Closed-Loop Control of Robotic 3D Clay Printing Using Machine Learning

Graduation Project
Xiaochen Ding
25th, June 2025

3D Clay Printing

- Complex geometries
- Sustainable materials
- Multi- scenarios

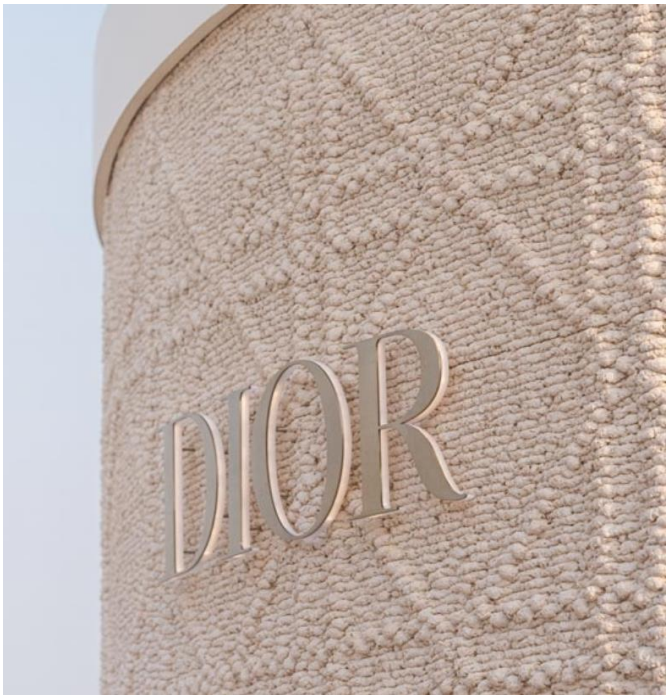


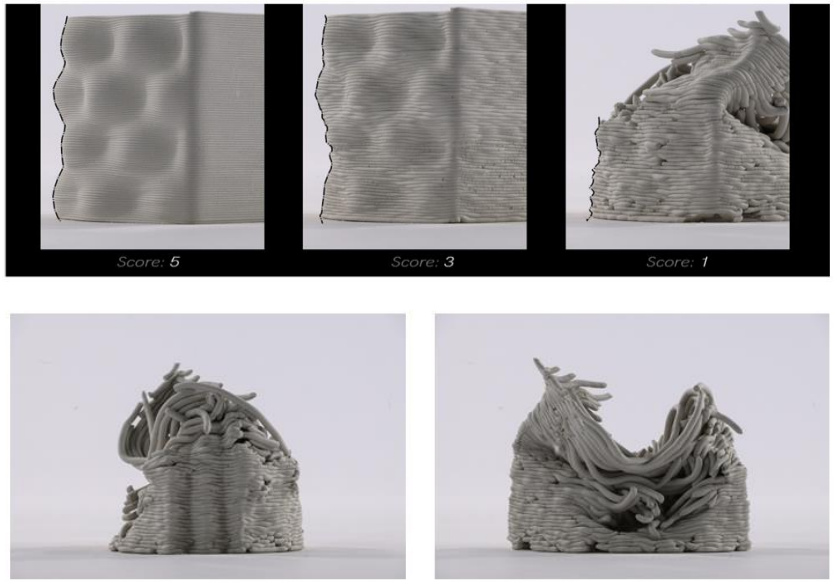
Image Source (from left to right):
https://au.pinterest.com/pin/31243791160165963/
https://studiorap.nl/Ceramic-House
https://www.3dwasp.com/en/3d-printed-pop-up-store-wasp-dior/
https://www.3dwasp.com/en/3d-printed-pop-up-store-wasp-dior/

Limitations

Layer deformation

Printing failures

(Gürsoy, 2018)



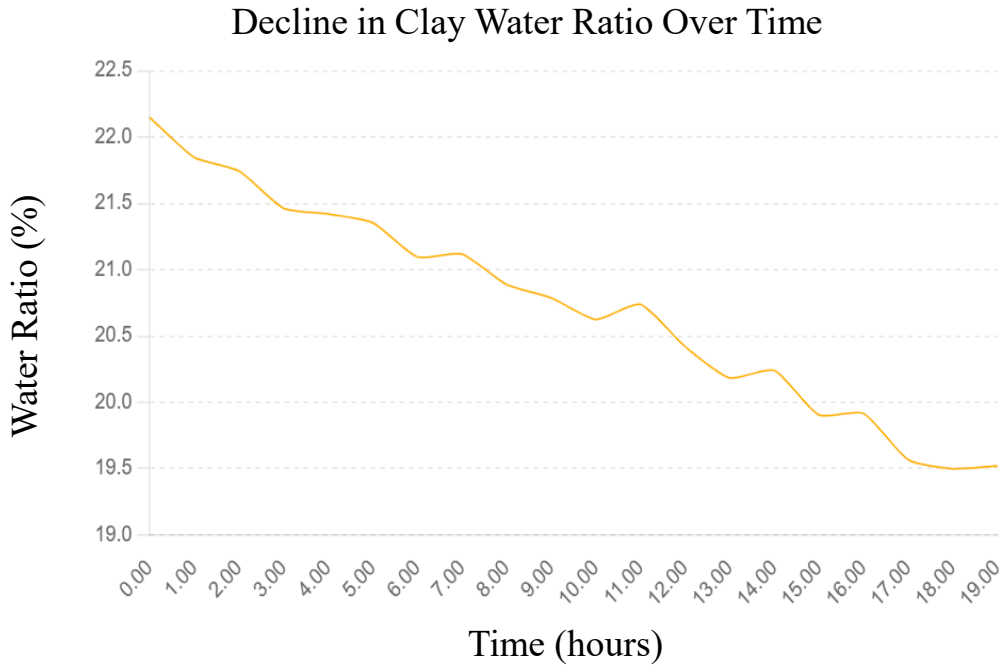
(Aşut et al., 2025)

Clay Mixing

Problem 1: Inconsistent Clay Mixture

Manual Mixing

Problem 2: Time-varying Clay Mixture



Illustrative Figure

Maunual Adjustment

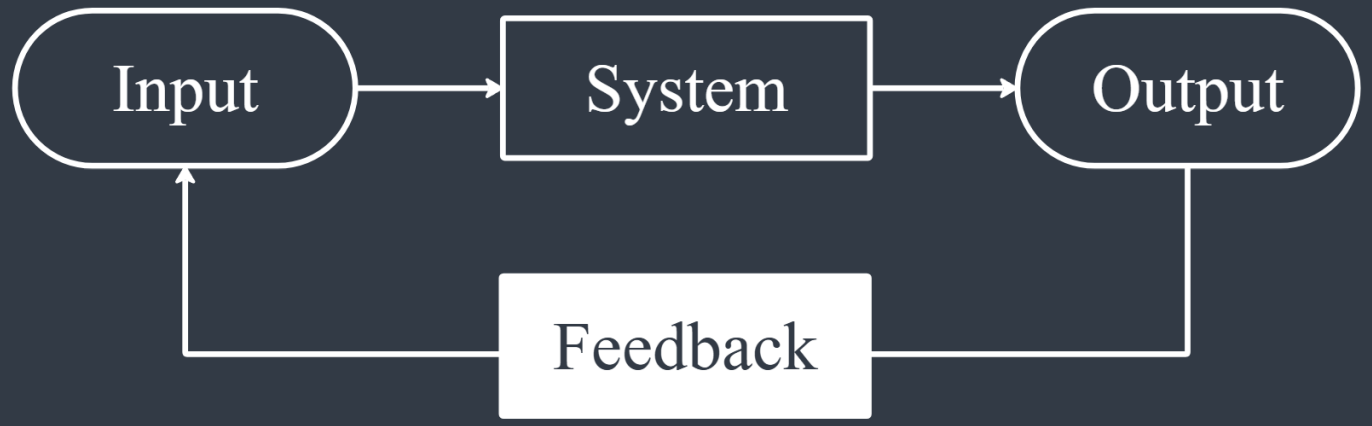
Image Sourcehttps://www.3dwasp.com/en/3d-printed-pop-up-store-wasp-dior/

Manual adjustments are time-consuming and difficult to scale.

Open-loop Control

Open-loop systems fail to adapt to these dynamic changes during printing.

Close-loop Control



Close-loop systems can realize dynamic adjustments during printing.

Comparisions

	Manual Adjustment	Open-loop Control	Close-loop Control
Problem 1	✅	✅	✅
Problem 2	✅	❌	✅
Stability	❌	✅	✅
Efficiency (Cost)	❌	✅	✅

Stability: The ability of a strategy to maintain consistent extrusion quality without sudden fluctuations.

Research Question

Can a machine learning-assisted closed-loop system enable real-time anomaly detection and correction in robotic 3D clay printing of overhang structures?

Objectives

1. Good Extrusion Quality

2. Overhang Success

Methods

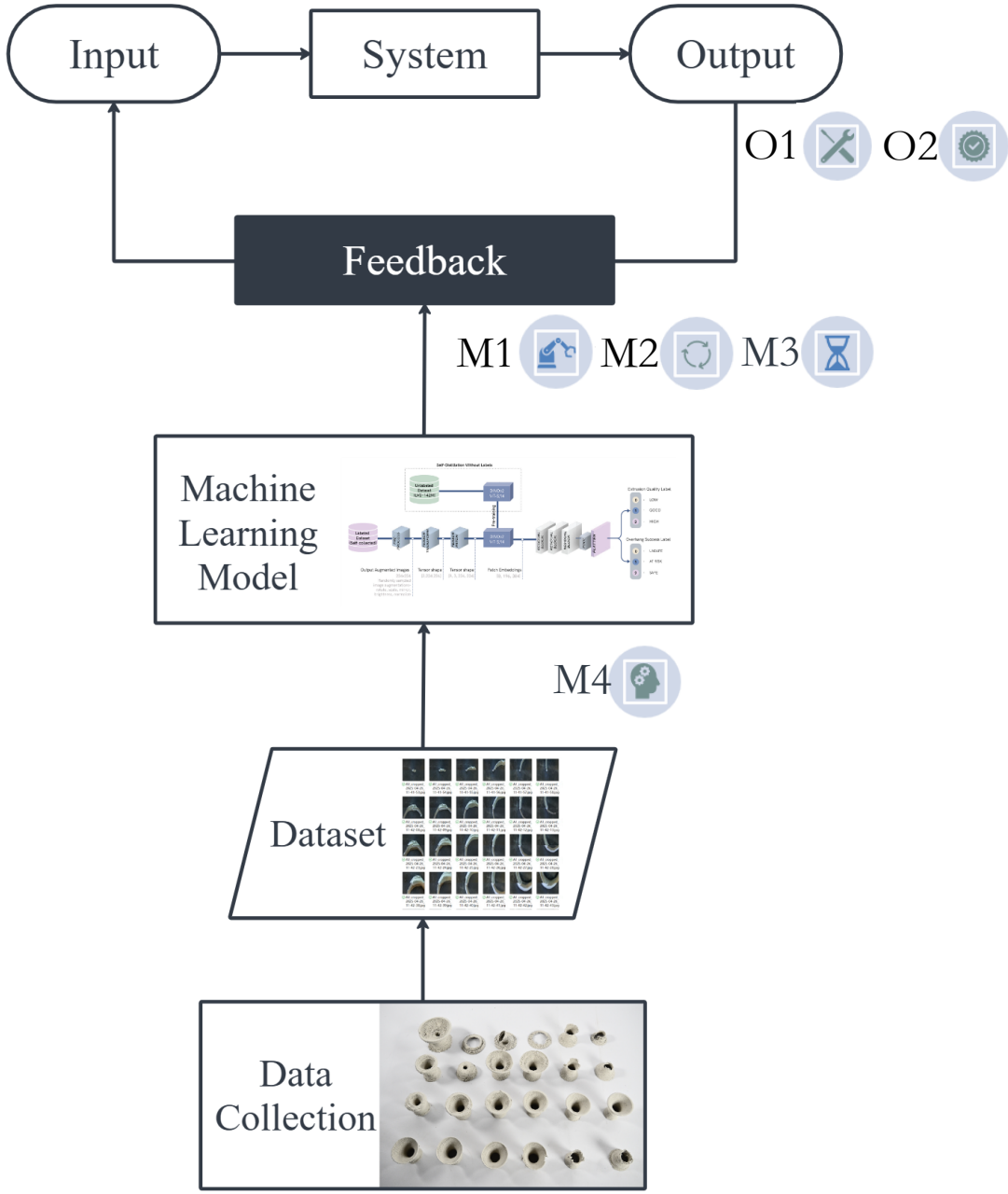
1. Robotic control

2. Close-loop calibration

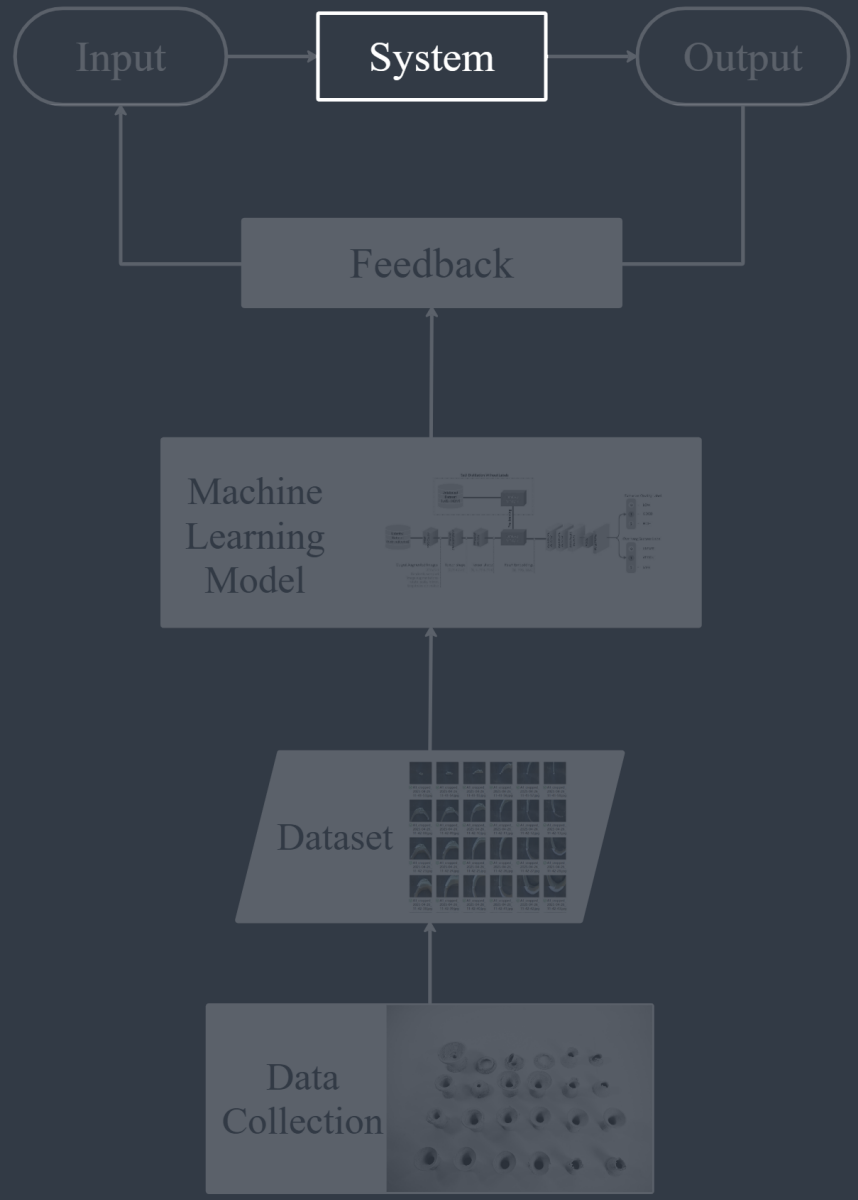
3. Real-time visual feedback

4. Multi-objective Machine Learning

Methodology & Workflow



Experimental Setup



6-axis robotic arm

UR5 robot

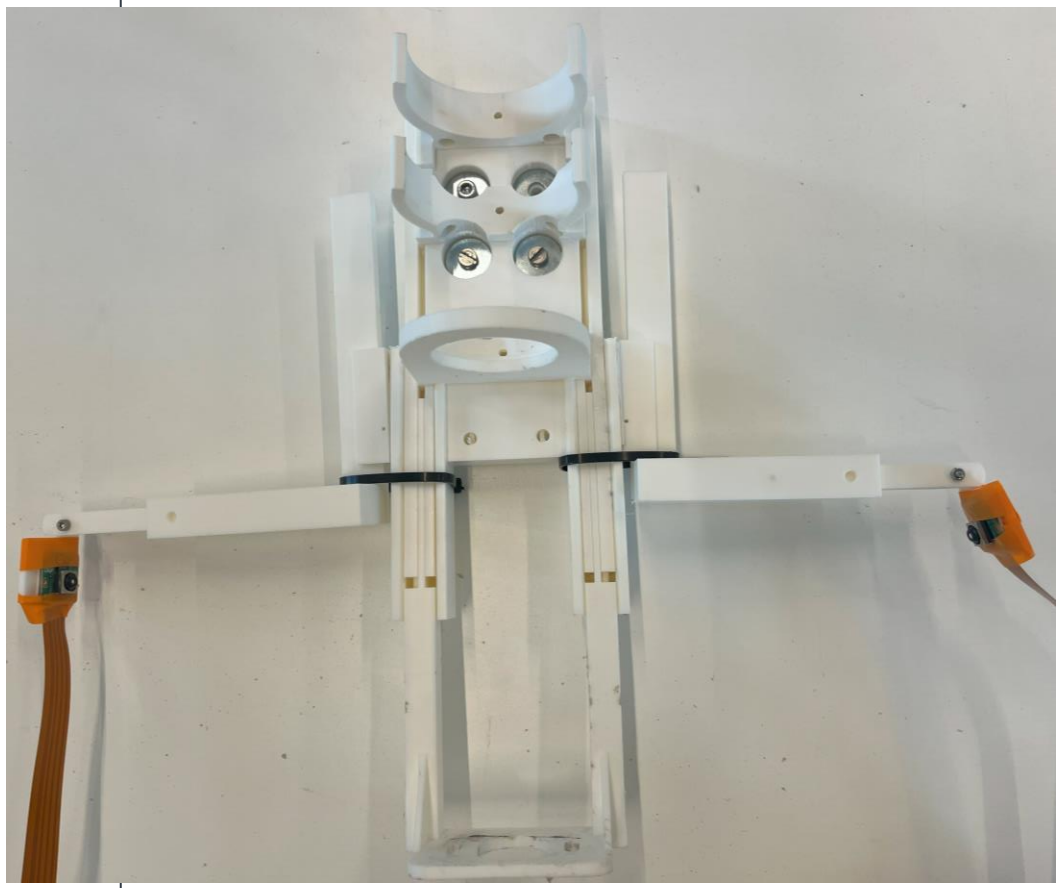
WASP LDM extruder (3mm nozzle)

1L Clay Tank

Pros:

- Flexibility of construction
- Practical feasibility (easy to scale up)

Frame Design



3. Real-time visual feedback

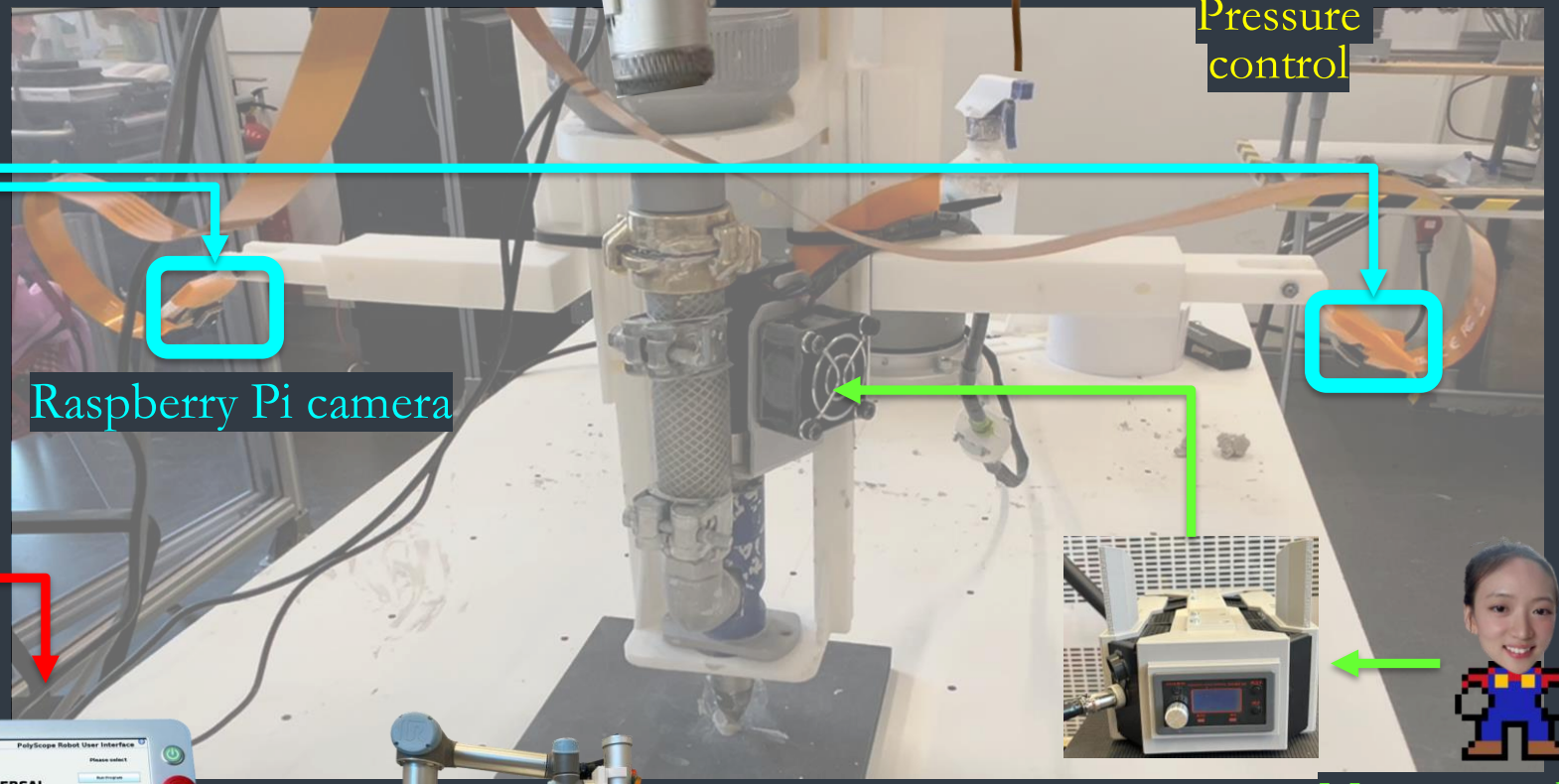
Self-design clay tank frame & camera arm

The entire setup, including extruder mount and camera system, was custom-fabricated and optimized for flexibility and experimental control.

Overall Connection

3. Real-time visual feedback

Photo Collection control

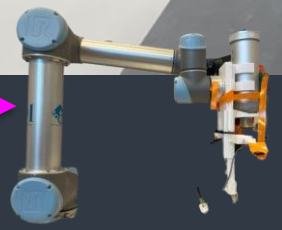


Pressure control

Raspberry Pi camera

PC

Robotic control



Motor speed control

Dataset

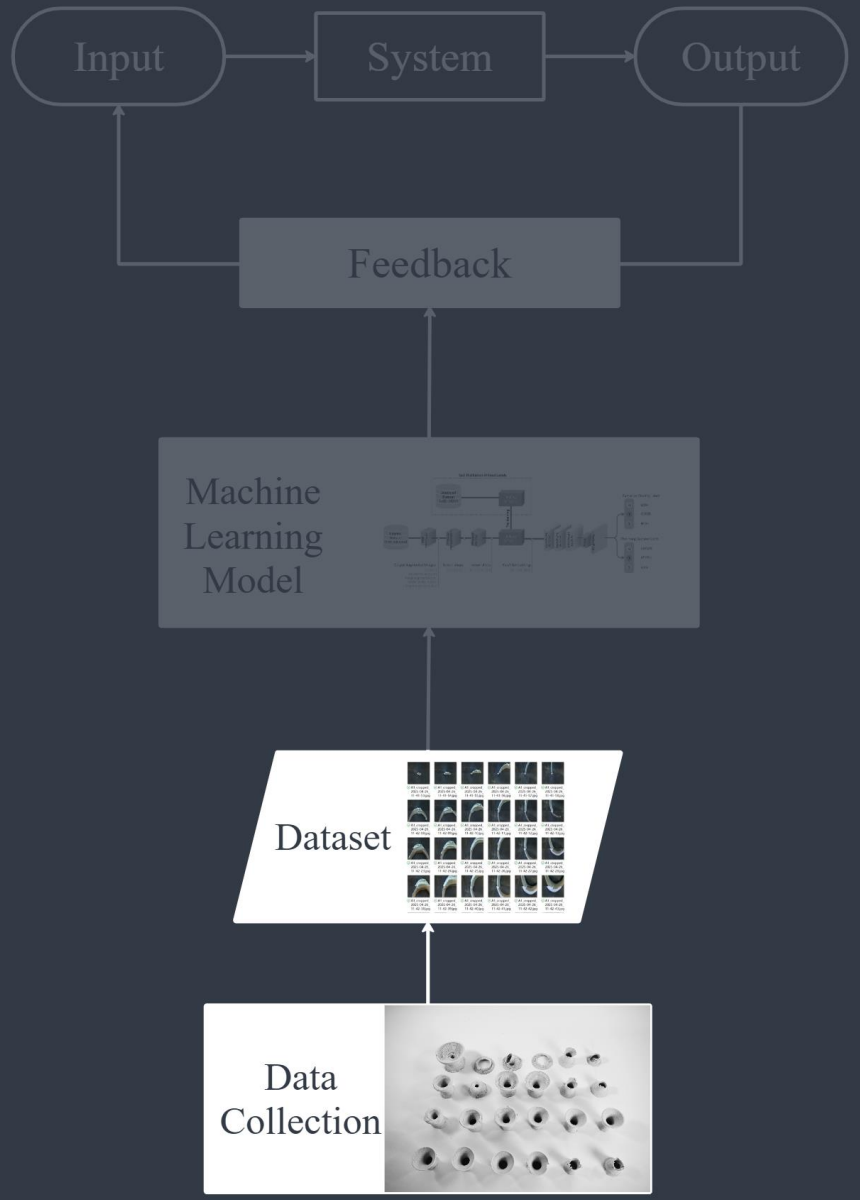
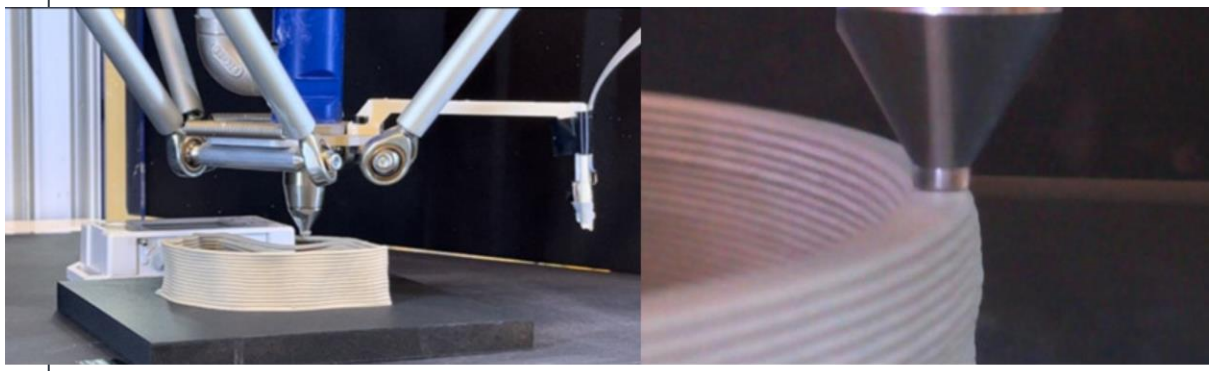
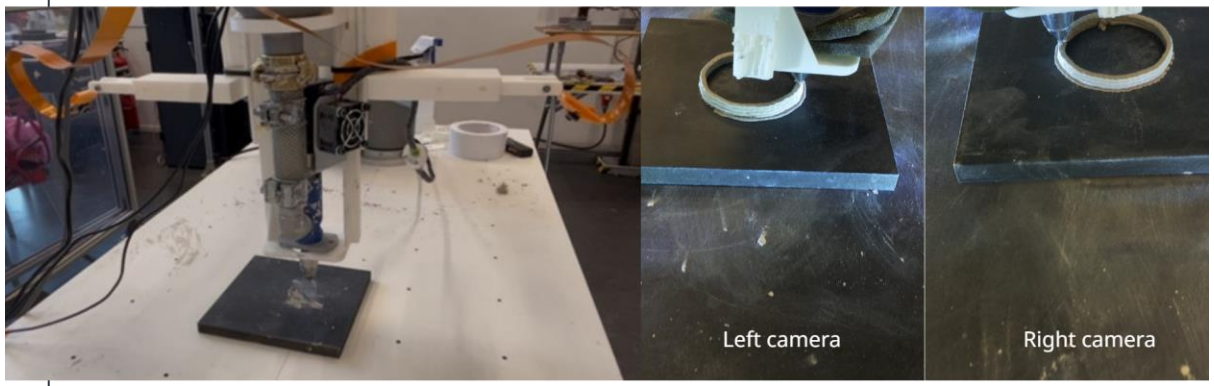

Input
System
Output
Feedback
Machine Learning Model
Dataset
Data Collection

Photo-taken

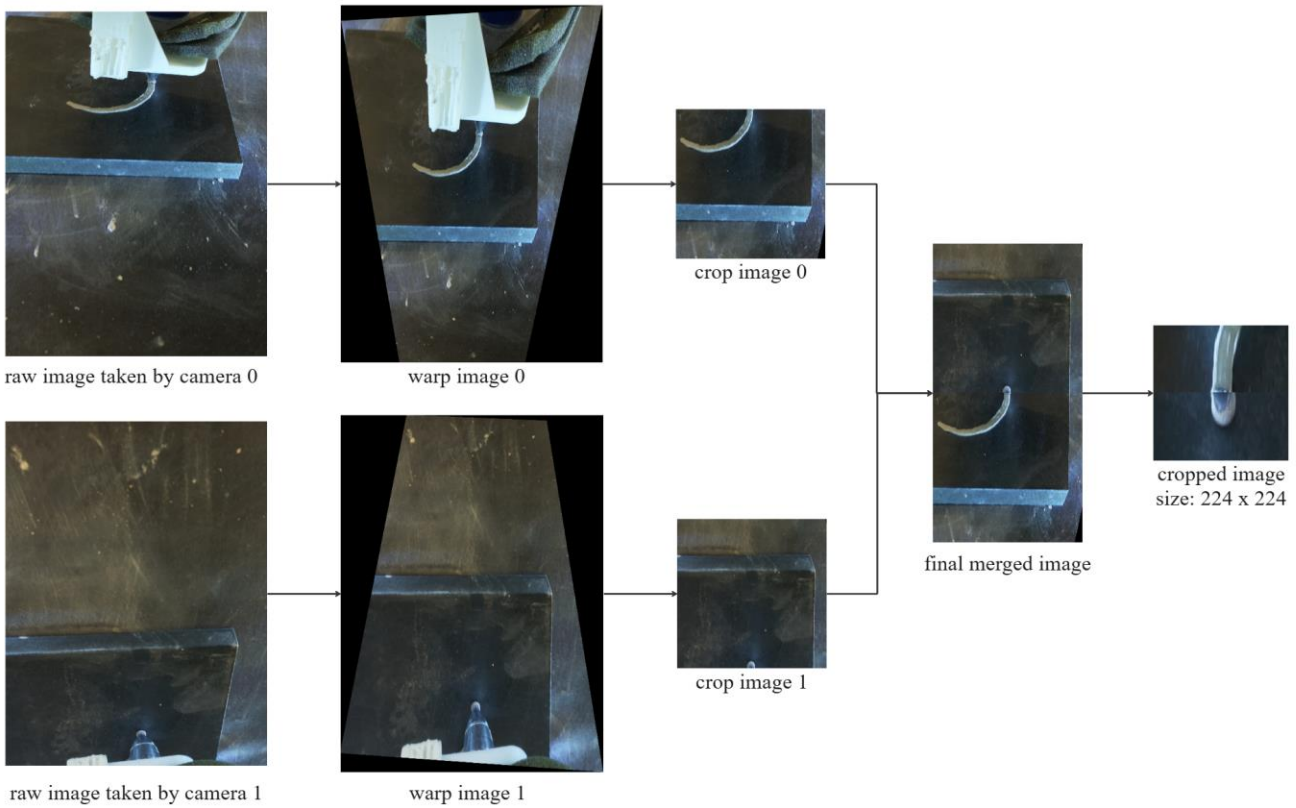


One camera strategy – side view



Two-camera strategy – full top view

Image Calibration

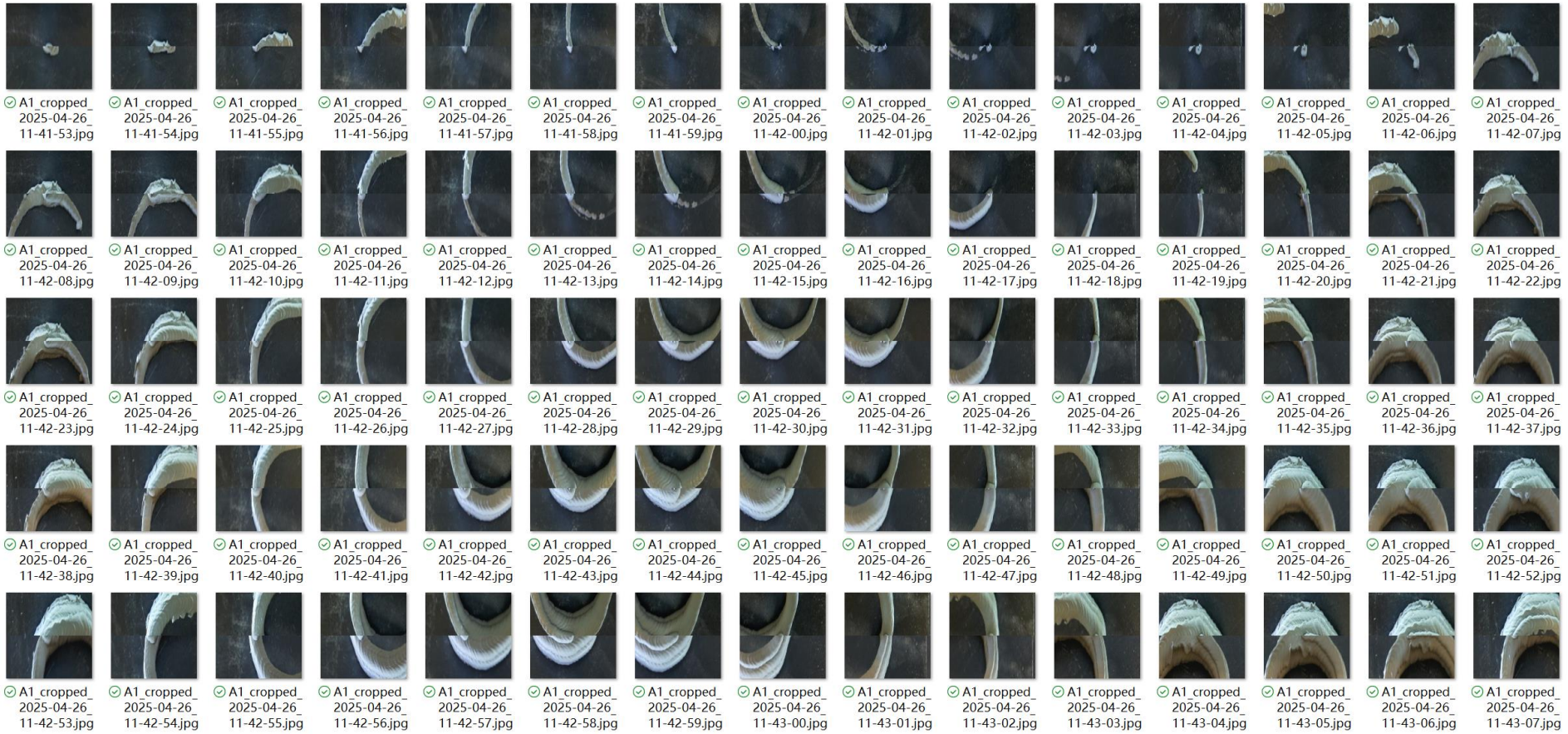


3500 × 4608 pixels

Guarantee the accuracy of data

Applicable to general experiment set-up

Dataset



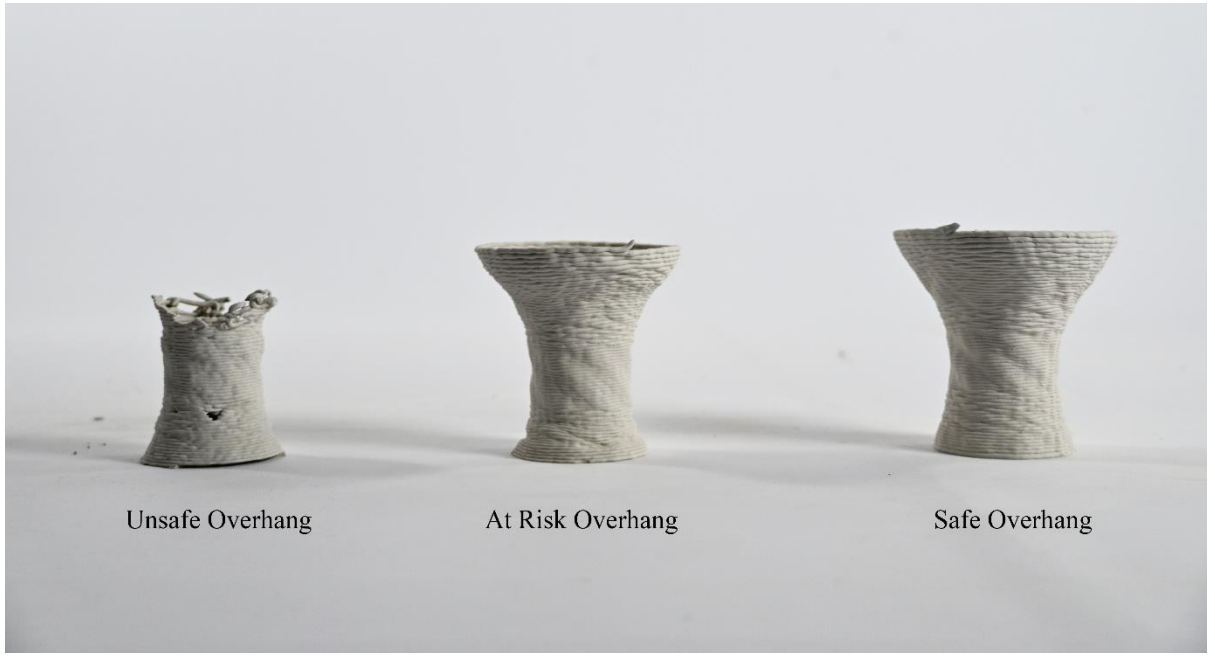
A total of 31,153 images were initially collected.

After image filtering, 17,553 image pairs were retained

Labelling Standard

1. Extrusion quality

2. Overhang success



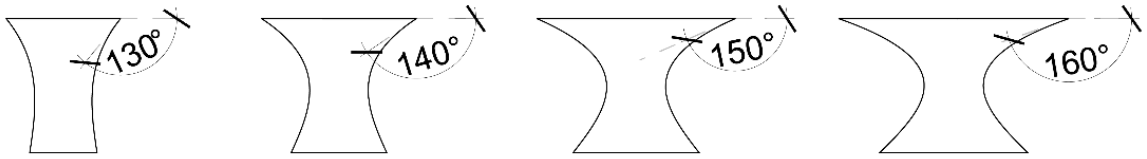
Parameter 1: Extrusion quality

(evaluated by shell thickness)

Parameter 2: Overhang success

(evaluated by contacting areas)

Labelling Summary



Angle 1 Angle 2 Angle 3 Angle 4

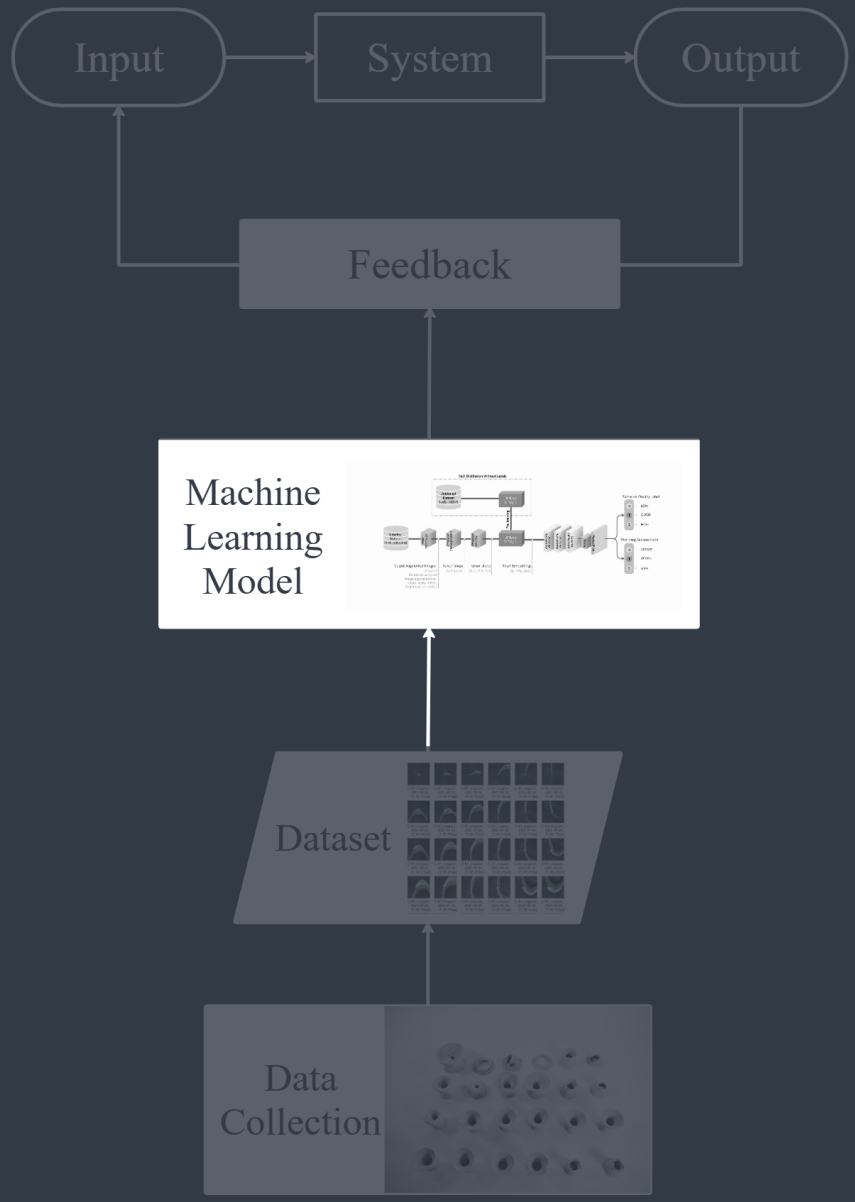
Speed / Angle	S1 0.1	S2 0.2	S3 0.3	S4 0.4	S5 0.5	S6 0.6	S7 0.7	S8 0.8	S9 0.9	S10 1
A1 130°	√	√	√	√	√	√	√	√	×	×
A2 140°	√	√	√	√	√	√	×	×	×	×
A3 150°	√	√	√	×	×	×	×	×	×	×
A4 160°	√	√	√	×	×	×	×	×	×	×

Legend:

Parameter1: Extrusion
- Under Extrusion, label: [0]
- Good Extrusion, label: [1]
- Over Extrusion, label: [2]

Parameter2: Overhang success
- Safe, label: [0]
- At risk, label: [1]
- Unsafe, label: [2]
- Failure (no data)

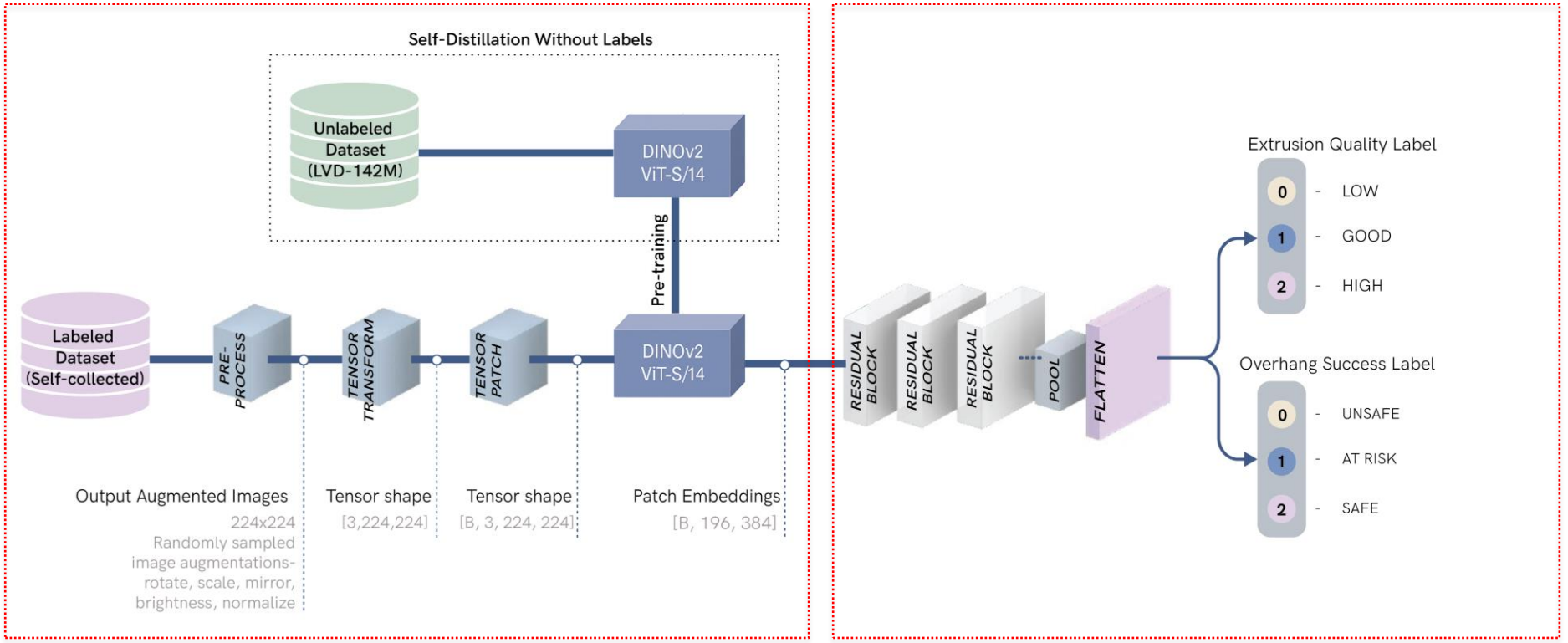
Machine Learning



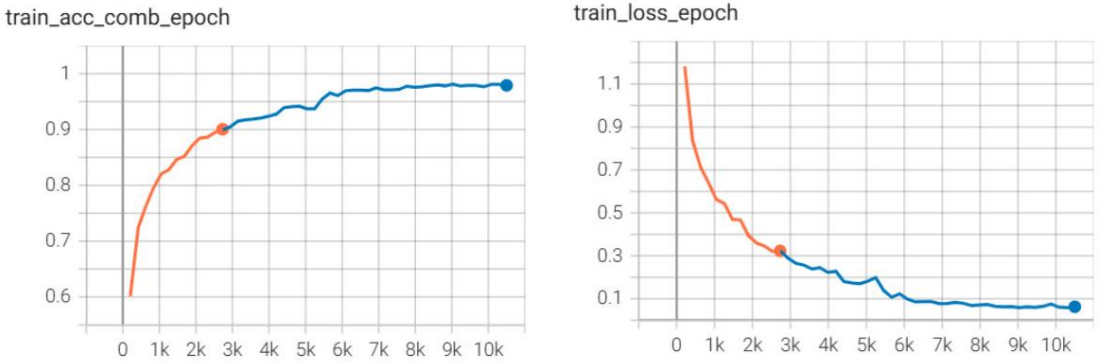
DINOv2-Based Hybrid Network Architecture

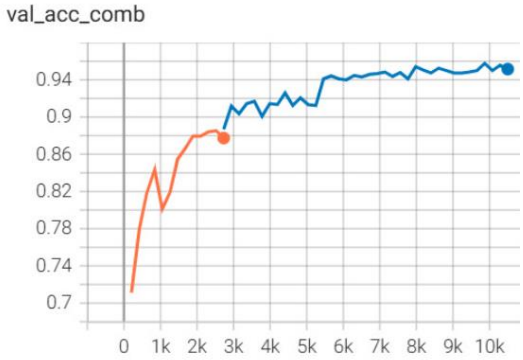
DINO v2

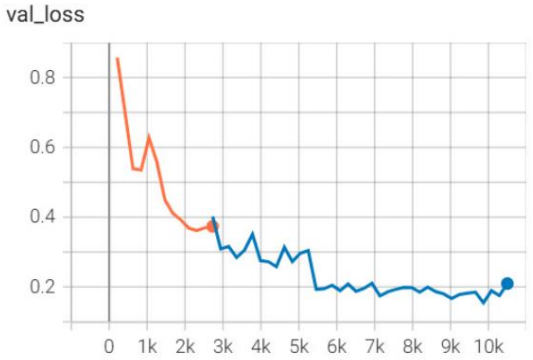
Resnet 56



ML Learning Curves Comparisons

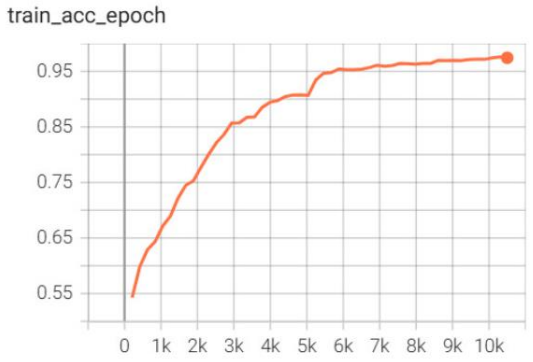


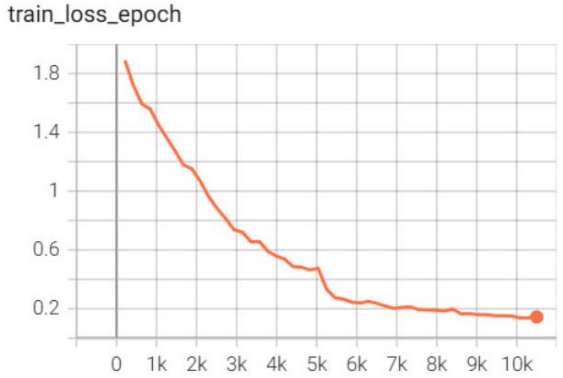


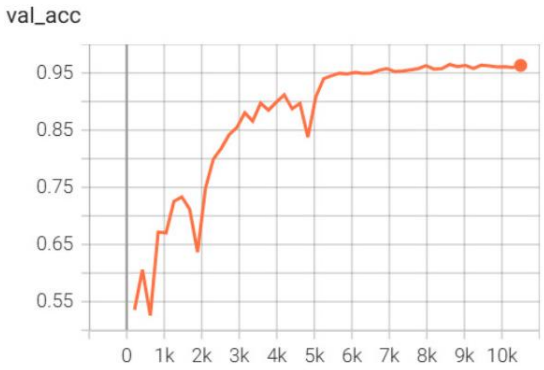


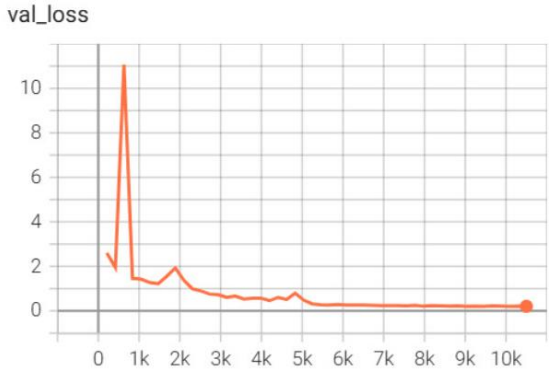
Hybrid ML model

Training time: 11 hours and 34 minutes







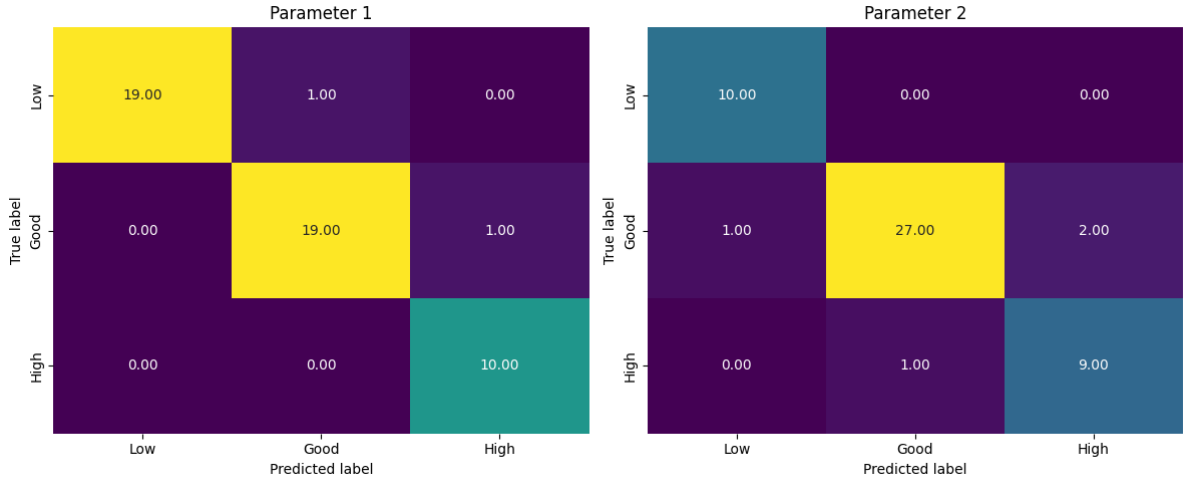


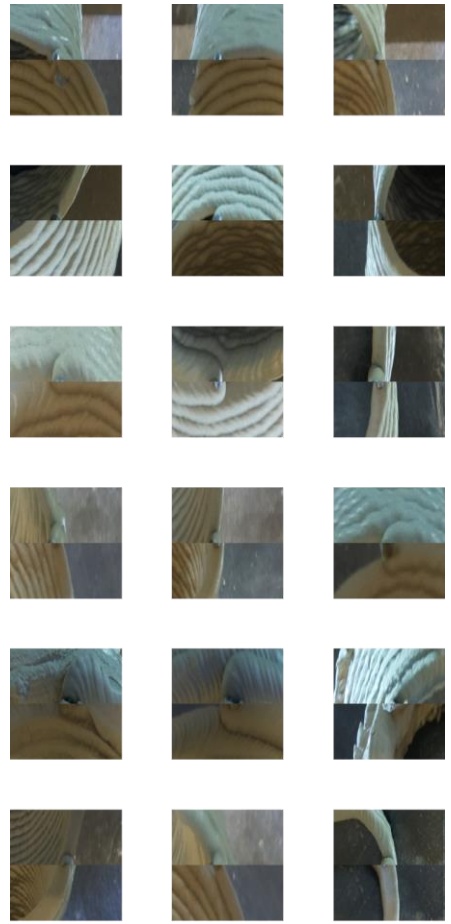
Resnet 56 ML model

Training time: 1 hour and 55 minutes

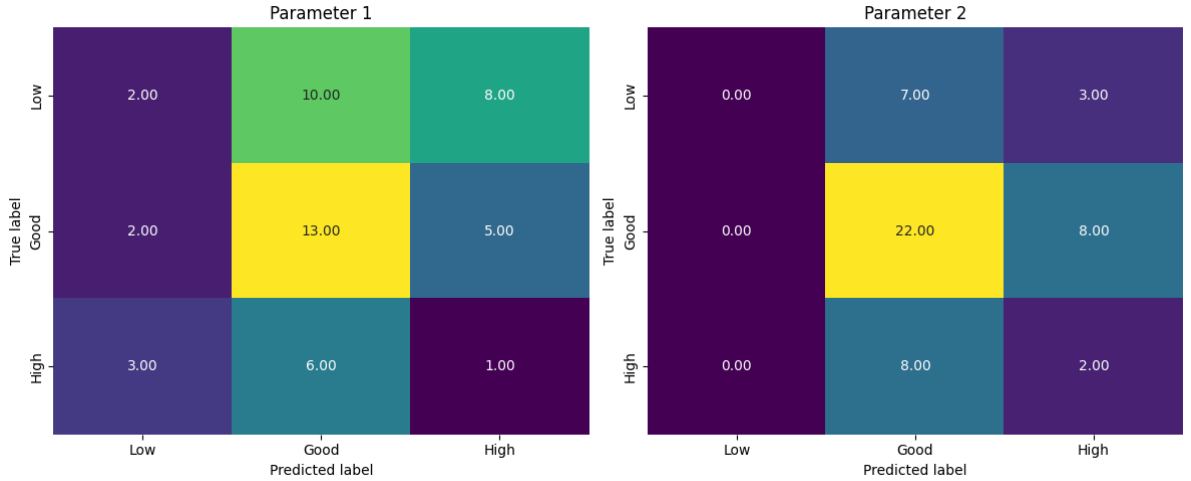
ML Prediction Accuracy Matrices

Hybrid

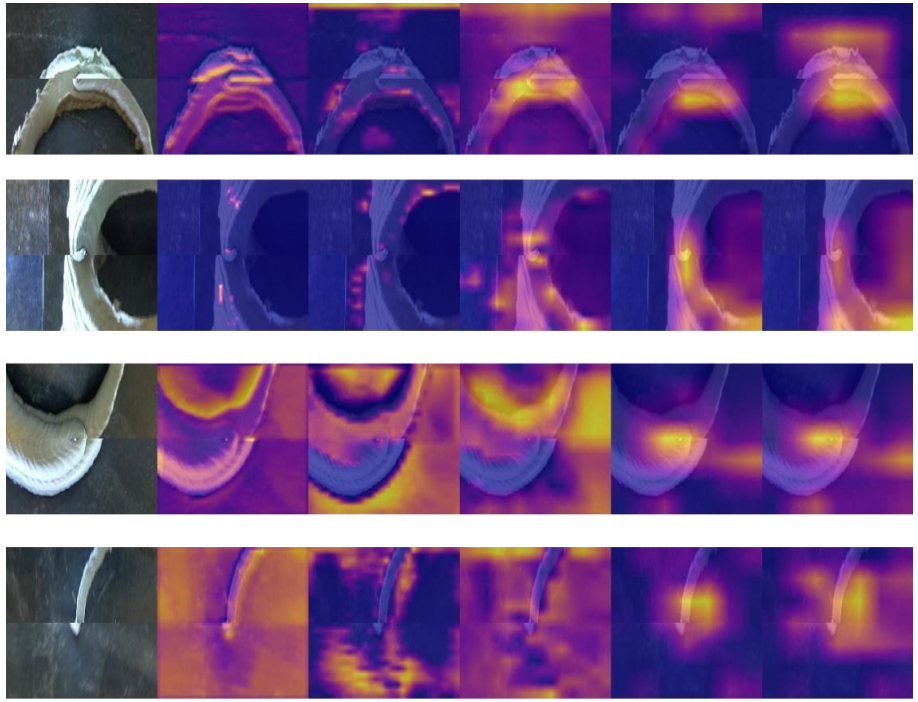




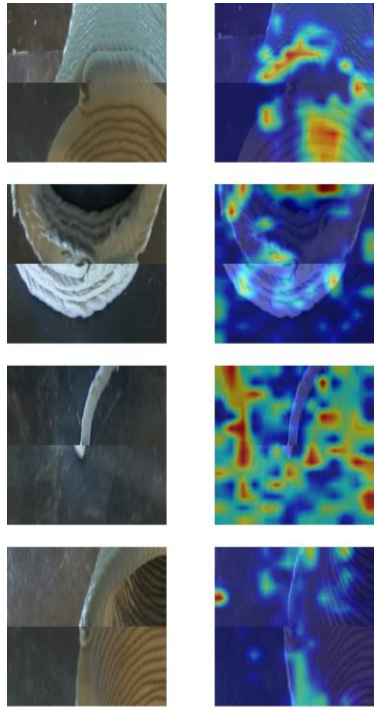
Resnet 56



Grad-CAM Visualization

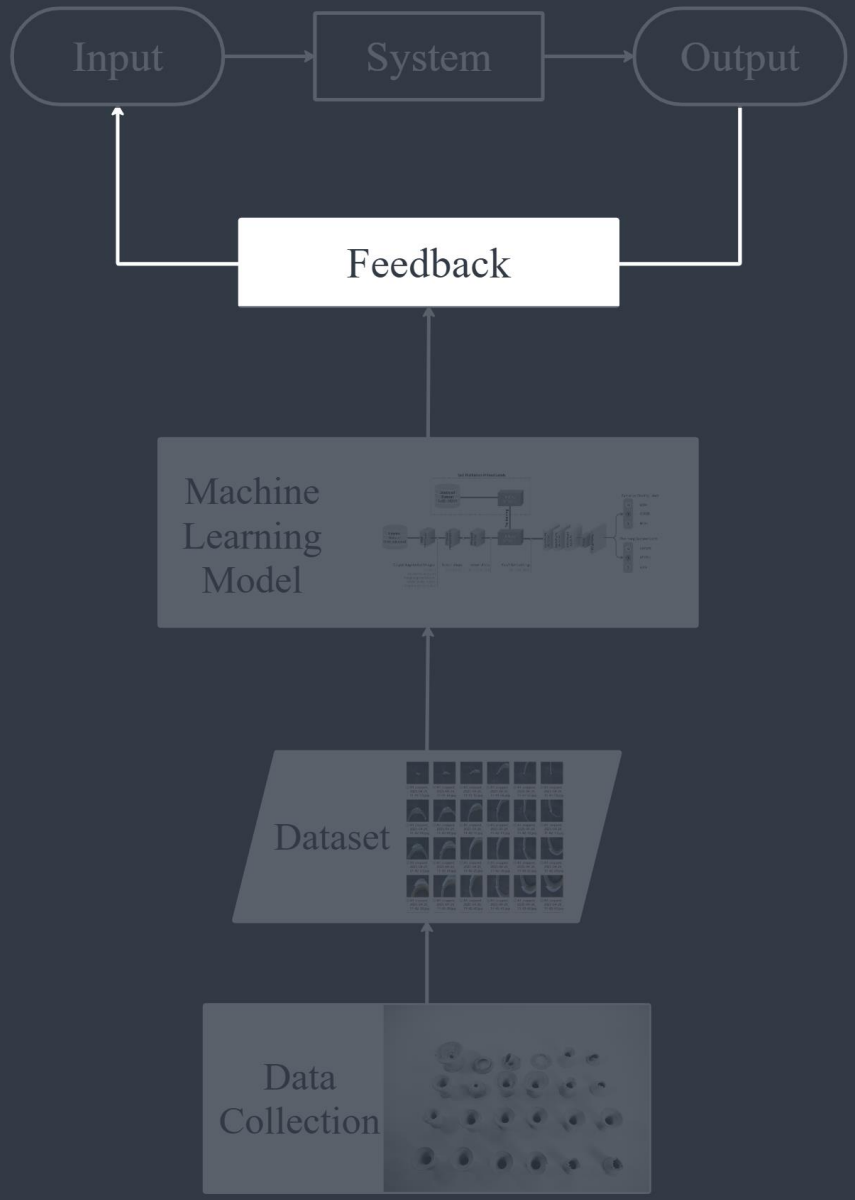


Resnet 56



DINO v2

Closed-Loop Real-Time Correction



Logic Table

1. Extrusion quality

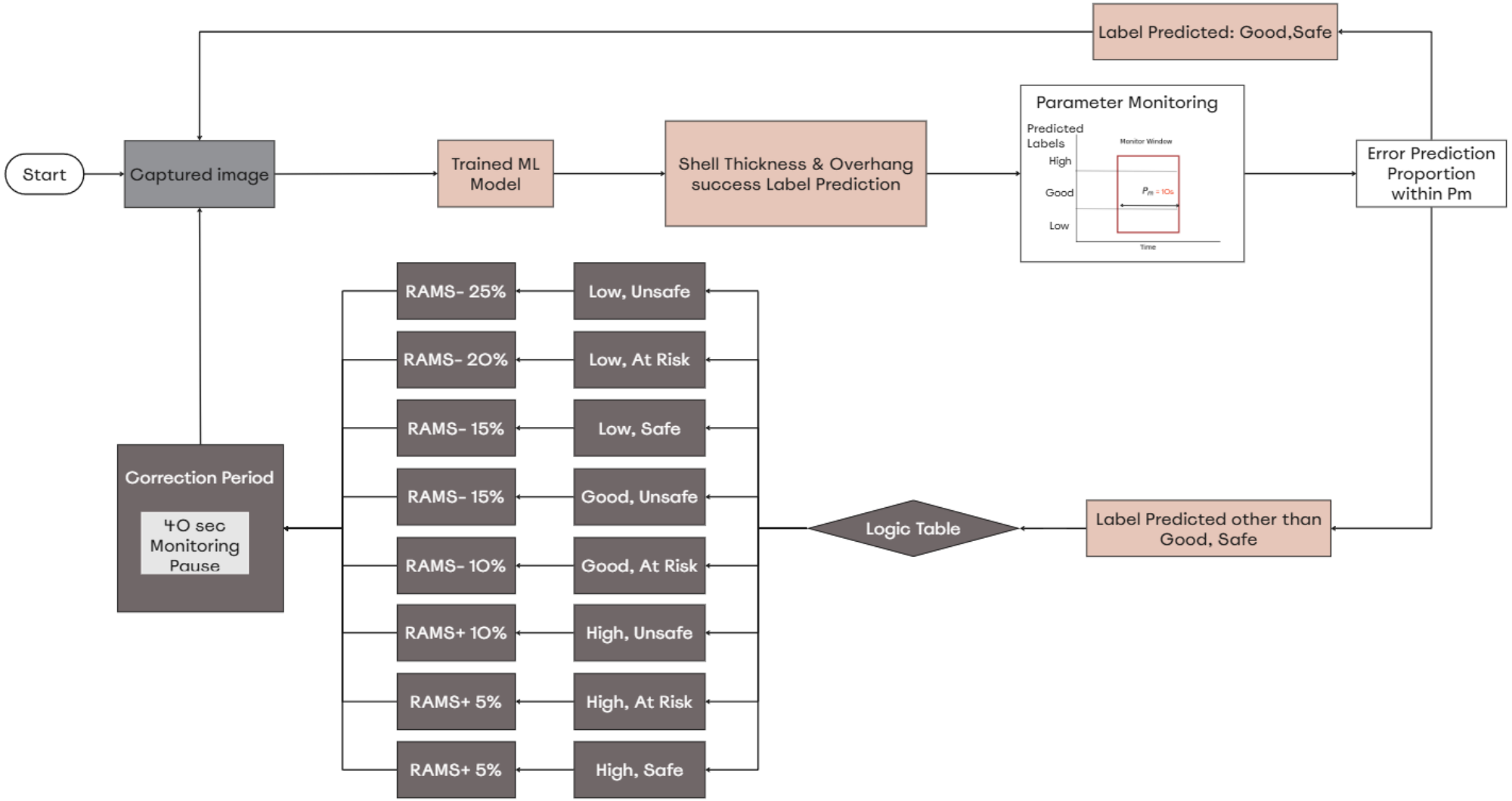
2. Overhang success

Logic table		
Extrusion Quality	**Overhang Success**	**Action on RAMS**
Low	Unsafe	Decrease by 25%
Low	At Risk	Decrease by 20%
Low	Safe	Decrease by 15%
Good	Unsafe	Decrease by 15%
Good	At Risk	Decrease by 10%
Good	Safe	No change
High	Unsafe	Increase by 10%
High	At Risk	Increase by 5%
High	Safe	Increase by 5%

$w = Q/(h \cdot v)$

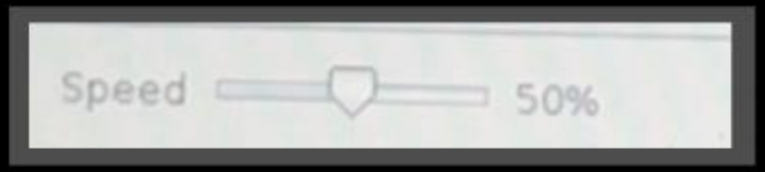
Closed-Loop Real-Time Correction

2. Close-loop calibration



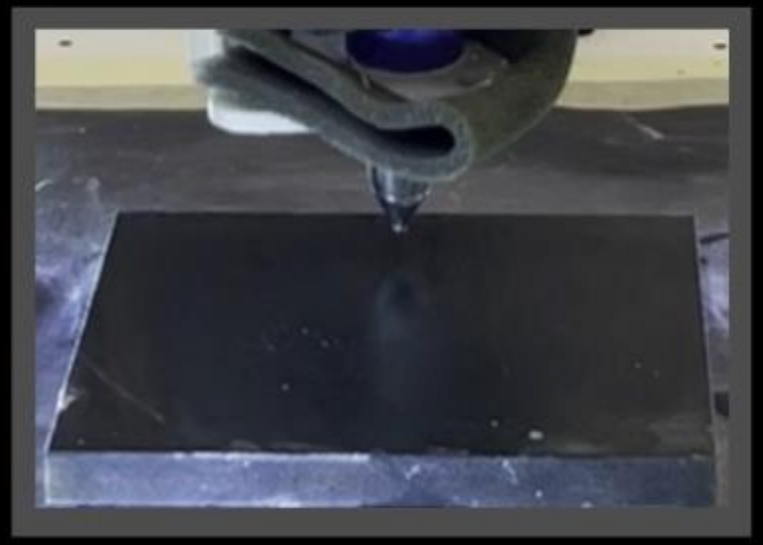
Robotic Clay 3D PRINTING

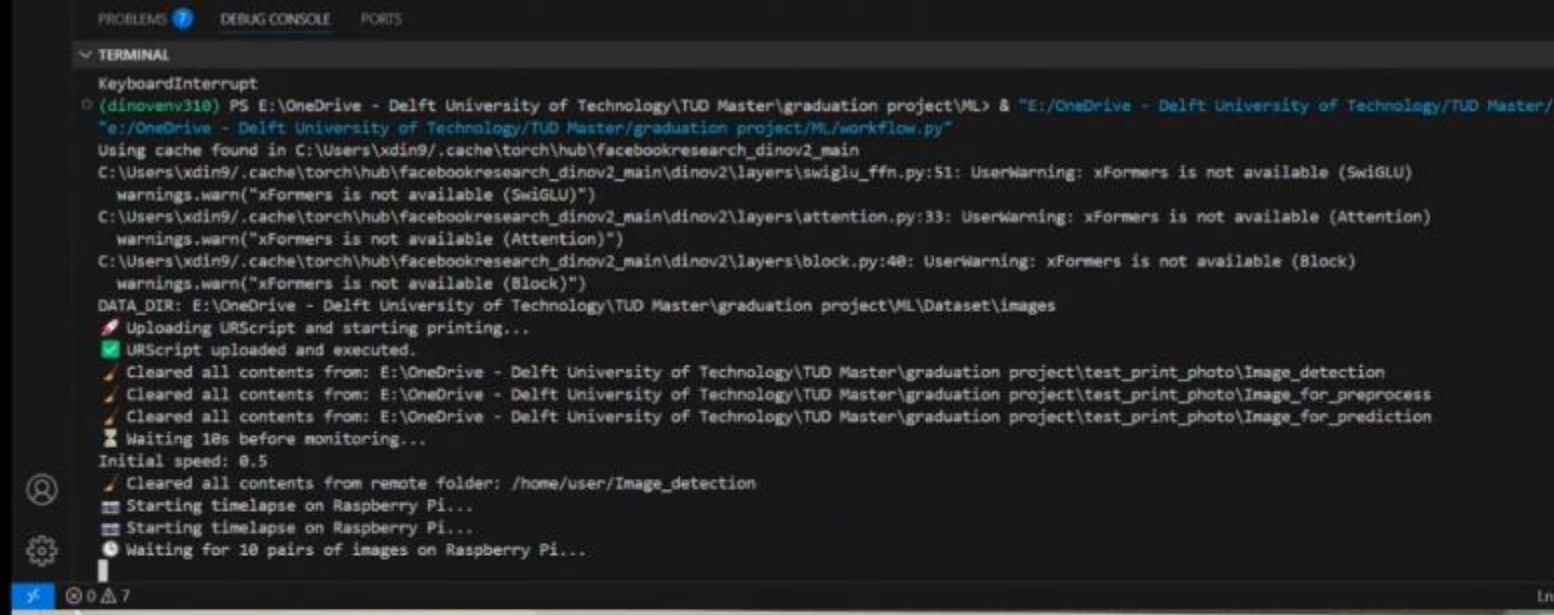
Current speed

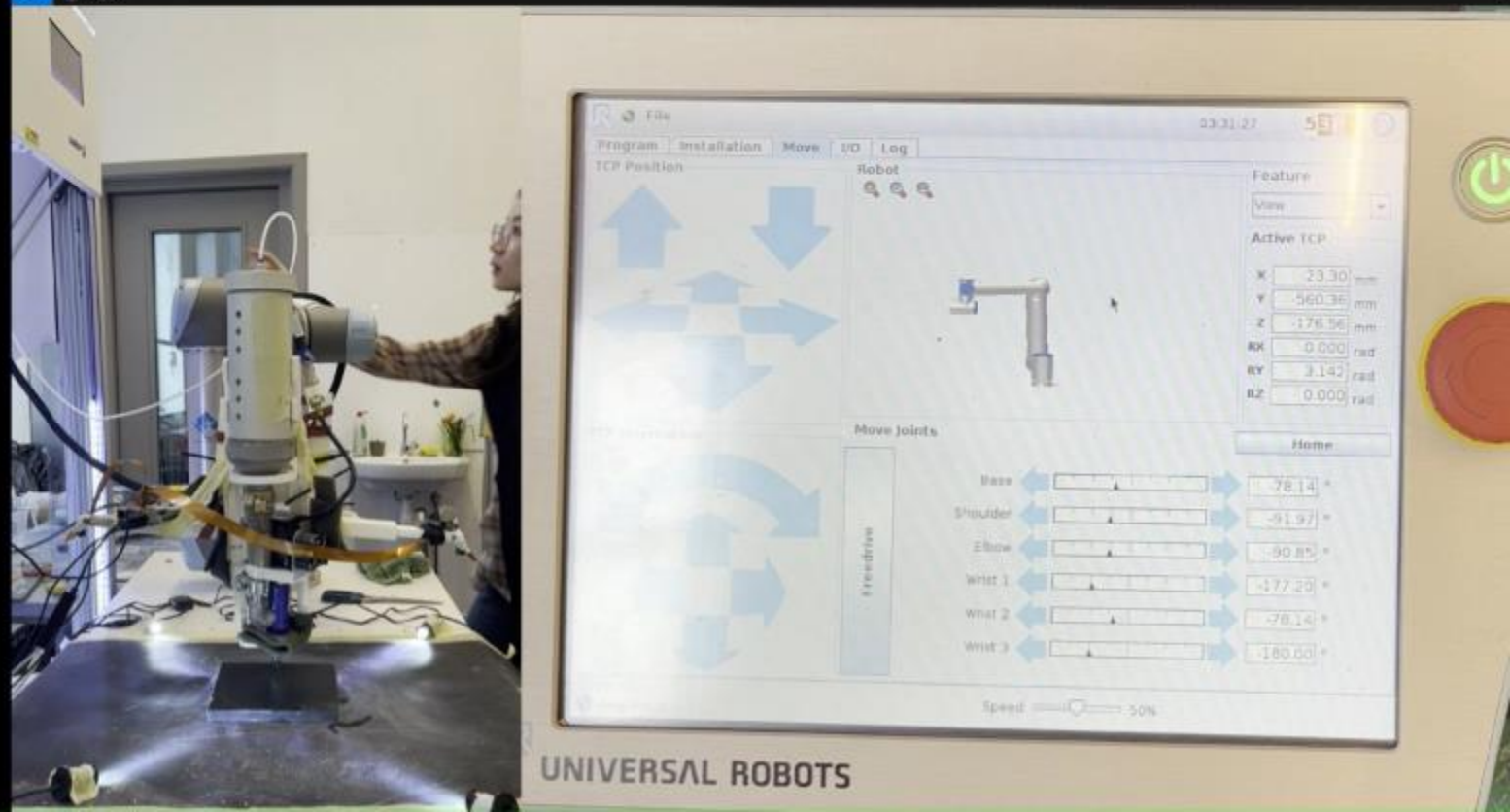


Terminal

Nozzle view







Validation

Objectives

1. Extrusion quality

2. Overhang success

Methods

1. Robotic control

2. Close-loop calibration

3. Real-time visual feedback

4. Multi-objective Machine Learning

Comparison & Evaluation

1. Extrusion quality

Default printing 1

Real-time calibration printing

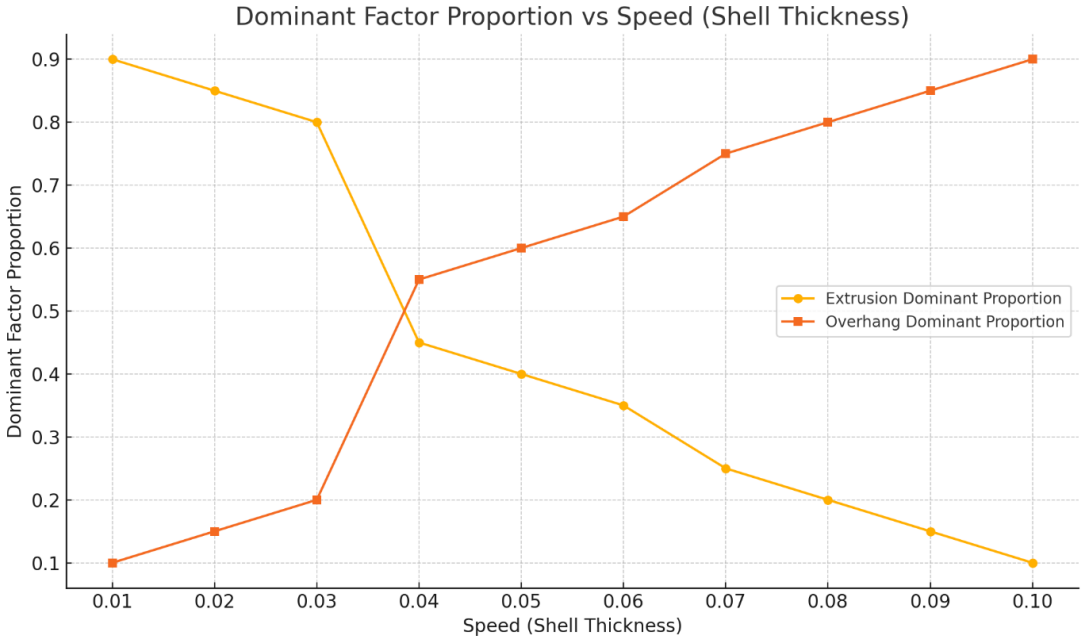
Comparison & Evaluation

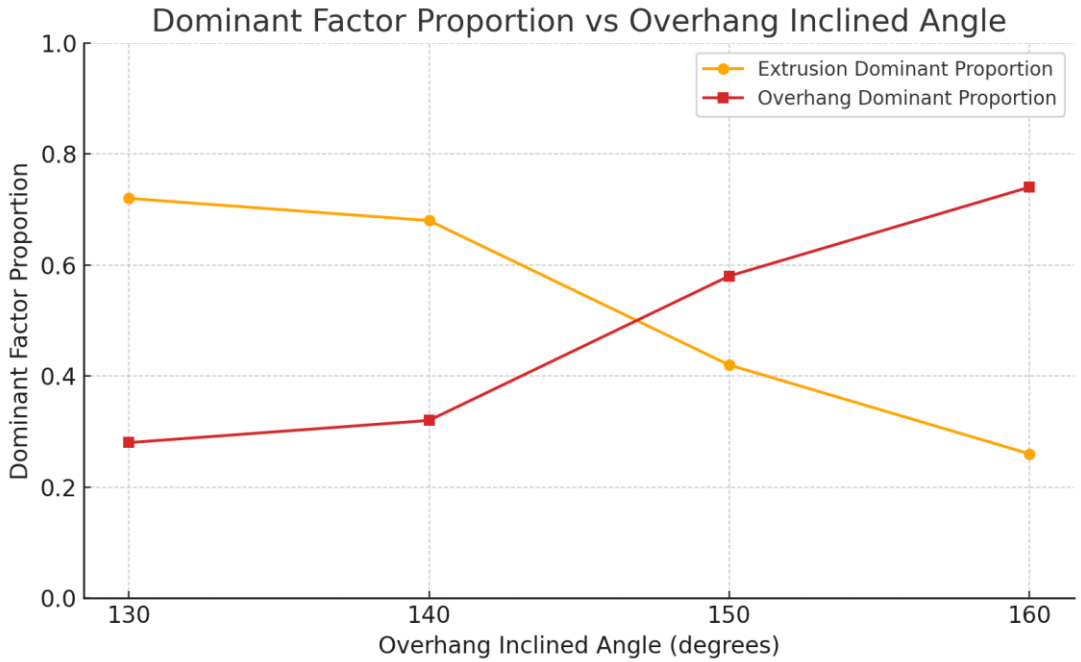
2. Overhang success

Default printing 2

Real-time calibration printing

Dominant Factor in Printing





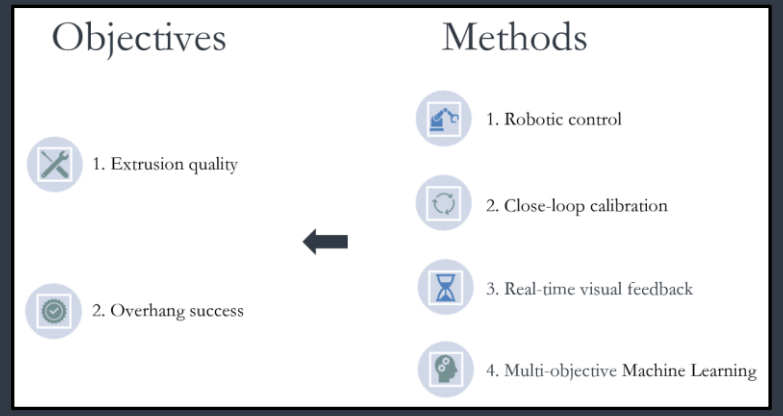
Resnet 56

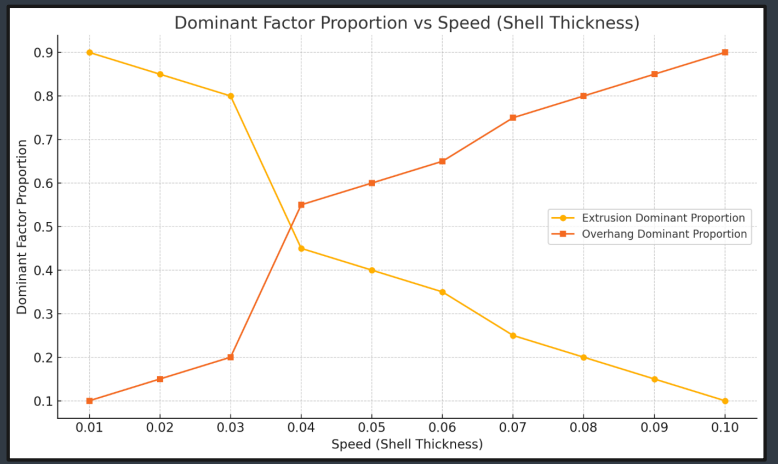
Conclusion & Future work

- AI-assisted close-loop control can improve the printability and accuracy of 3DCP.
- Research objects achieved
- Prediction accuracy: Hybrid ML model works better than conventional Resnet 56.
- Grad-CAM: Highlight the Need for a Hybrid ML Model
- AI for Science: dominant factor change finding in ML

Future work:

- Scaling to gantry systems
- Material expansion (e.g., concrete)





Thank you!