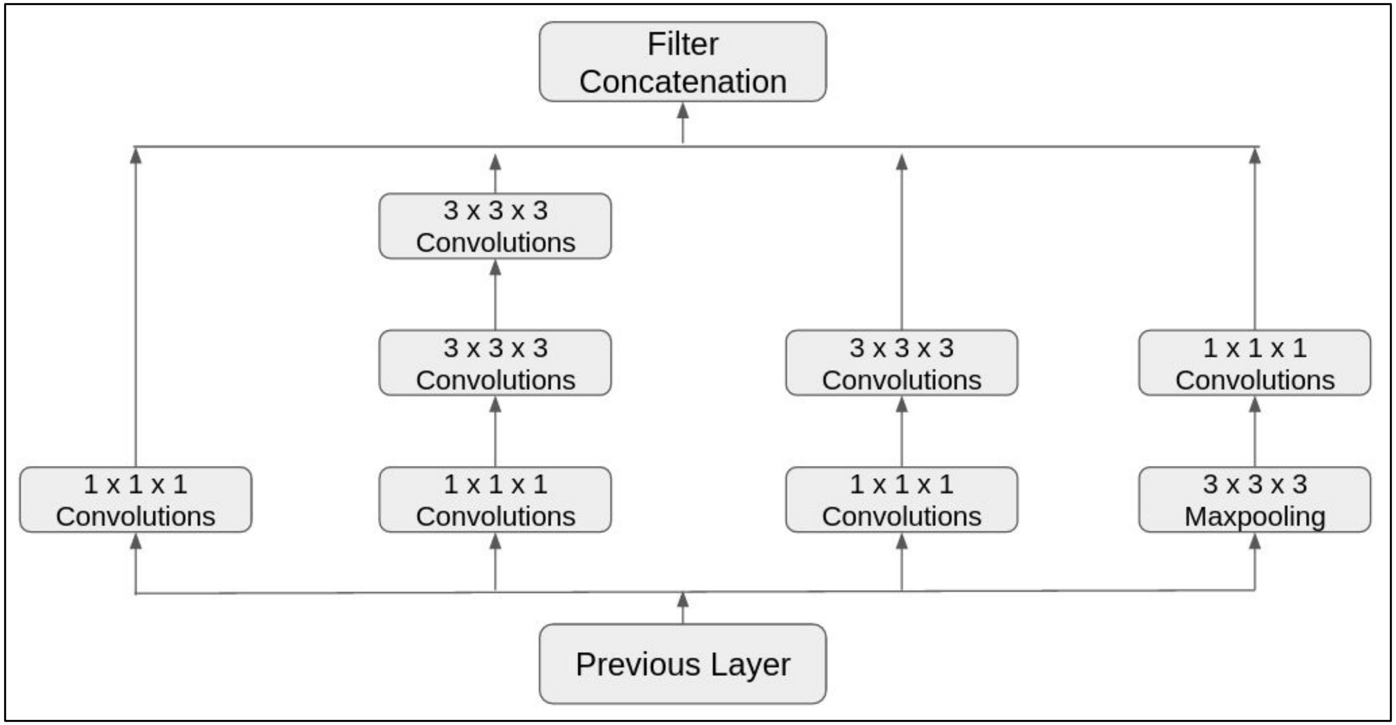
InceptionNet V1 Architecture



- Basic intuition: **Let's go wider.**
- Number of trainable parameters: **9.6M**
- To capture the salient features having varying dimensions, choosing right kernel size is difficult.
- Each InceptionNet V1 block has kernel sizes 1,3 and 5 operating at the same level.
- InceptionNet V1 block repeated 4 times.

InceptionNet V3 Architecture



- Number of trainable parameters: **17.9M**
- Improvement over InceptionNet V1
- Disadvantage of InceptionNet V1: **Large reduction** in spatial dimension due to kernel size 5 x 5 x 5.

Implementation Details

1. **Activation Function:**
   - ReLU[1] activation for all layers except for the final layer.
   - Sigmoid[1] activation for the final layer.

2. **Loss Function:**
   - Binary cross entropy loss[2] used.

$$\boxed{BCE = -\sum_{i=1}^{C=2} t_i log(f(s_i)) = -t_1 log(f(s_1)) - (1 - t_1) log(1 - f(s_1))}$$

[1] Activation Functions: Comparison of Trends in Practice and Research for Deep Learning

[2] Generalized Cross Entropy Loss for Training Deep Neural Networks with Noisy Labels

VOLKSWAGEN DATA:LAB

Implementation Details

3. **Weight Initialization:**
    - Kaiming normal[3] weight initialization with **Fan-out mode** was used.
    - Weights follow normal distribution as shown below:

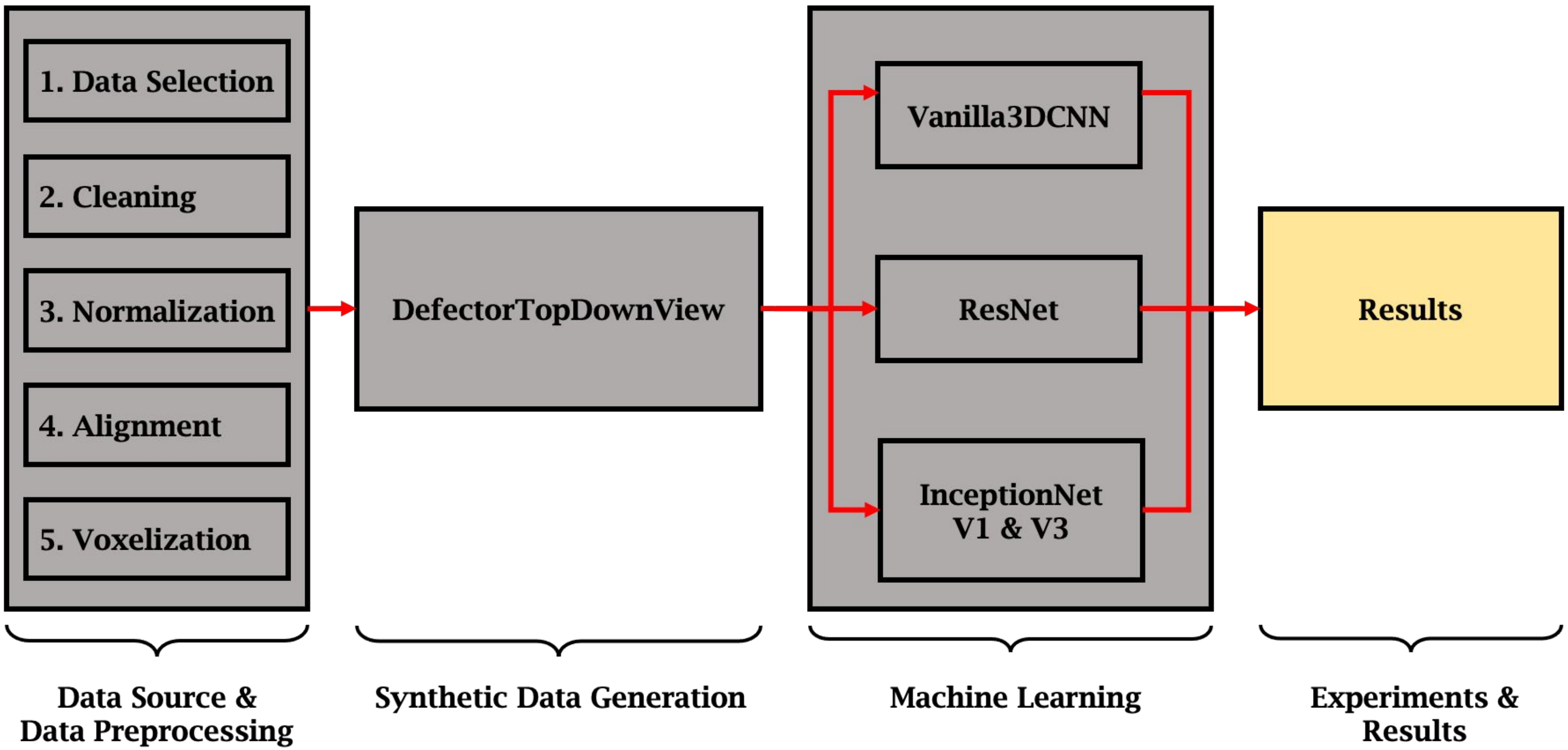
$$W \sim N\left(0, \sqrt{\frac{2}{n}}\right)$$

4. **Optimizer:**
    - Momentum based optimization algorithm is the default algorithm for all architectures.
    - Adam optimizer[4] used: Computes **adaptive learning rates** for each parameter.

4. **Dataset:**
    - Total data samples: 7430
    - Train/Validation split (random): 80/20, 5944 (train) and 1486 (validation)
    - Law of large numbers: train and validation set are **balanced**

[3] Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification.

[4] Adam : A Method for Stochastic Optimization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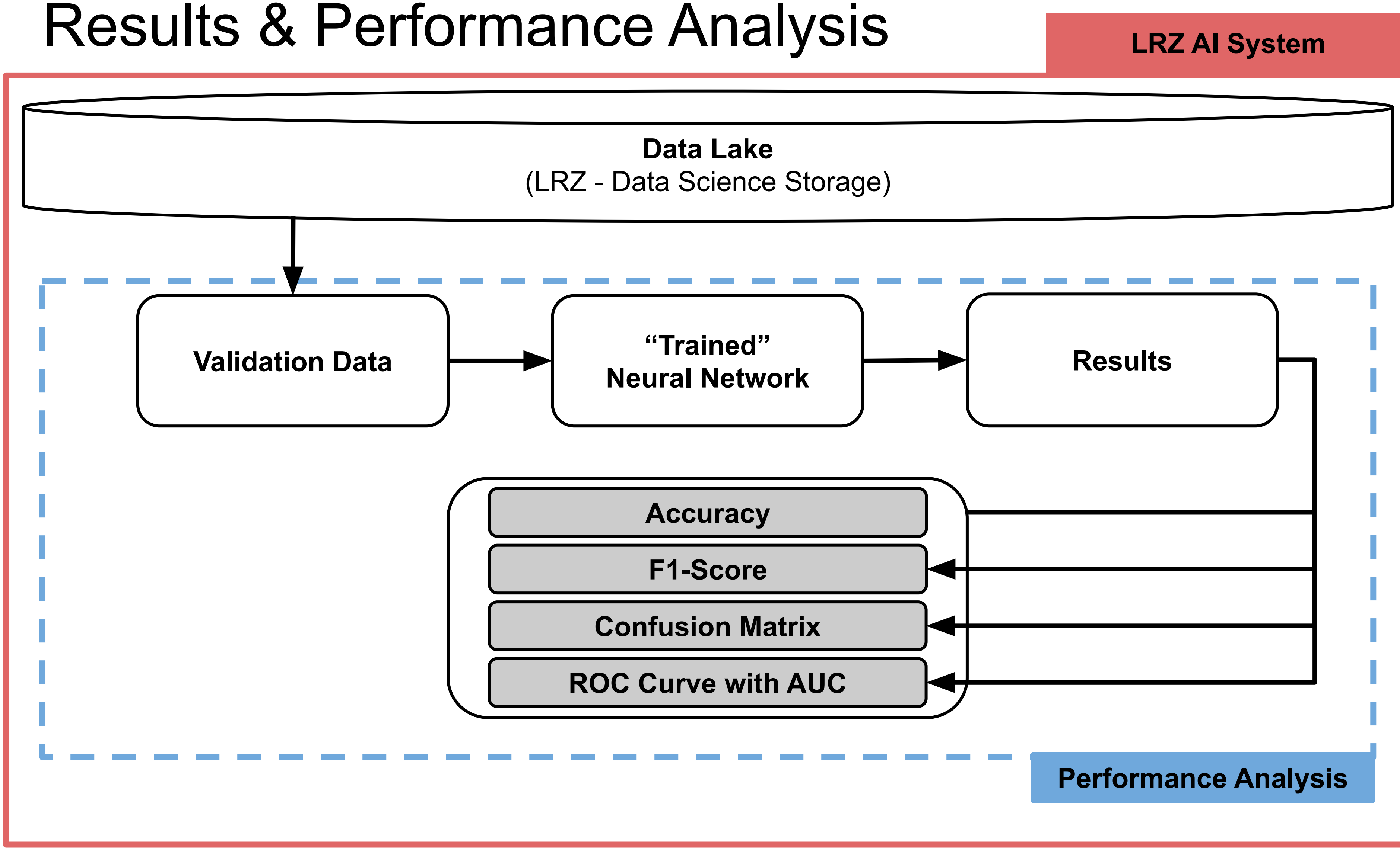
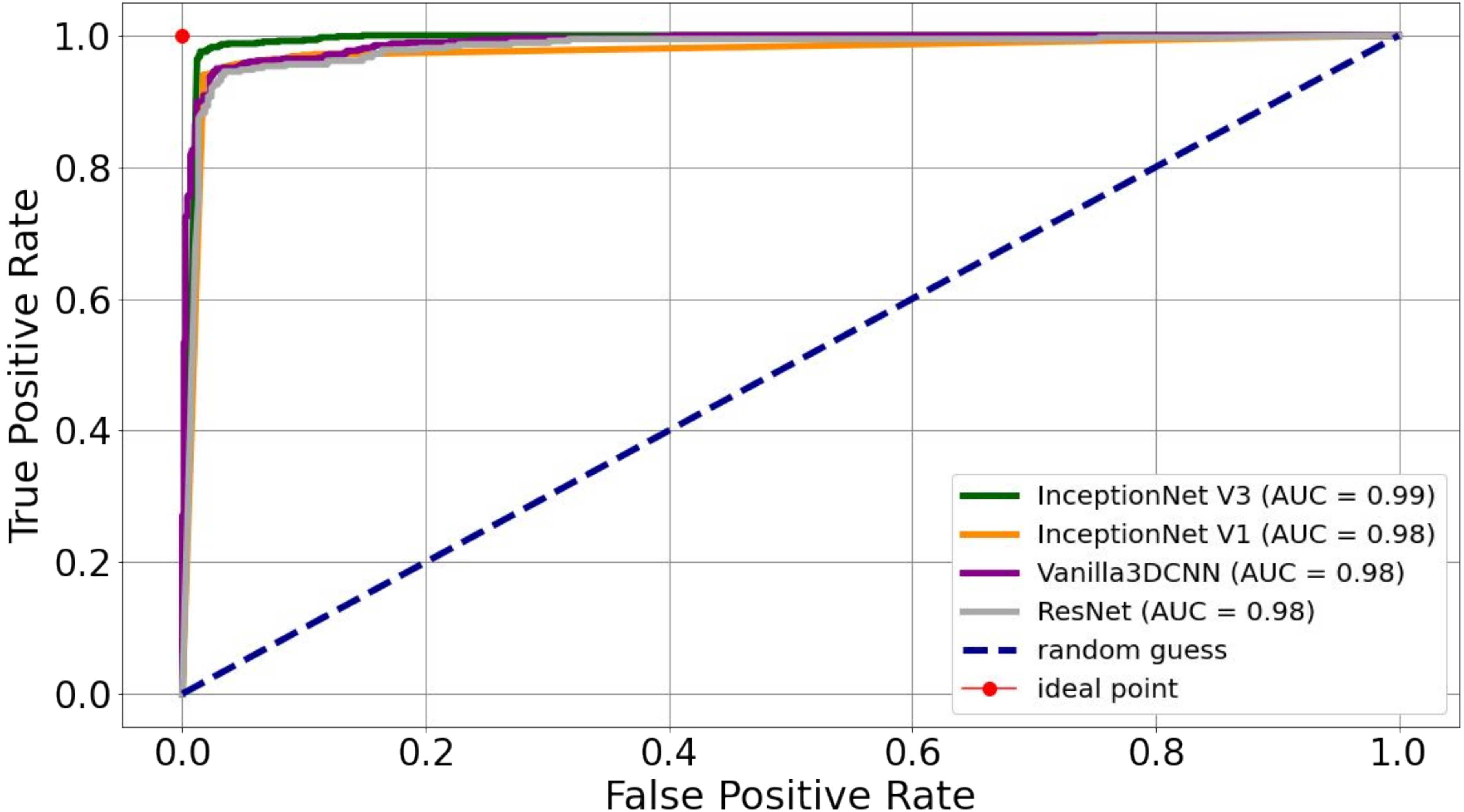
Results & Performance Analysis

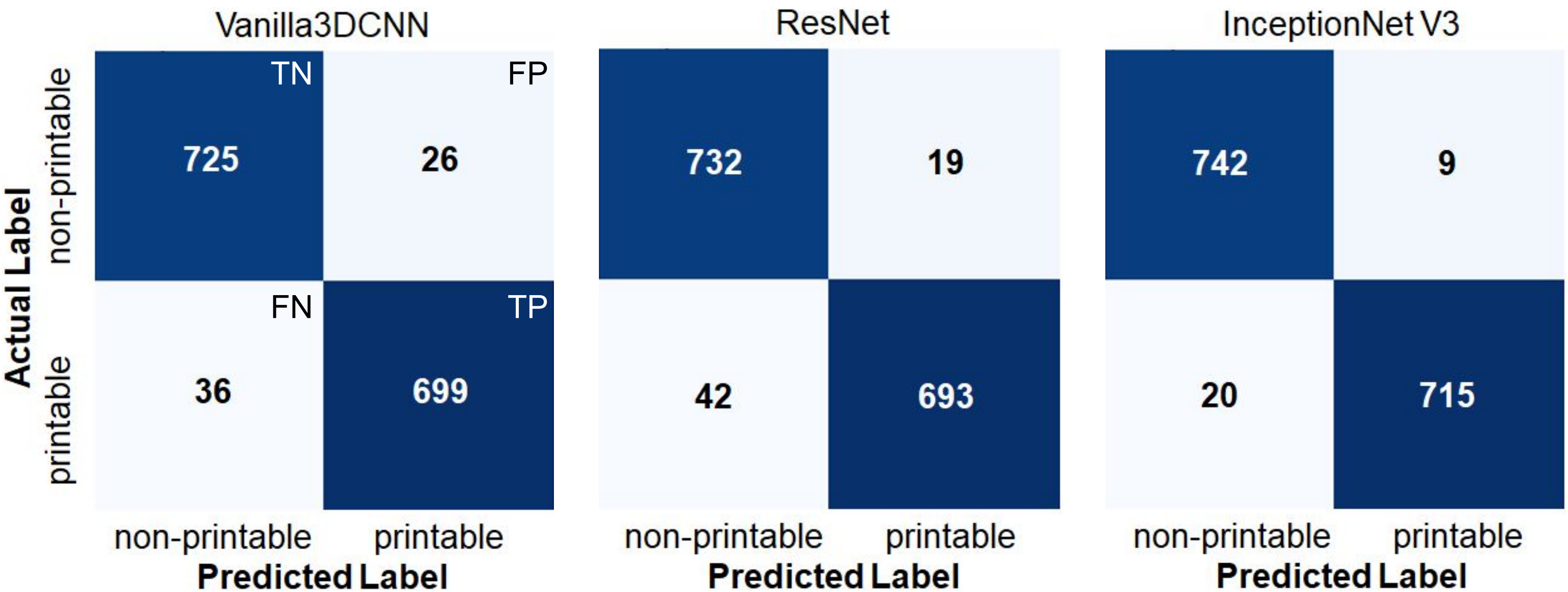


ROC$^{(1)}$ Curve with AUC$^{(2)}$



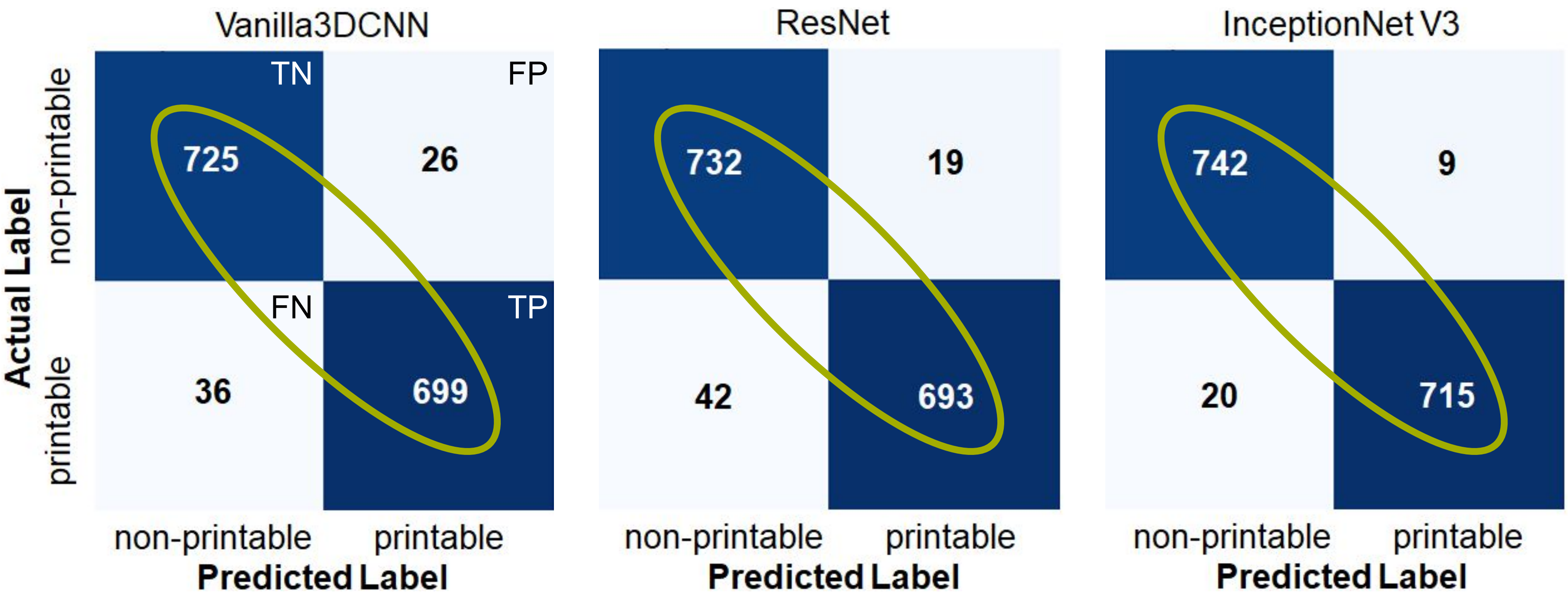
(1) ROC: Receiver Operating Characteristic
(2) AUC: Area under the ROC Curve

Confusion Matrix



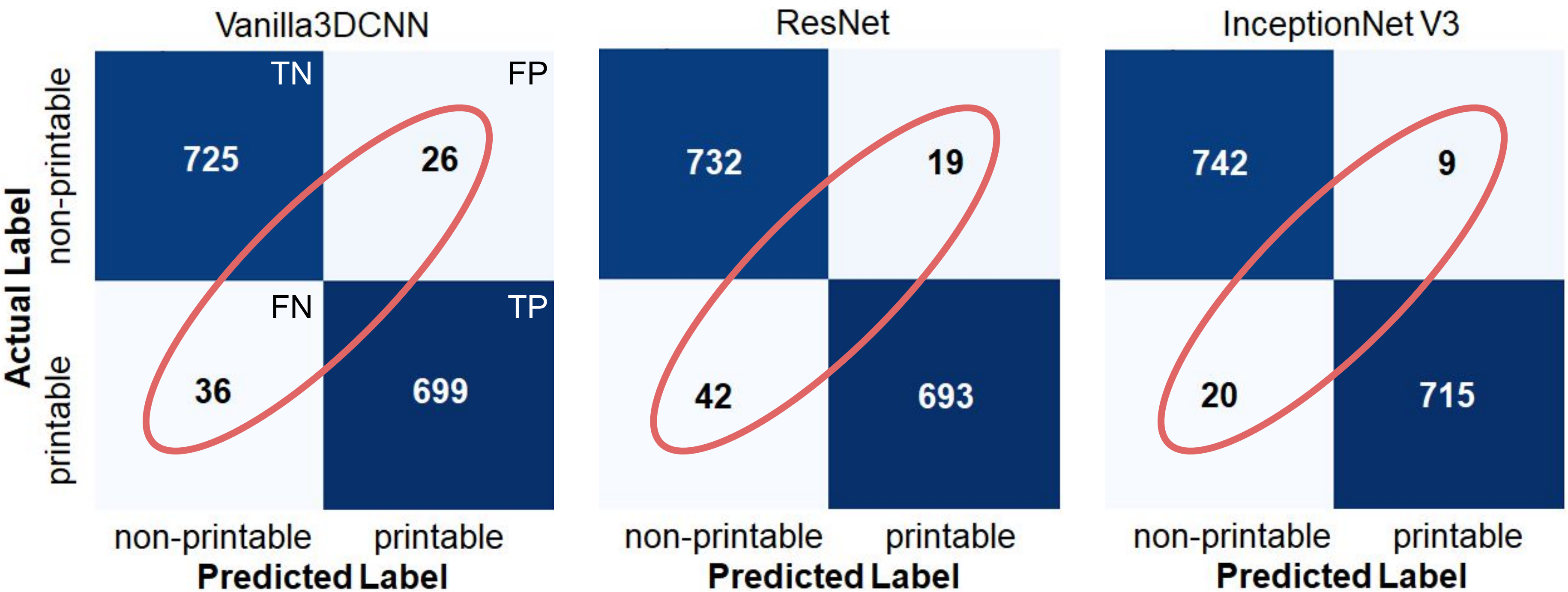
- **Diagonal elements:** correct prediction (TN & TP)
- **Off-diagonal elements:** wrong predictions (FN & FP)

Confusion Matrix



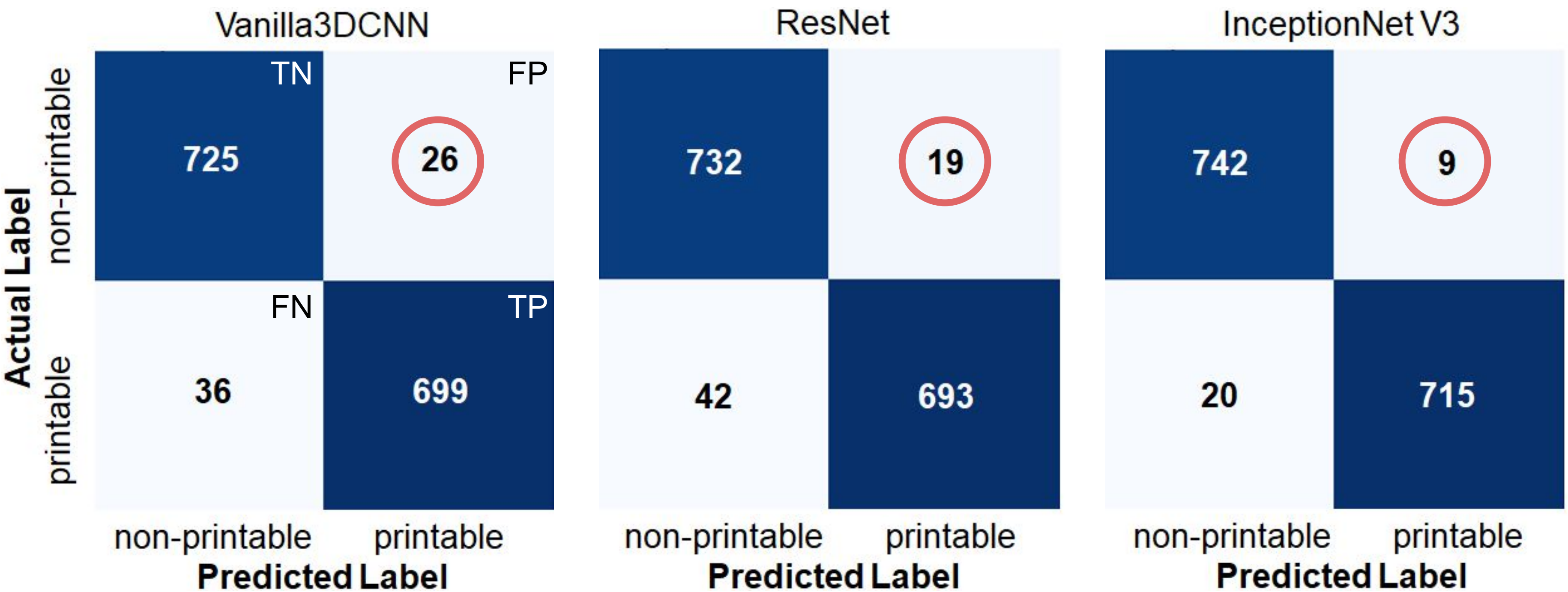
- **True Negatives > True Positives** (for all classifiers)
- **True Negatives:** Method of adding defects works pretty well
- **True Positives:** Assumption of all initial models being printable does not hold

Confusion Matrix



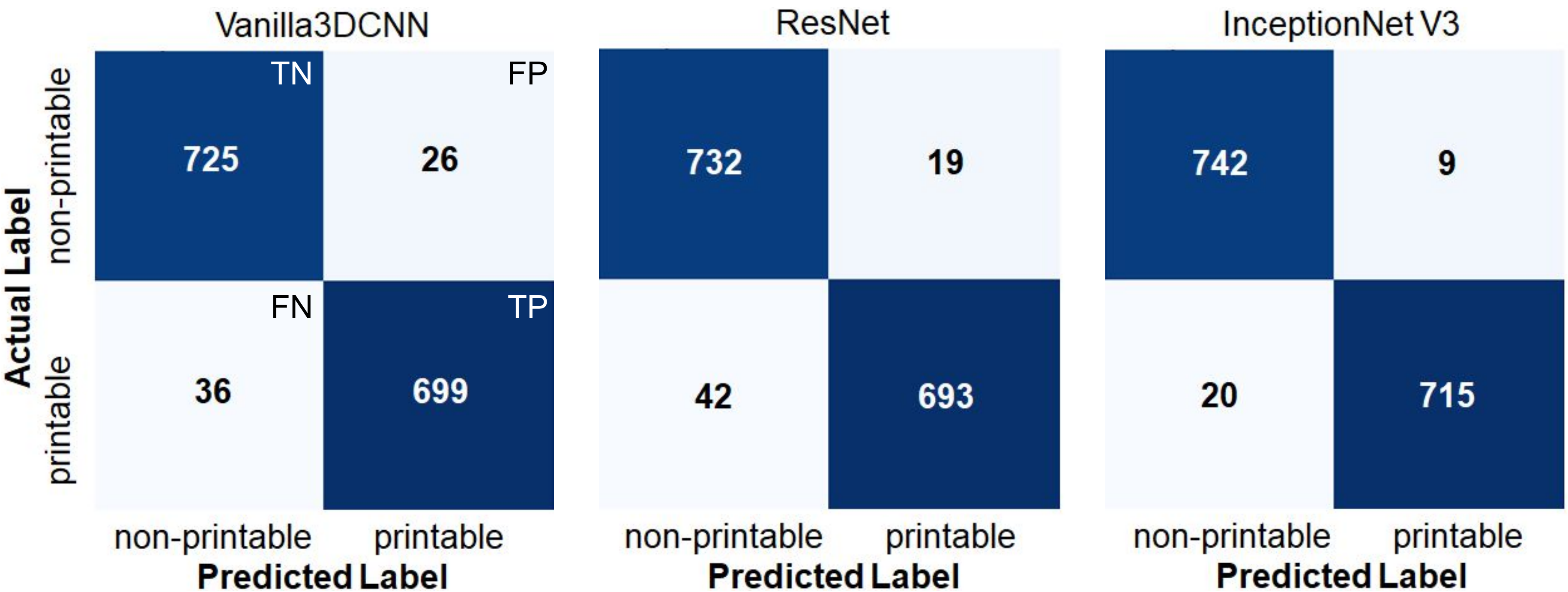
- **Very few off-diagonal elements:** Good overall performance
- **False Negatives > False Positives** (for all classifiers)

Confusion Matrix



- **Avoid:** False Positives (FP) over False Negatives (FP)
- **Additive Manufacturing:** False Positives waste time & material
  False Negatives require manual check by engineer

Confirm Results: Accuracy(1) & F1-Score(2)

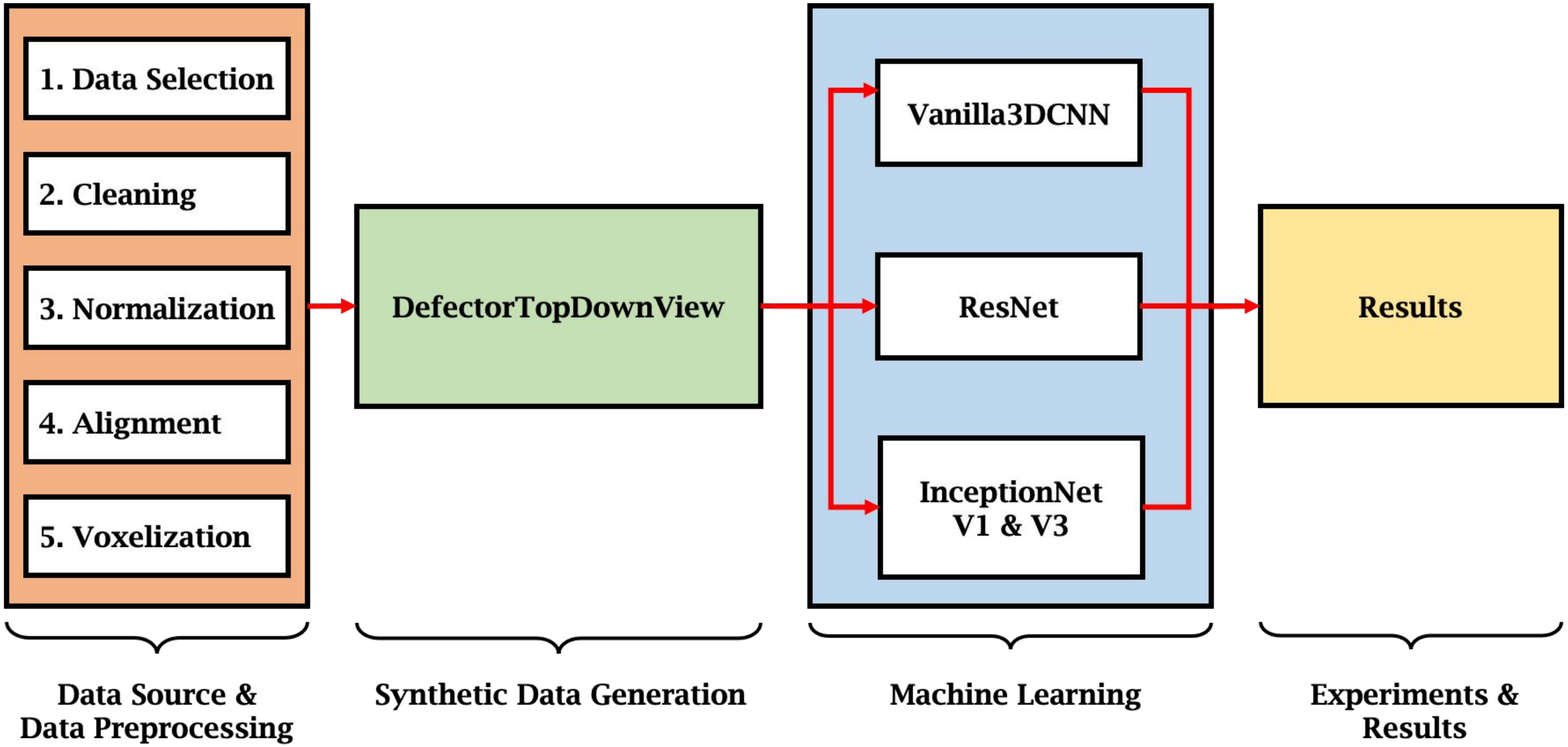


Accuracy	F1-Score
95.8 %	0.957

Accuracy	F1-Score
95.9 %	0.959

Accuracy	F1-Score
98.1 %	0.980

(1) In this case: balanced accuracy
(2) F1-Score ∈ [0, 1]; harmonic mean of precision(3) and recall(4)
(3) Precision: *How often is it correct when a positive is predicted:* TP/(FP+TP)
(4) Recall: *How often is a positive predicted when it actually is positive:* TP/(FN+TP)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Wrap up

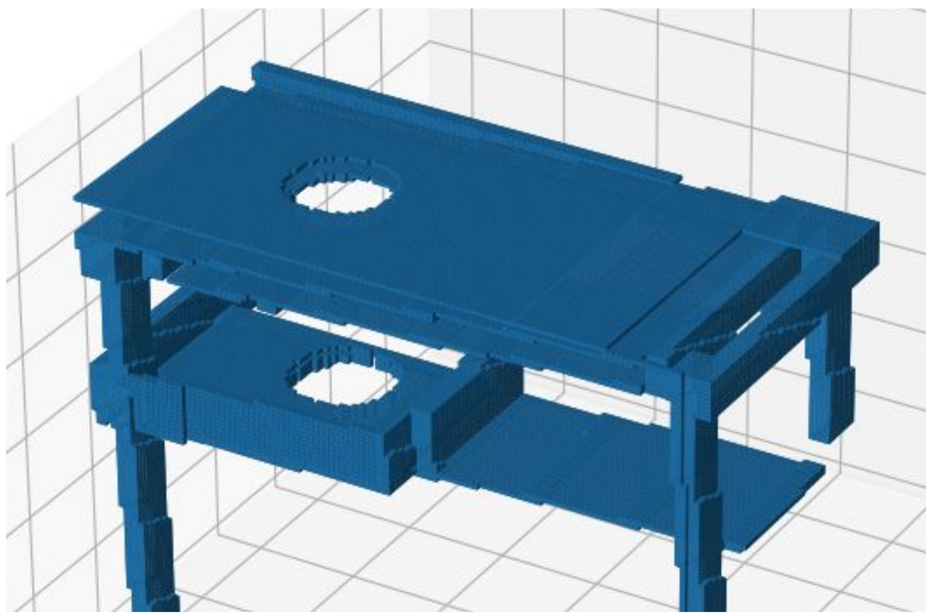
- Good performance of the model using the AMC dataset.
- **Limitations:**
  - Assumption of printability of the models selected
  - Restricted model selection
  - Failure of the defectors in some specific cases

Improvements: Evaluation methods

- Generate an additional test set from another chunk of the **ABC dataset** or from the **Thingi10K dataset**
- **Explainable AI techniques** for better understanding of the performances of the deep learning models.

Improvements: DefectorTopDownView Similarity Check Add-on

- The information given for the tdv could be misleading.
- **Global** and a **local** uniformity **check** for the area that will be removed by the defector.

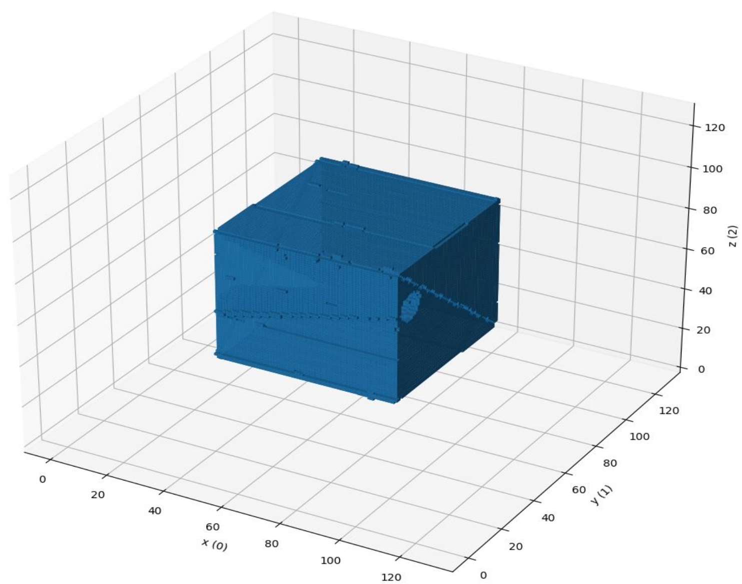


3D model labeled by the defector as manufacturable

Improvements: DefectorTopDownView Rotation Add-on

Insert rotated holes with random angles as a generalization of DefectorTopDownView

- Add a padding to the 3D models
- Rotate the models randomly throughout the x,y and z axes by the angles ϕ_x, ϕ_y, ϕ_z
- Insert the hole using DefectorTopDownView
- Rotate back the model



3D model augmented by a rotated hole

Potential Future Work

The defector is a deterministic algorithm with **limited capabilities**

- Use **self supervision:**
  - Train on original 3D models without artificial defect using an autoencoder
  - Use the encoder as feature extractor and stack final layer for binary classification
  - Train using expert labeled data
- **Few-shot** learning methods.
- Train **generative adversarial networks** (GANs) on a dataset of few complex models that are expert-labeled and generate new models with complex defects.

Thank you for your attention!

Additional slides

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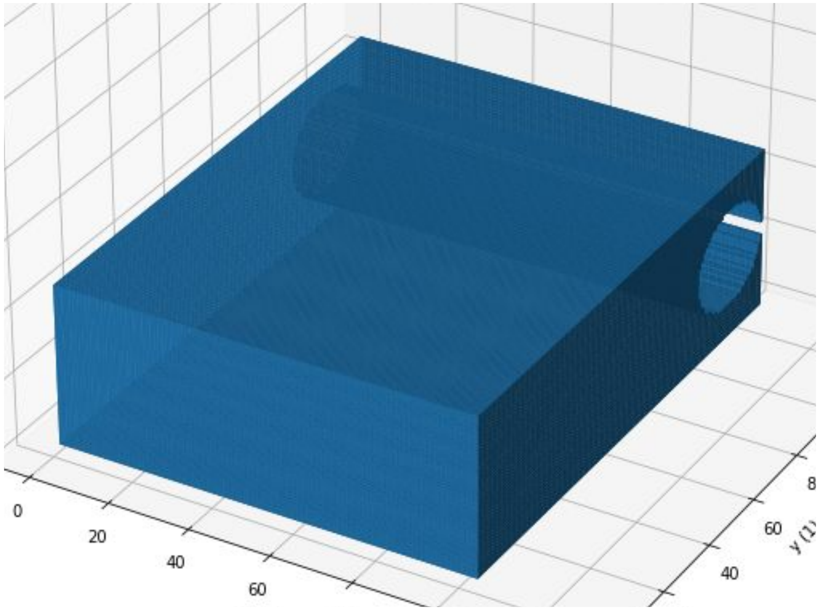
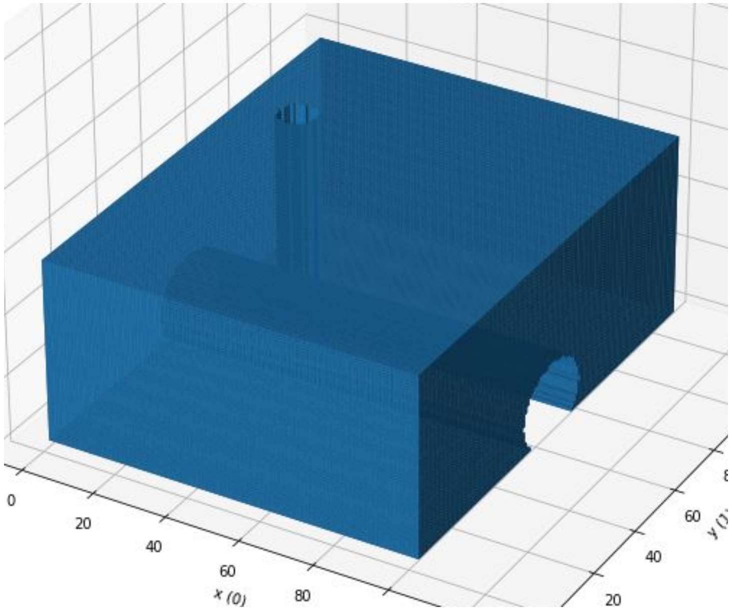
Additional slides
Synthetic Data Generation

Limitations examples 1/2

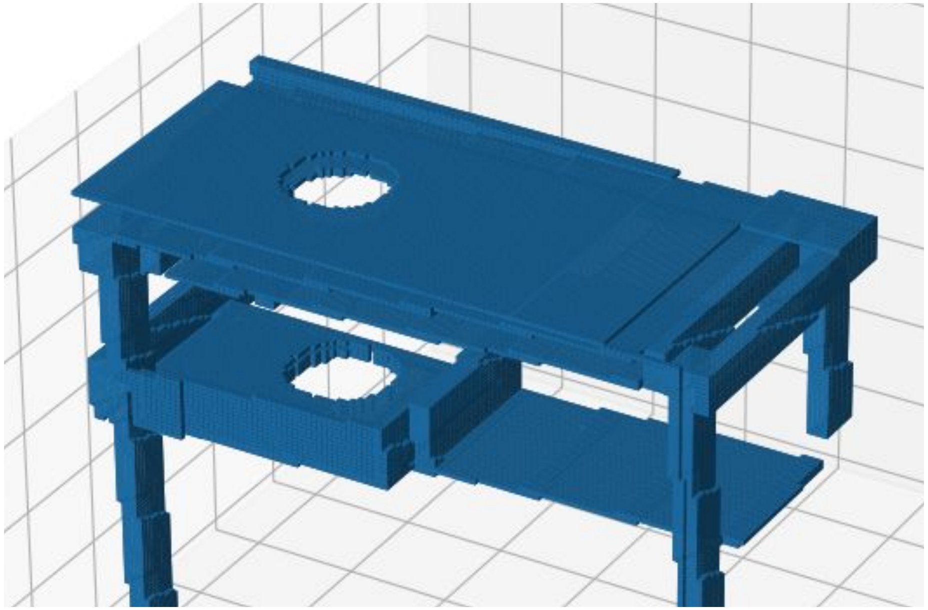
Selected 3D models **already contain holes**



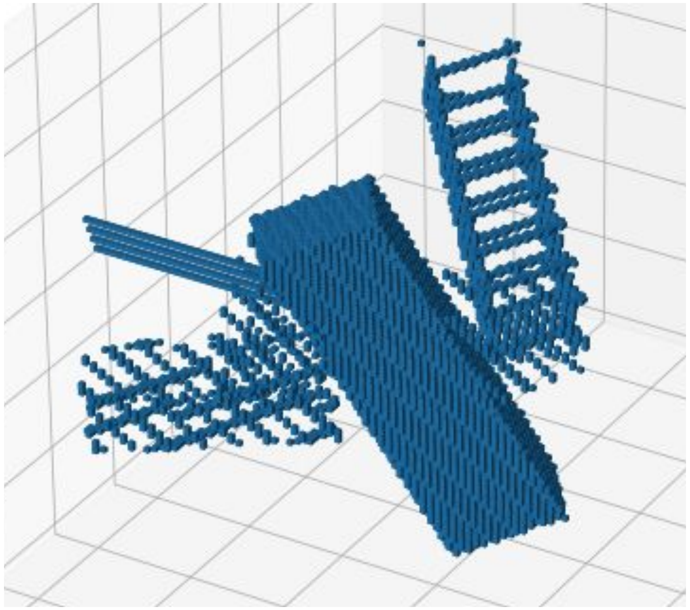


Limitations examples 2/2

Difficult and not detected 3D structure of the model



3D model **too complex**



Additional slides
Deep Learning

Detailed description of Vanilla3DCNN

Vanilla3DCNN Architecture		
Layer Name	**Output Size**	**CNN - Layers**
conv_1	120 x 120 x 120 x 32	9 x 9 x 9/1,32
conv_2	114 x 114 x 114 x 64	7 x 7 x 7/1, 64
Maxpool layer	57 x 57 x 57 x 64	2 x 2 x 2 maxpool,stride 2
conv_3	53 x 53 x 53 x 96	5 x 5 x 5/1, 96
Maxpool layer	26 x 26 x 26 x 96	2 x 2 x 2 maxpool,stride 2
conv_4	24 x 24 x 24 x 128	3 x 3 x 3/1, 128
Maxpool layer	12 x 12 x 12 x 128	2 x 2 x 2 maxpool,stride 2
Average pool layer	11 x 11 x 11 x 128	2 x 2 x 2 maxpool,stride 1
Maxpool layer	1 x 1 x 1 x 128	11 x 11 x 11 maxpool,stride 1
FC_1		32-d fc,ReLU
FC_2		Scalar value, Sigmoid

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Detailed description of ResNet

ResNet Architecture		
Layer Name	**Output Size**	**CNN - Layers**
conv_1	64 x 64 x 64 x 64	5 x 5 x 5/2,64 (Same)
	32 x 32 x 32 x 64	3 x 3 x 3 maxpool,stride 2
conv_2	32 x 32 x 32 x 64	(3 x 3 x 3/1,64) x 2
		(3 x 3 x 3/1,64) x 2
conv_3	16 x 16 x 16 x 128	(3 x 3 x 3/2,128) x 2
		(3 x 3 x 3/2,128) x 2
conv_4	8 x 8 x 8 x 256	(3 x 3 x 3/2,256) x 2
		(3 x 3 x 3/2,256) x 2
Maxpool layer	4 x 4 x 4 x 256	5 x 5 x 5 maxpool,stride 1
Average pool layer	1 x 1 x 1 x 256	4 x 4 x 4 average pool,stride 1
conv_5	1 x 1 x 1 x 1024	(1 x 1 x 1,256)
FC_1		512-d fc,ReLU
FC_2		128-d fc,ReLU
FC_3		64-d fc,ReLU
FC_4		Scalar value,Sigmoid

Detailed description of InceptionNet V1

InceptionNet_v1 Architecture									
Type	**Patch_size/Stride**	**Output_size**	**Depth**	**#1 x 1 x 1**	**#3 x 3 x 3 reduce**	**#3 x 3 x 3**	**#5 x 5 x 5 reduce**	**#5 x 5 x 5**	**Pool Proj**
Convolution	5 x 5 x 5/1	64 x 64 x 64 x 64	1						
Max pool	2 x 2 x 2/2	32 x 32 x 32 x 64							
Convolution	3 x 3 x 3/1	32 x 32 x 32 x 192	1						
Max pool	2 x 2 x 2/2	16 x 16 x 16 x 192							
Inception(3a)		16 x 16 x 16 x 256	2	64	96	128	16	32	32
max pool	2 x 2 x 2/2	8 x 8 x 8 x 256	0						
Inception (4a)		8 x 8 x 8 x 512	2	192	96	208	16	48	64
Max pool	2 x 2 x 2/2	4 x 4 x 4 x 512	0						
Inception(5a)		4 x 4 x 4 x 1024	2	384	192	384	48	128	128
Maxpool	2 x 2 x 2/2	2 x 2 x 2 x 1024	0						
Inception(6a)		2 x 2 x 2 x 1024	2	384	192	384	48	128	128
Average pool	2 x 2 x 2/1	1 x 1 x 1 x 1024	0						
Dropout	p = 0.4								
FC1		512							
FC2		64							
FC3		1							

Detailed description of InceptionNet V3

InceptionNet_v3 Architecture										
Type	**Patch_size/Stride**	**Output_size**	**Depth**	**#1 x 1 x 1**	**#3 x 3 x 3 reduce_1**	**#3 x 3 x 3 reduce_2**	**#3 x 3 x 3**	**#3 x 3 x 3 reduce**	**#3 x 3 x 3**	**Pool Proj**
Convolution	5 x 5 x 5/1	128 x 128 x 128 x 64	1							
Max pool	2 x 2 x 2/2	64 x 64 x 64 x 64								
Convolution	3 x 3 x 3/1	64 x 64 x 64 x 192	1							
Max pool	2 x 2 x 2/2	32 x 32 x 32 x 192								
Inception 3		32 x 32 x 32 x 256	3	32	64	64	128	64	64	32
max pool	2 x 2 x 2/2	16 x 16 x 16 x 256	0							
Inception 4		16 x 16 x 16 x 512	2	128	128	128	128	64	128	128
Max pool	2 x 2 x 2/2	8 x 8 x 8 x 512	0							
Inception 5		4 x 4 x 4 x 1024	2	128	256	256	384	256	384	128
Maxpool	2 x 2 x 2/2	2 x 2 x 2 x 1024	0							
Inception 6		2 x 2 x 2 x 1024	2	128	256	256	384	256	384	128
Average pool	2 x 2 x 2/1	1 x 1 x 1 x 1024	0							
Dropout	p = 0.4									
FC1		512								
FC2		64								
FC3		1								

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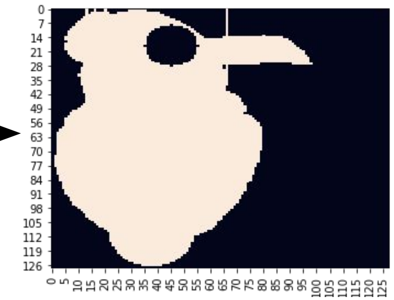
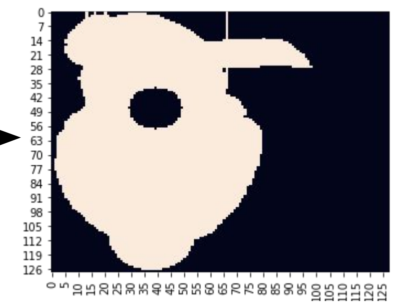
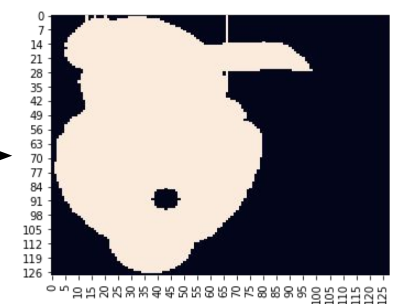
Additional slides
Results & Performance Analysis

False Prediction Analysis[1]

Label	Defect Location	Count
non-printable	border	4
printable	middle	6
non-printable	middle	9
printable	no-defect	10





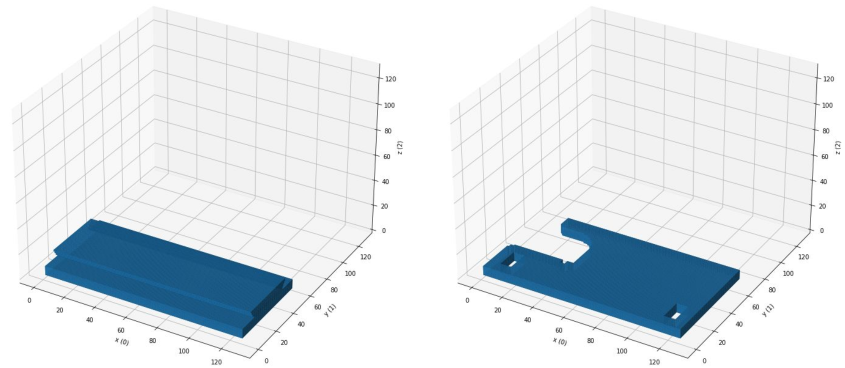


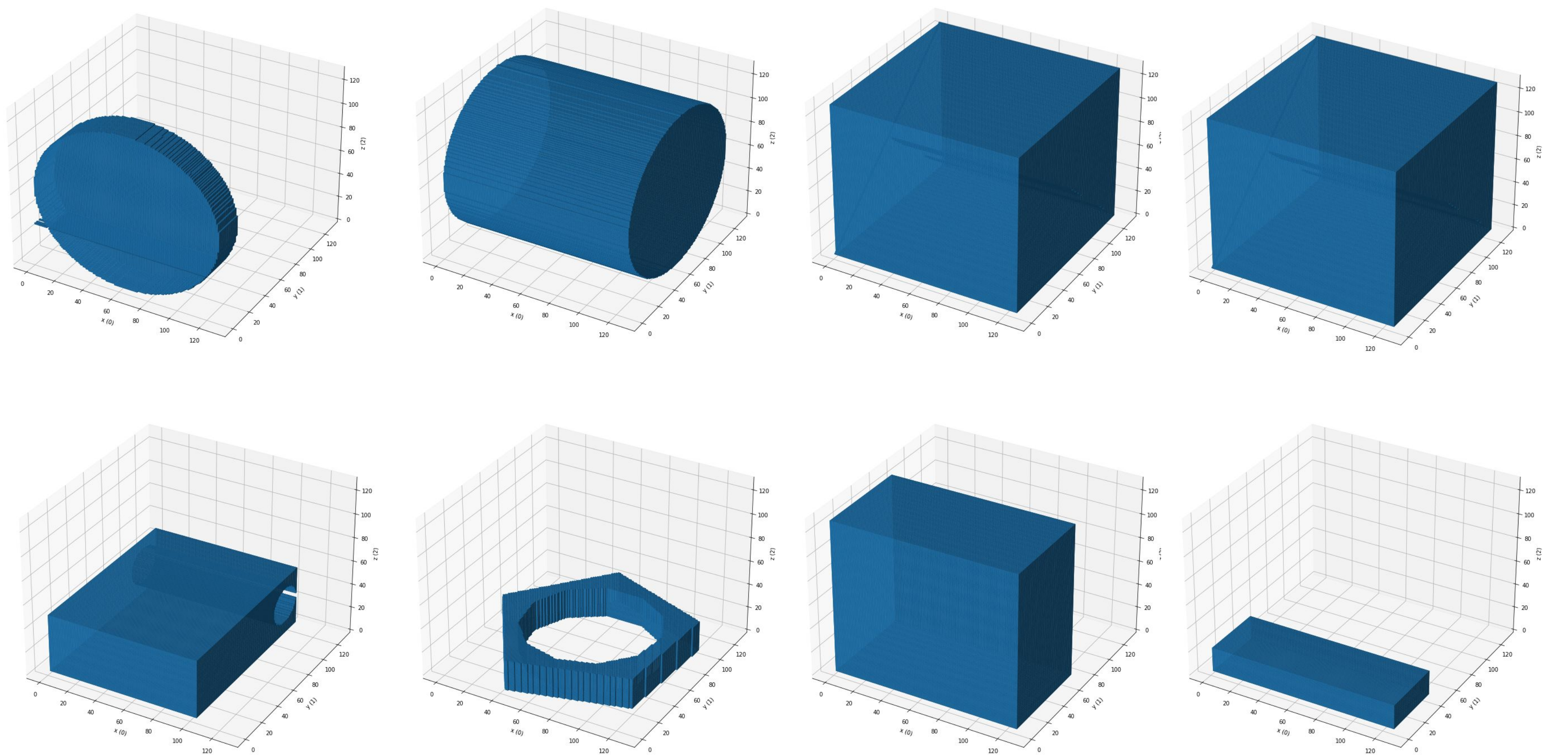
(1) Utilized neural network model: InceptionNet V3

VOLKSWAGEN DATA:LAB

False Prediction Analysis(1)

printable - no defect added

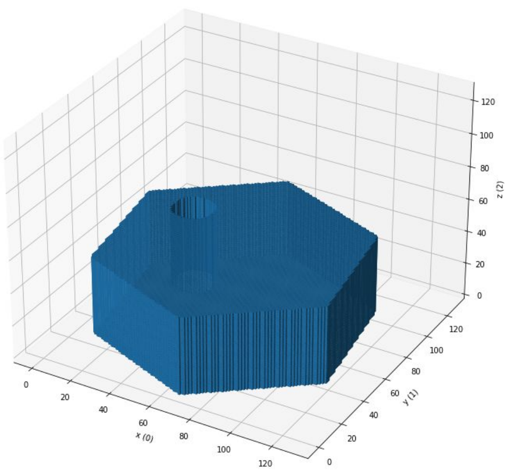


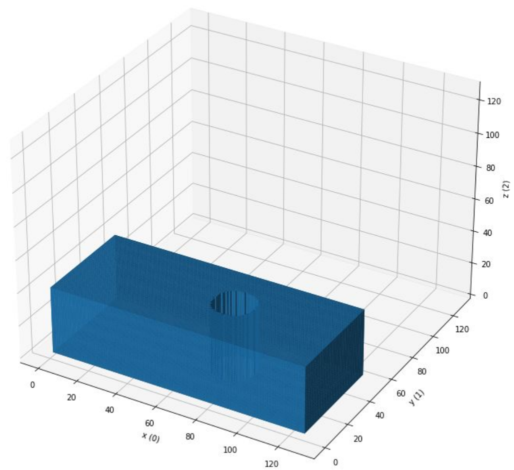


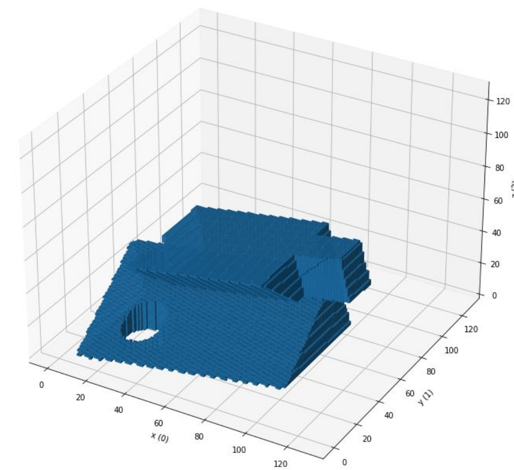
(1) Utilized neural network model: InceptionNet V3

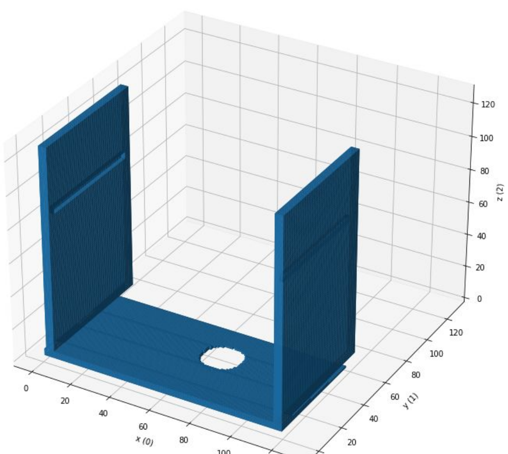
False Prediction Analysis(1)

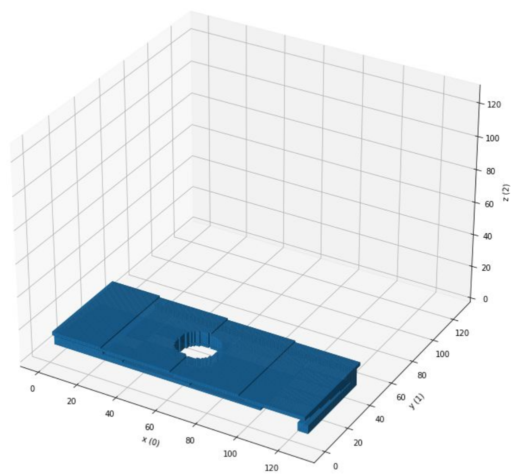
printable - middle

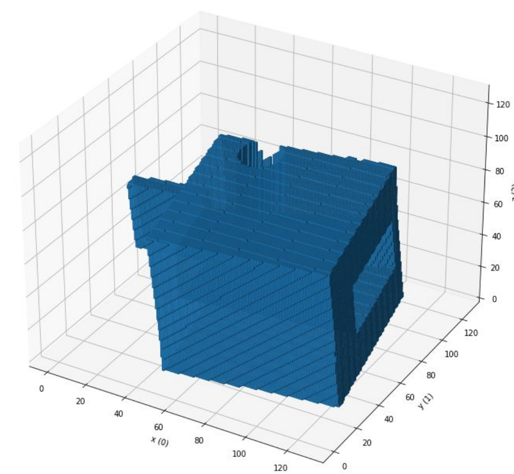








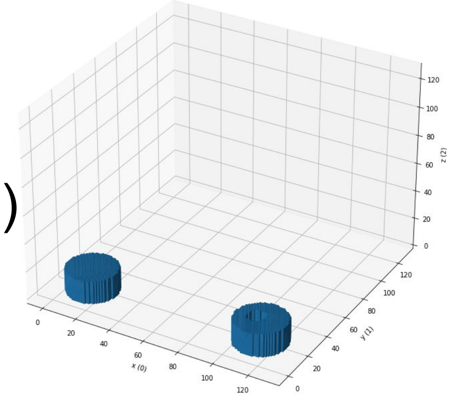
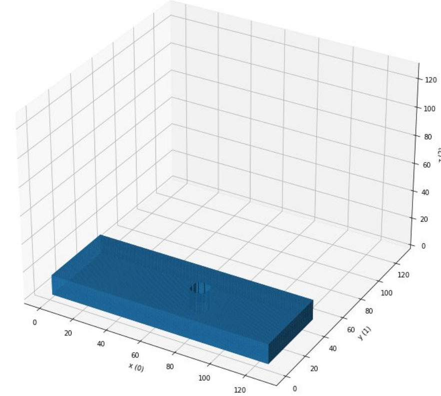
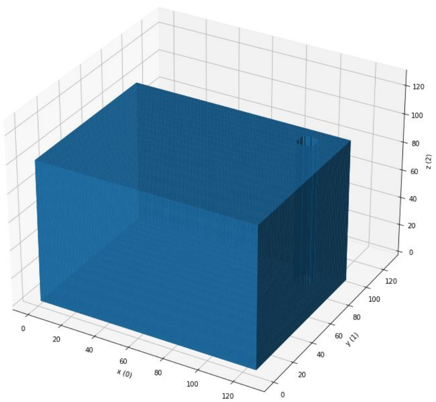
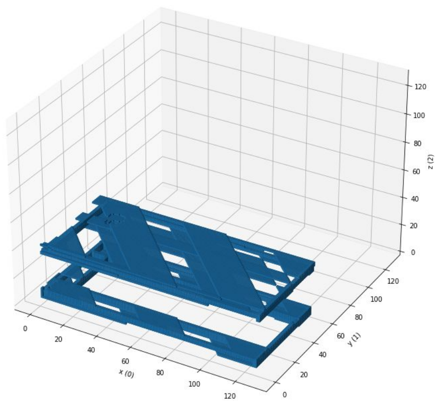
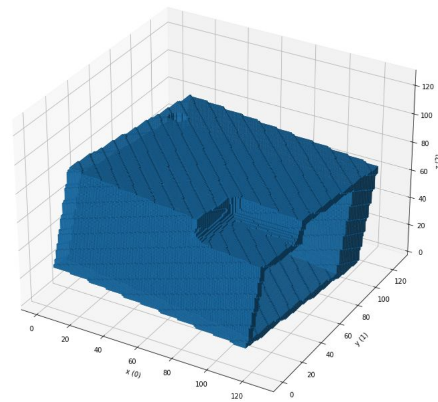
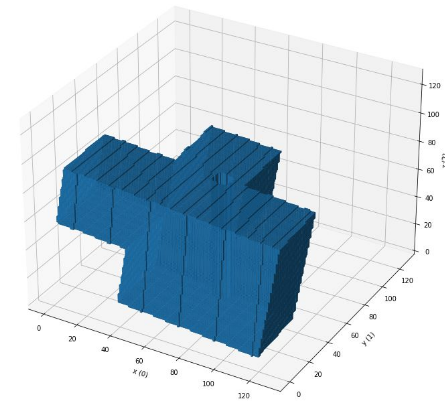
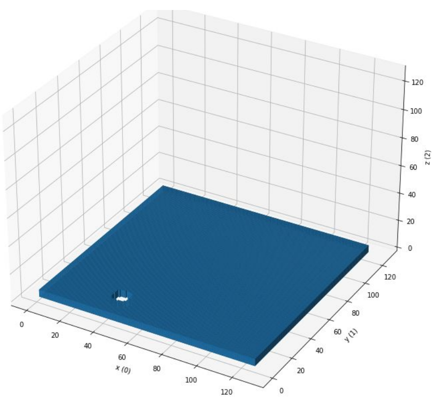
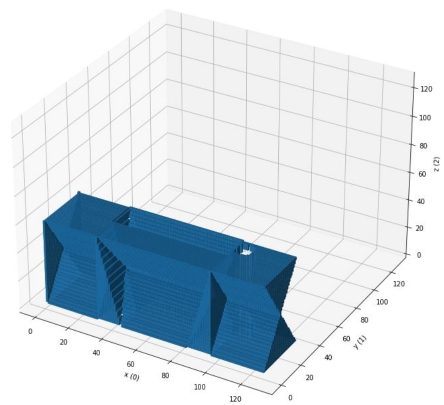
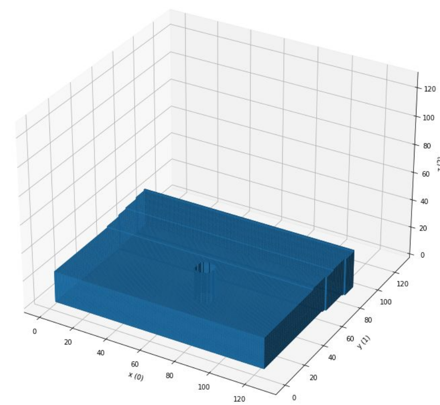




(1) Utilized neural network model: InceptionNet V3

False Prediction Analysis[1]

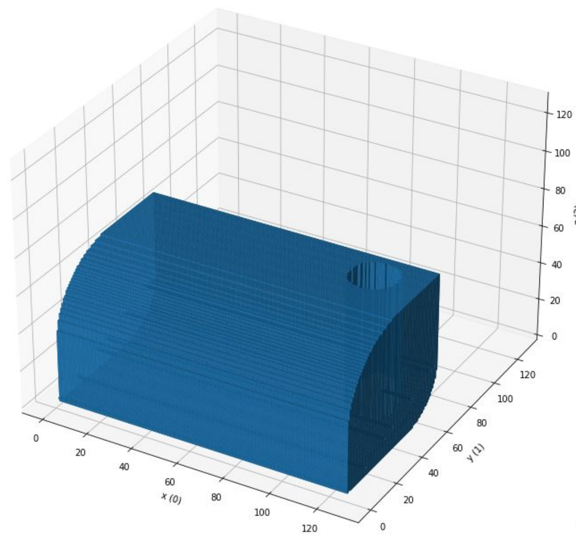
non-printable - middle

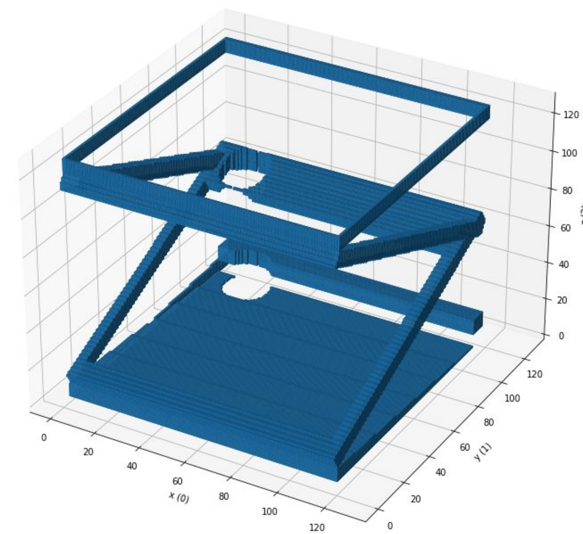










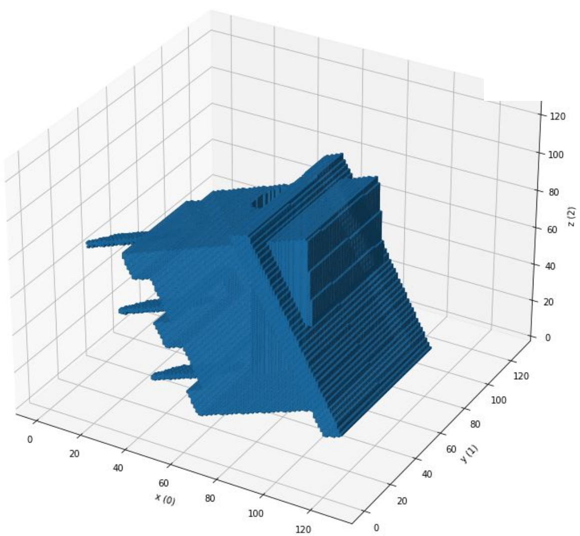
(1) Utilized neural network model: InceptionNet V3

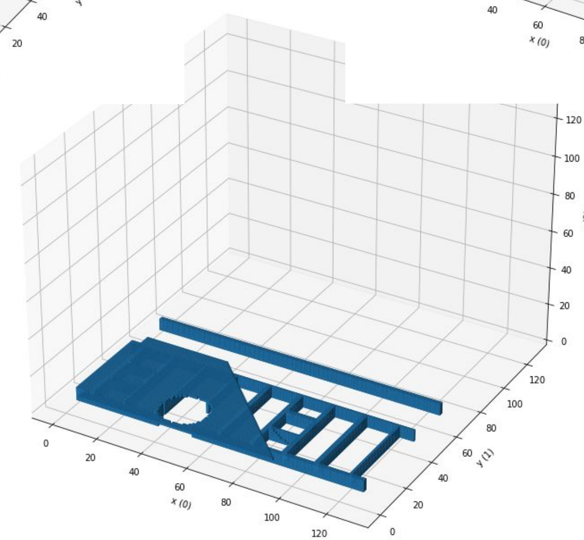
False Prediction Analysis(1)

non-printable - bord









(1) Utilized neural network model: InceptionNet V3