Improving the Precision of Direct-Write 3D Printing via Computer Vision and Machine Learning

Yuhan Liu, SEAS (DMD) 2025
Jiakun Liu, Yucong Hua, and Jordan R. Raney
School of Engineering and Applied Science, Mechanical Engineering and Applied Mechanics

Introduction

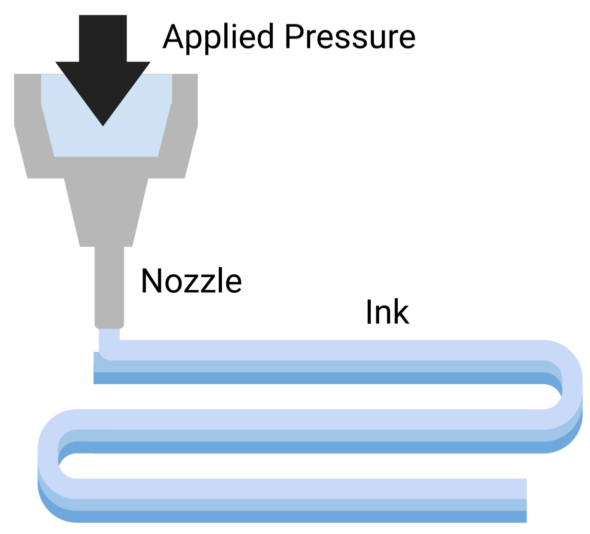
Direct-Ink-Writing (DIW) 3D Printing

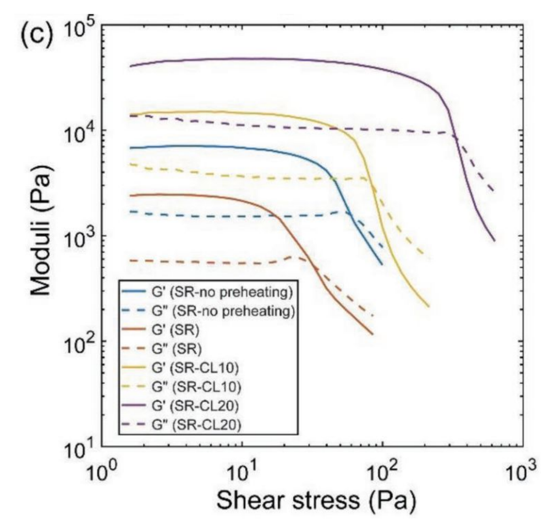
Direct-Ink-Writing (DIW) is an additive manufacturing method that produces 3D structures with desired designs and compositions.

During DIW, viscoelastic inks are methodically pushed through a nozzle, layer by layer, to construct scaffolds and various 3D forms on a digitally controlled platform.

Polymers, ceramics, glass, cement, and any other materials that show viscoelasticity, could all be used for DIW printing.

DIW's efficiency and versatility have attracted significant research and industrial field attention.





Viscoelastic properties of a certain DIW ink

"3D Printing of Amylopectin-Based Natural Fiber Composites." Advanced materials technologies. 4.11 (2019)

Limitations and Errors

Like any manufacturing process, DIW printing is susceptible to errors, including over/under-extrusion and ink clogging, that result in defects, hindering intended structural performance.

Machine Learning x Computer Vision x Multithreading

We combine Convolutional Neural Networks (CNN) with image processing techniques and multithreading, to identify and resolve DIW 3D printing errors.

This approach contributes to improving print quality and efficiency, while also advancing the broader understanding of intelligent additive manufacturing.

Prior Research

CNNs have proved useful on 3D printing images in training data, but struggle during live predictions in establishing causal relationship between error and parameter involved.

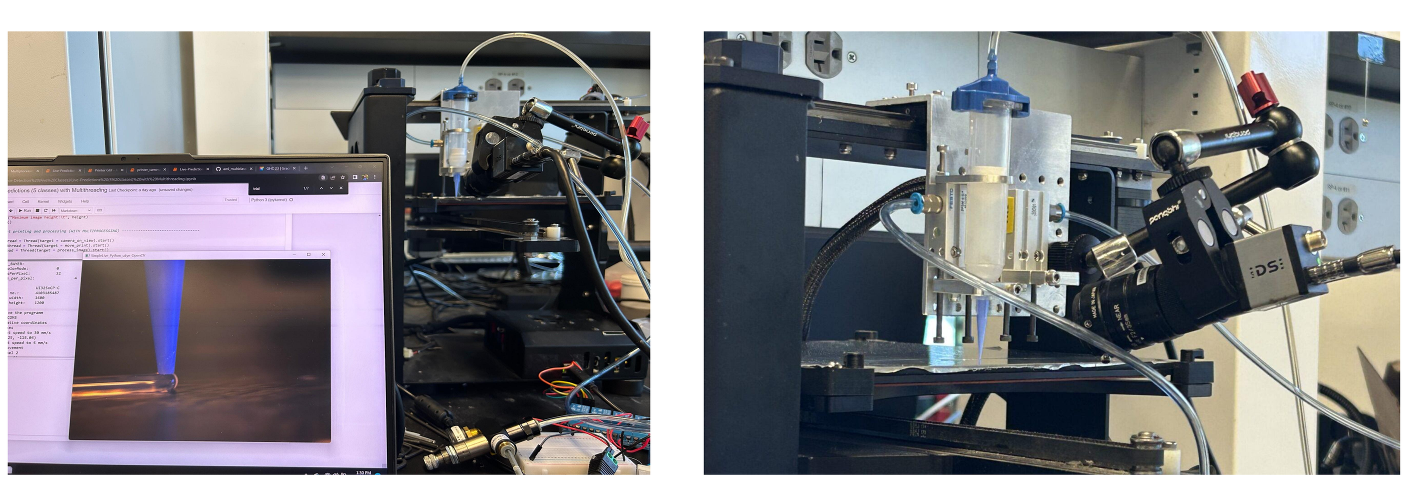
Many algorithms base predictions on internal layers and overall structure of the object, which cannot be examined until printing has completed.

Our Objective

To design a CNN that classifies various error types in real-time by analyzing close-up images of the nozzle and the extruded soft material.

This dynamic approach improves on static image analysis by enabling instantaneous adjustments to printing parameters and error mitigation at inception.

Experiment: 3D Printer Setup



Customized DIW 3D Printer

- The printer uses compressed air to generate pressure that extrudes material.
- Our chosen material is silicone polymer Polydimethylsiloxane (PDMS) with applications from microfluidics to soft robotics.
- Printer motion is controlled using G-Code generated by Python
  - G-Code was modified so that the printer extruded lines in steps, allowing for interruptions if an error is encountered.

iDS Imaging Camera (uEye Compact Power)

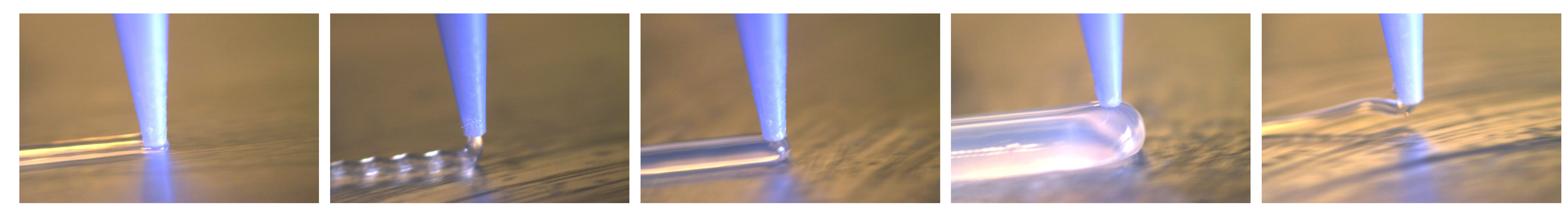
- Attaches to the nozzle of the 3D printer so that the tip of the nozzle and the extruded ink is visible and in-focus throughout printer movement.

Experiment: Learning Algorithm

Error Classification

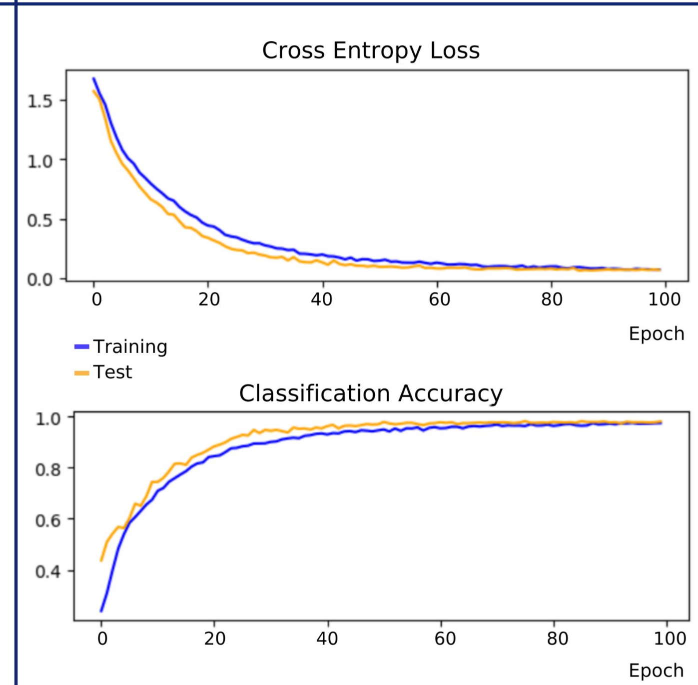
We identify four structure-compromising error types, resulting in a five-class multi-classification algorithm: high pressure, low pressure, nozzle too close, and nozzle too far, and good quality.

We draw causal relationships between the parameters that cause and correct these errors, namely nozzle height and printing speed, both of which are G-code-modifiable.



Nozzle Too Close | **Nozzle Too Far** | **Good Quality** | **High Pressure** | **Low Pressure**

Training the Neural Network

Dataset	Architecture	Learning Curves
Artificially-simulated errors ~1,000 manually-labeled images for each of 5 classes ~20% of images randomly assigned to test set.	3-Block Visual Geometry Group (VGG): • 3x3 Convolutional Layer • Max Pooling Layer (2D) • Dropout Regularization Softmax Activation Stochastic Gradient Descent Optimization Categorical Cross Entropy Loss Function	

Performing Live Predictions

Three concurrent threads:

1. **Display live camera feed**

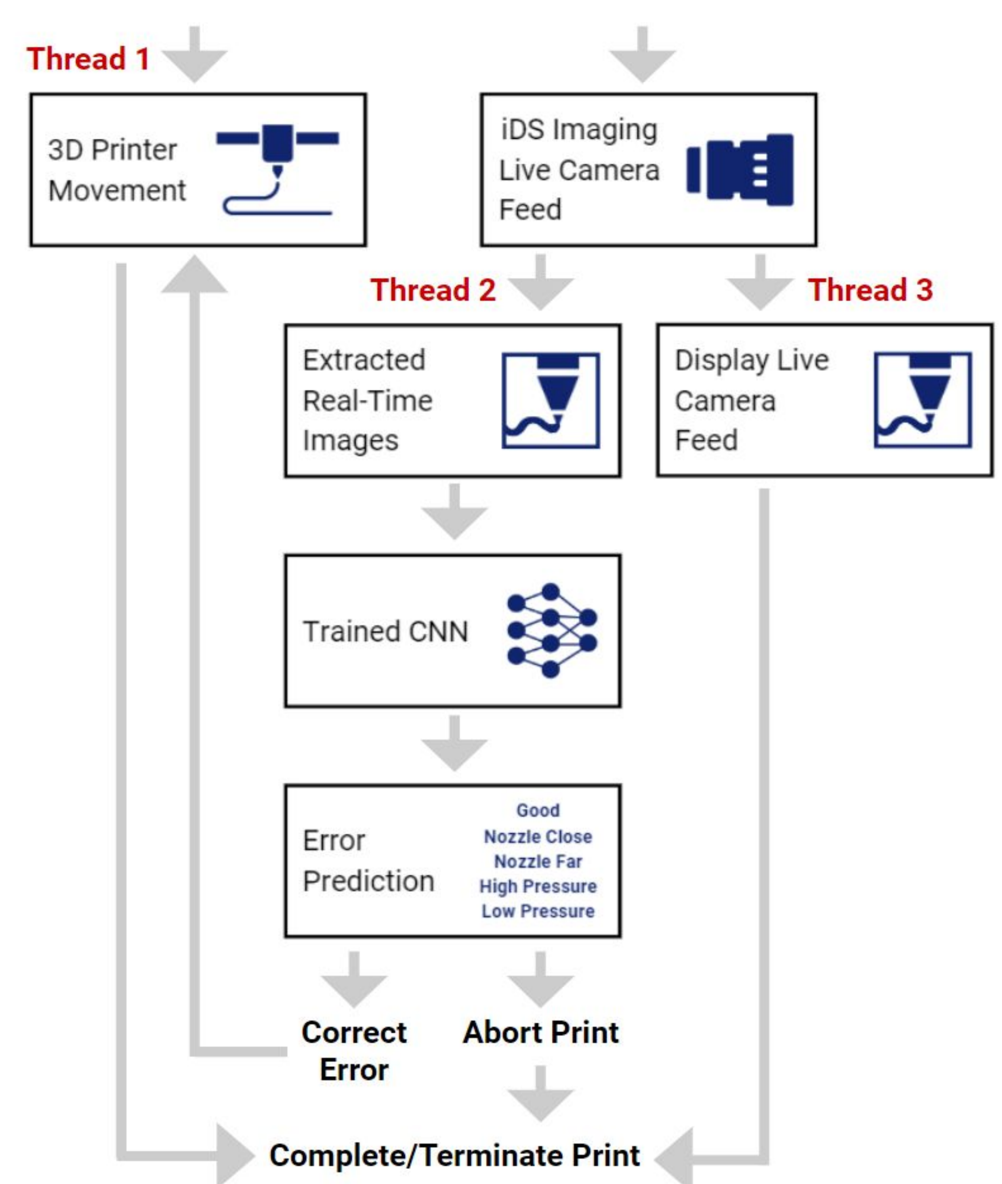
   Allows user to monitor nozzle and extruded material

2. **Printer Movement**

   Runs modified G-Code and waits for changes from image processing thread

3. **Image Processing**

   Extracts image to be processed by model on regular intervals and sends appropriate signal to printer movement thread



Results

Video Demo

Testing the Model by Random Error Introduction

- Added function in printer movement thread that simulates random nozzle movement in order to test model against more natural error cases.
- Achieved an 87% accuracy against 371 test images. Robustness subject to future training and studies

Next Steps

- Train new models to identify multi-directional and multi-layer DIW errors caused by visual differences
- Continue to explore the ability of the current setup to increase 3D printing accuracy in more comprehensive scenarios.

References and Acknowledgements

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