Digital Twinning of Micro-Plasma Metal Additive Manufacturing

Mid-semester BTech Project Evaluation

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Objective

Developing a real-time process parameter adjustment system using Machine Learning models to dynamically control:

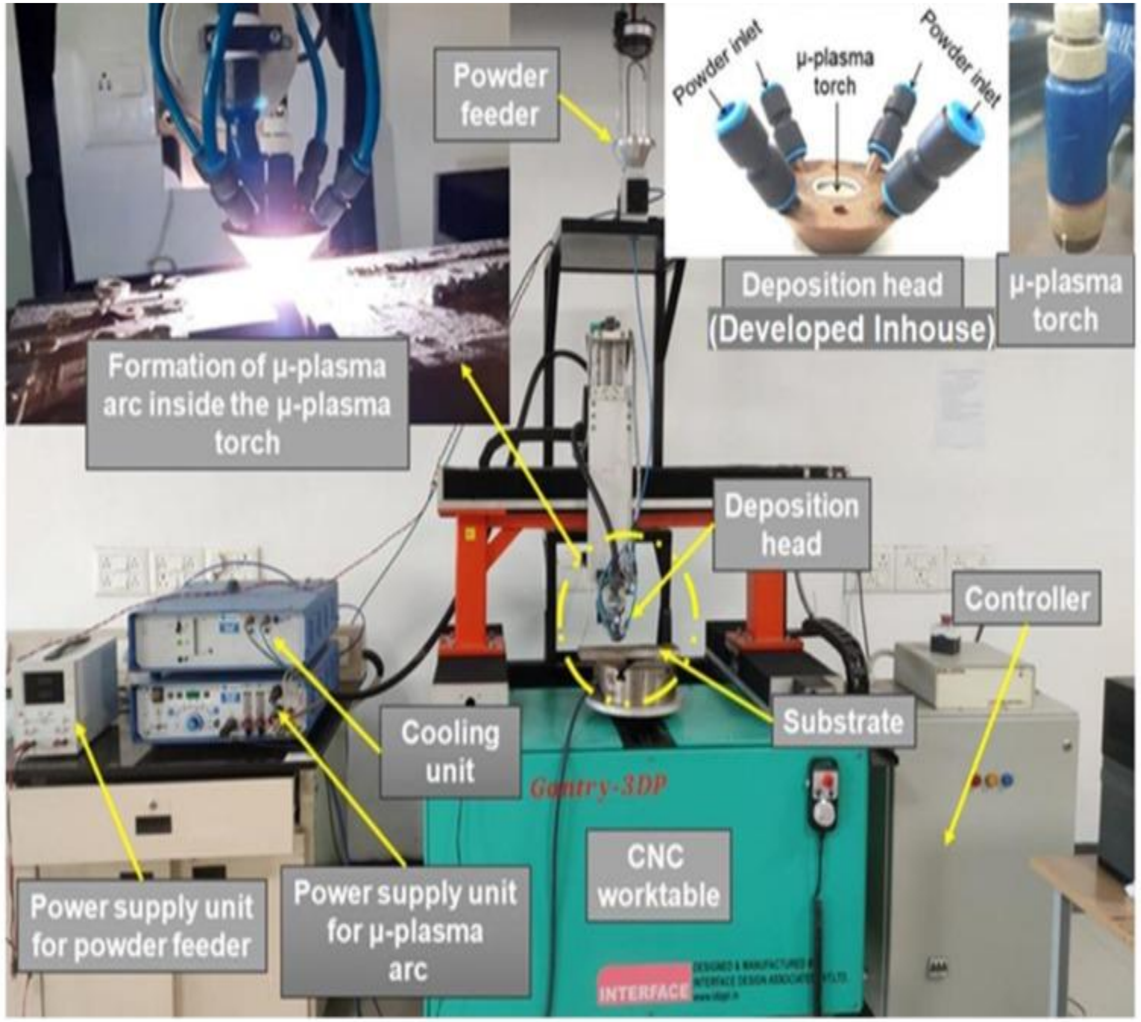
- Powder feed rate
- Microplasma current
- Traverse speed / feed rate

- Aim is to achieve uniform deposition and reduce waviness.

- In the future, create a digital twin control framework to monitor deposition quality and auto-correct process parameters in real time to ensure consistent layer geometry.

Terminology

- **Powder Feeder** – Delivers the metallic powder to the deposition head.
- **µ-Plasma Torch** – Generates the micro-plasma arc for localized melting.
- **Deposition Head (Developed In-house)** – Combines the powder and arc to form the deposition on the substrate.
- **Controller** – Regulates motion and process parameters.
- **Power Supply Units** – Independent units for the powder feeder and µ-plasma arc.
- **Cooling Unit** – Maintains thermal stability of the torch and electronics.
- **Substrate** – Base plate on which Metal deposition occurs



Introduction

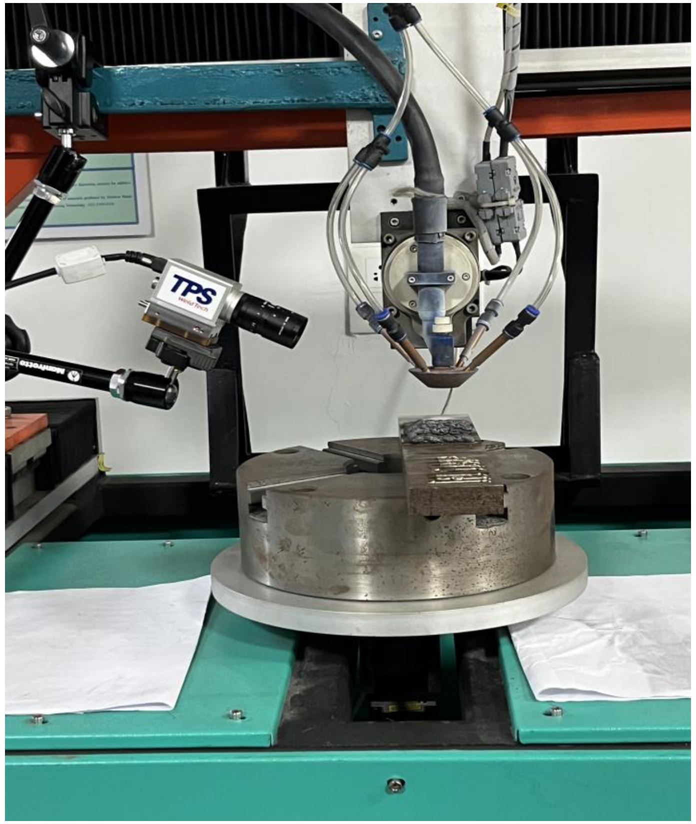
This project builds an image-driven digital twin for micro-plasma metal additive manufacturing (μ-PMAM). It utilizes camera images and machine data to predict deposition and automatically adjust the powder feed rate and microplasma current to maintain uniformity.

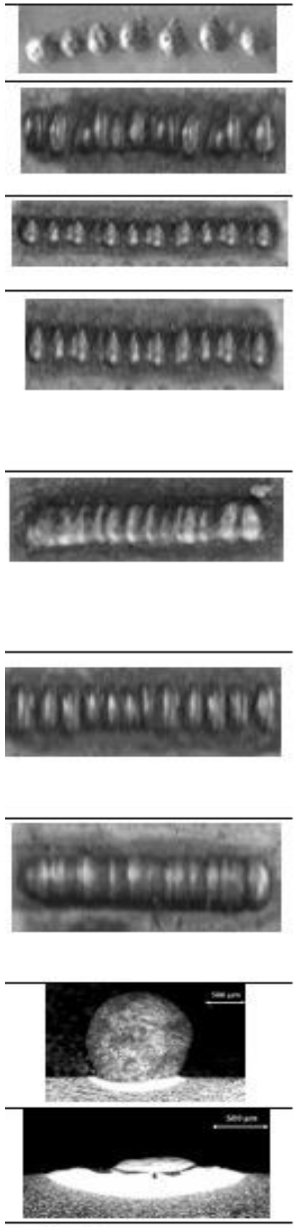
What is Additive Manufacturing (AM)?

Making parts by adding material layer by layer.

What is Micro-Plasma Additive Manufacturing (μ-PMAM)?

μ-PMAM is a **metal AM process** that uses a **micro-plasma arc** as the heat source.
Fine metallic powder is injected into the plasma, melts, and forms a **metal deposition** that solidifies to create the part.



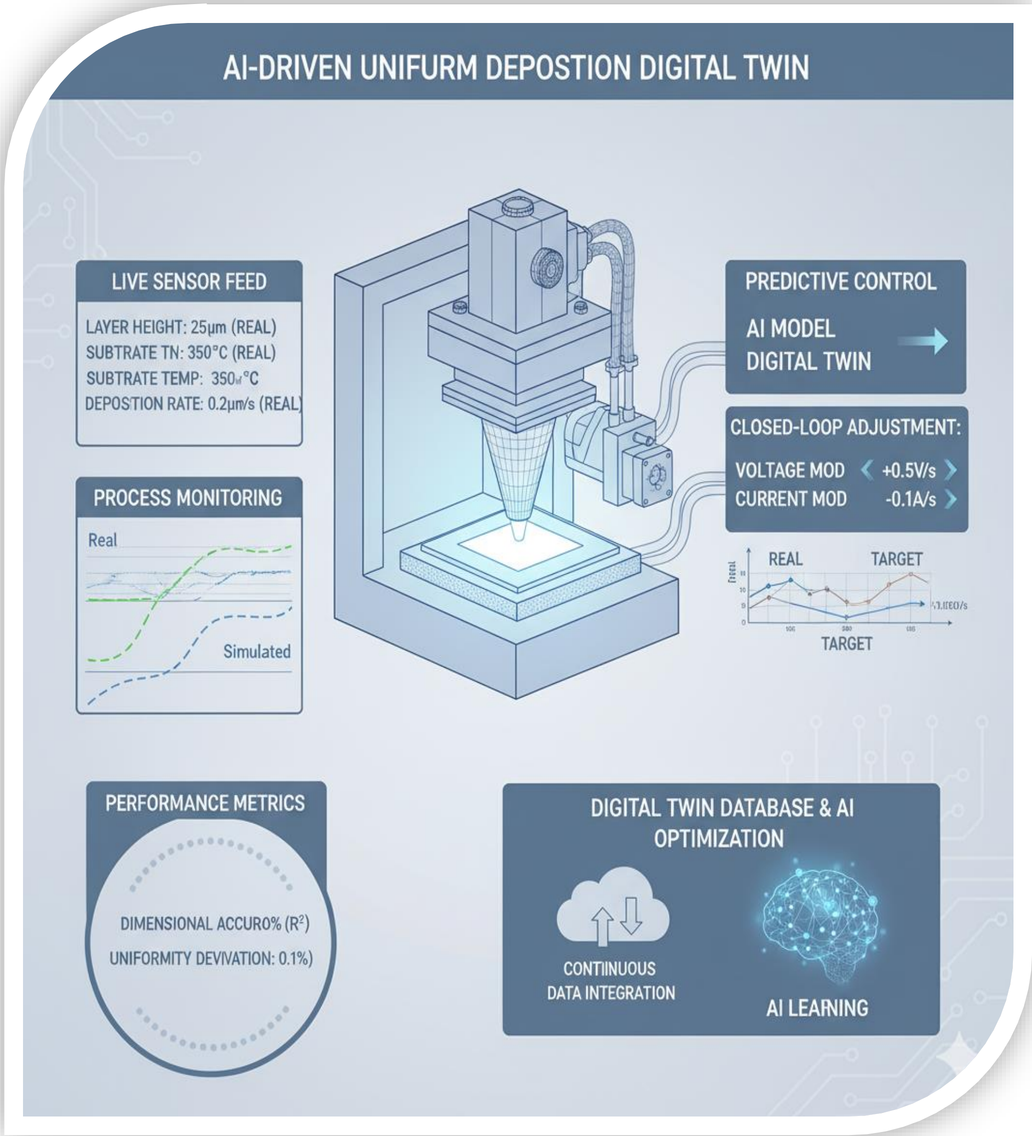


Introduction

Why Use a Digital Twin for Micro–Plasma AM?

A **Digital Twin** is a real-time virtual copy of the machine and process.

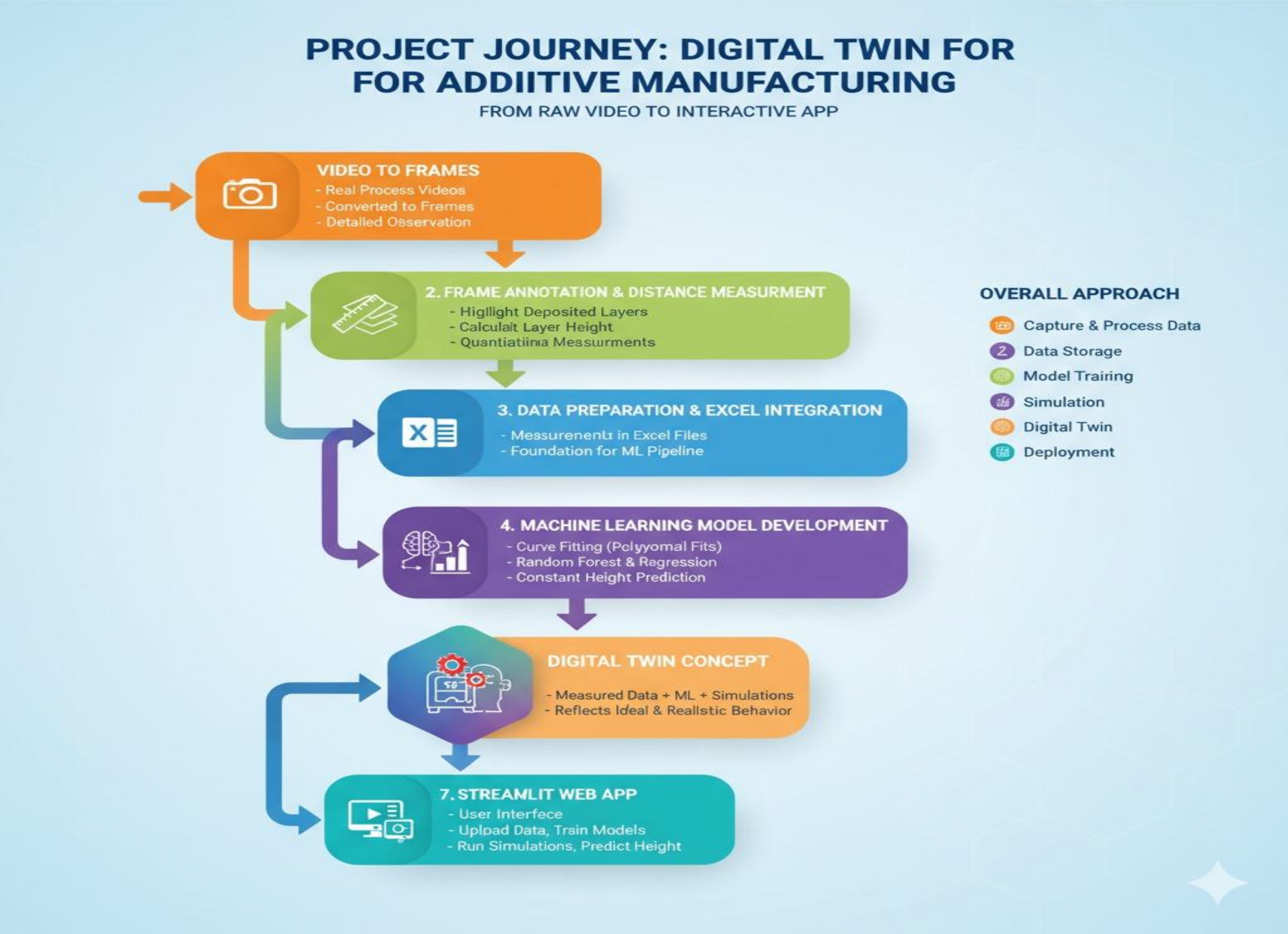
- Changes the parameter **IN-SITU .**
- **Enables Real time Feedback for deposition and simutaneously change parameter to get uniformity .**



Process Parameter

- **Microplasma Current(I)**
- **Powder Feed Rate(gm/min)**
- **Travel Speed (mm/min)**

Work Journey

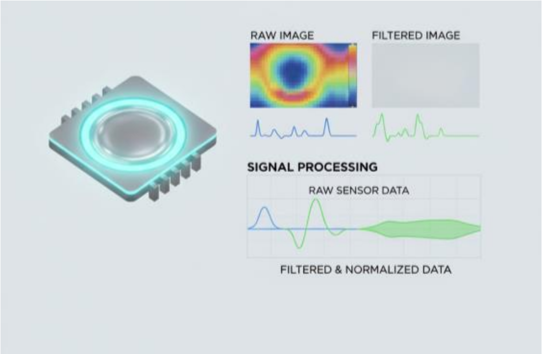


Methodology

1. Data Acquisition

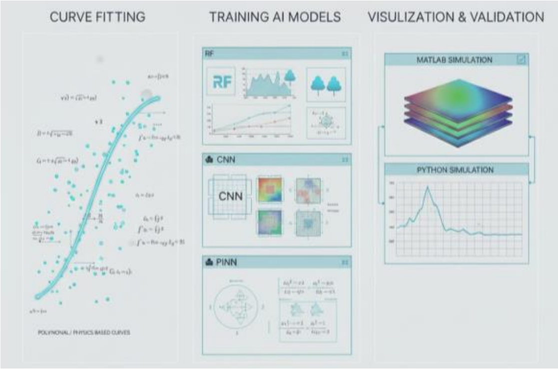
Conduct experiments at varied powder feed rate, Current , Traverse speed /feed rate.
We had used high-resolution camera (Xiris XVC-1000/1100 Weld Camera) .

2. Image & Signal Processing



Apply computer vision AND ML for reliable Height calculation varying with time .

3. Modelling & Simulation

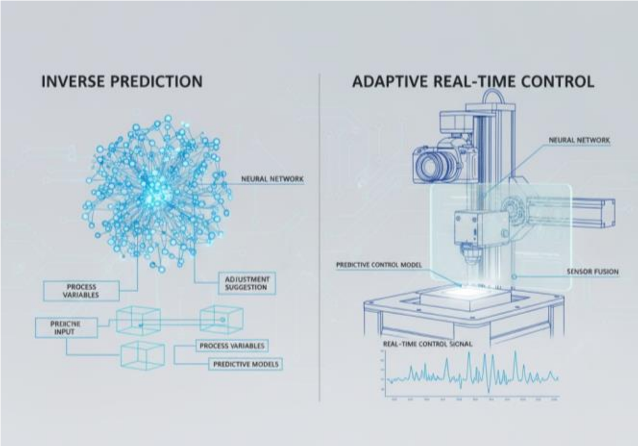


Fit polynomial-based curves to time–height data (RF, regression , R2 method) to map process and run MATLAB simulations to visualize and validate deposition.

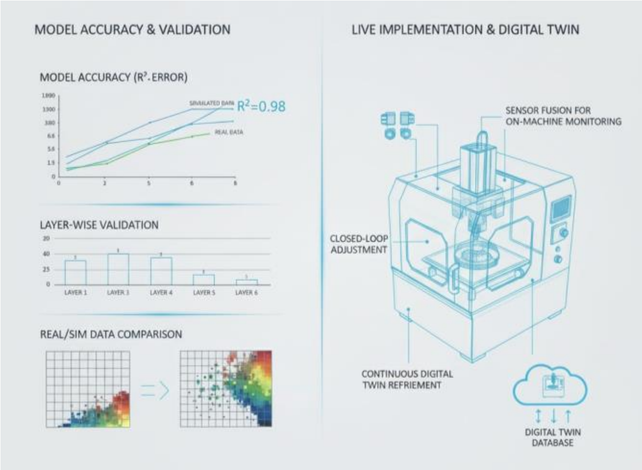
Methodology

4. Inverse Modeling & Control

5. Performance & Real-Time Implementation



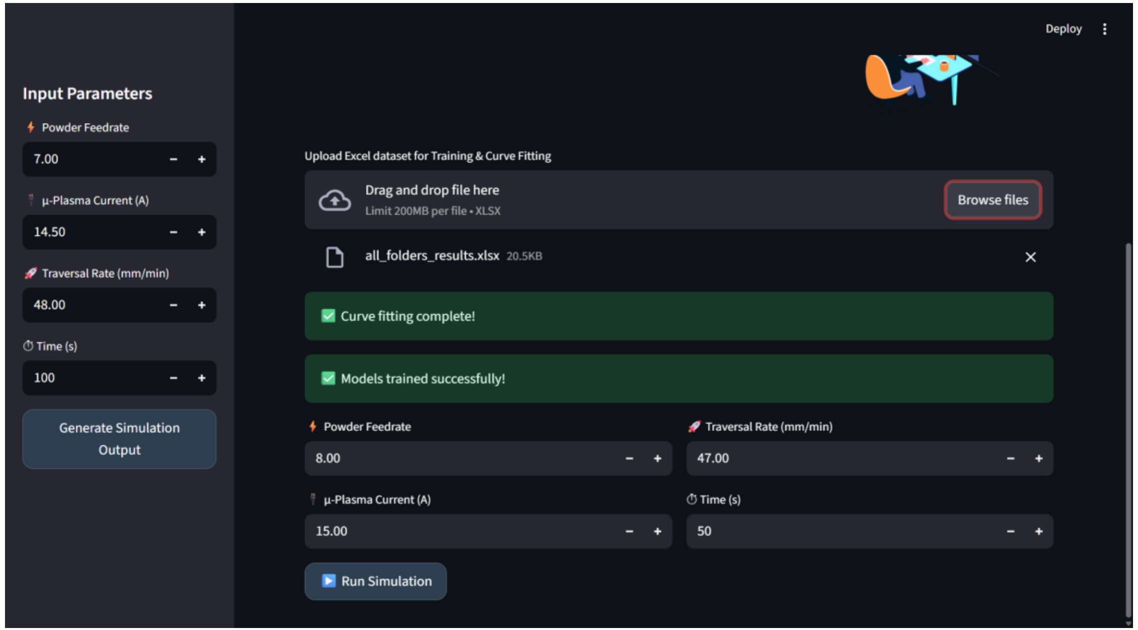
Use neural networks for inverse predictions, suggesting powder feed rate and current adjustments for target heights .



(Work To Be Done)

Improving model accuracy (R^2, error) against real – time data, perform layer-wise validation, and deploy live—using sensor closed-loop adjustment, and continuous digital twin refinement

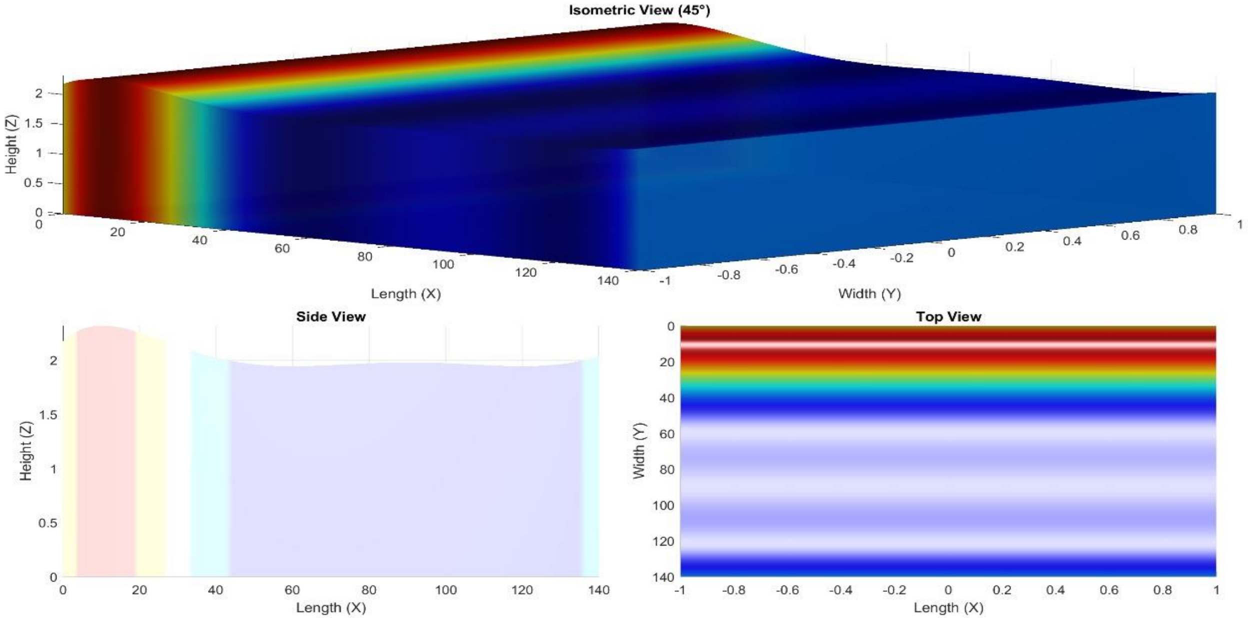
Work Done Till Now

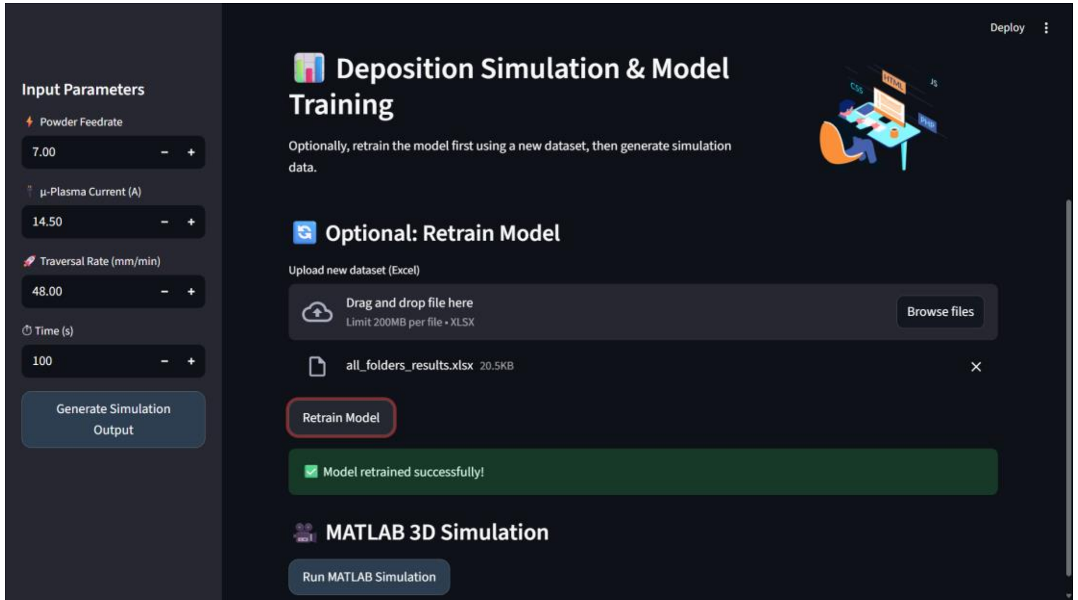


Developed a user-friendly web application for simulating additive manufacturing deposition processes, integrating MATLAB tools.

Enabled users to input process parameters like Powder Feed Rate , microplasma current, Traverse speed and generate instant simulation results.

Work Done Till Now

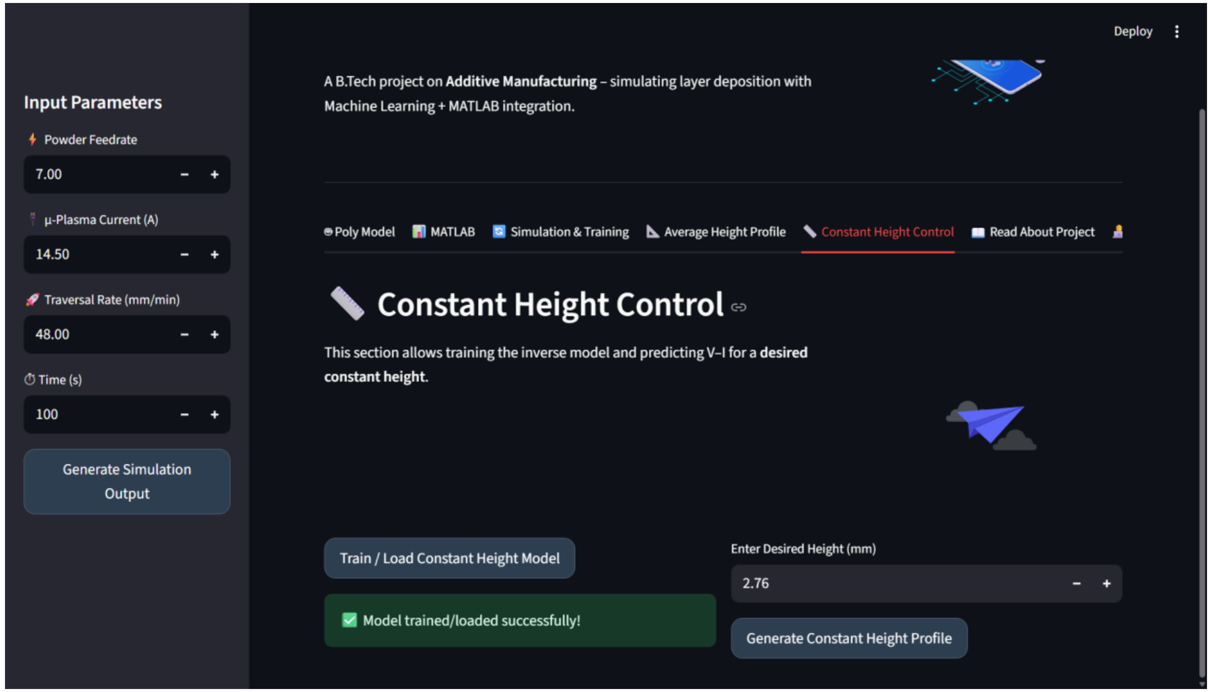




Implemented real-time 3D MATLAB animations of layer deposition. 2 to 6 degree polynomial

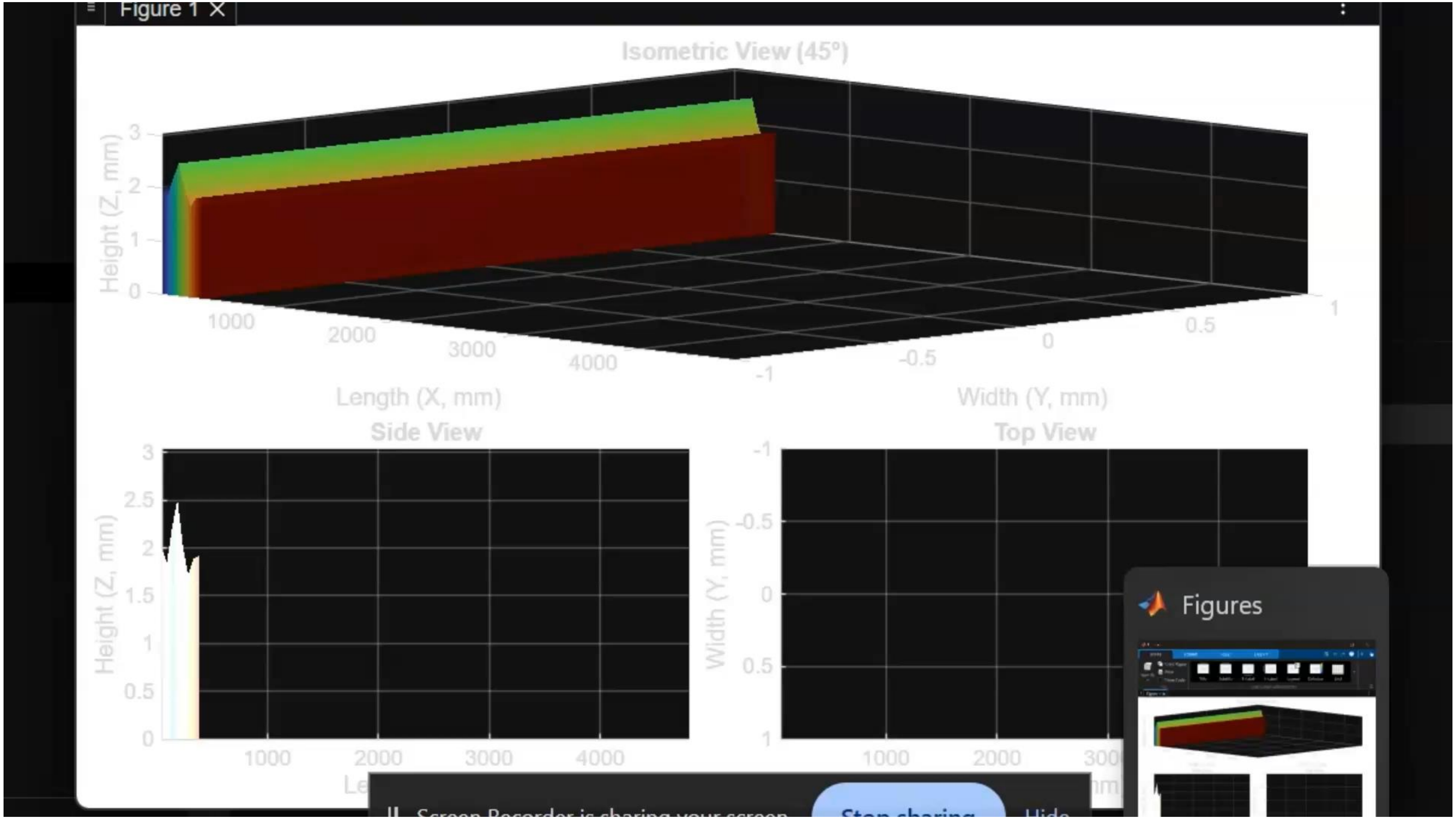
Added modules for model retraining with new datasets .

Work Done Till Now

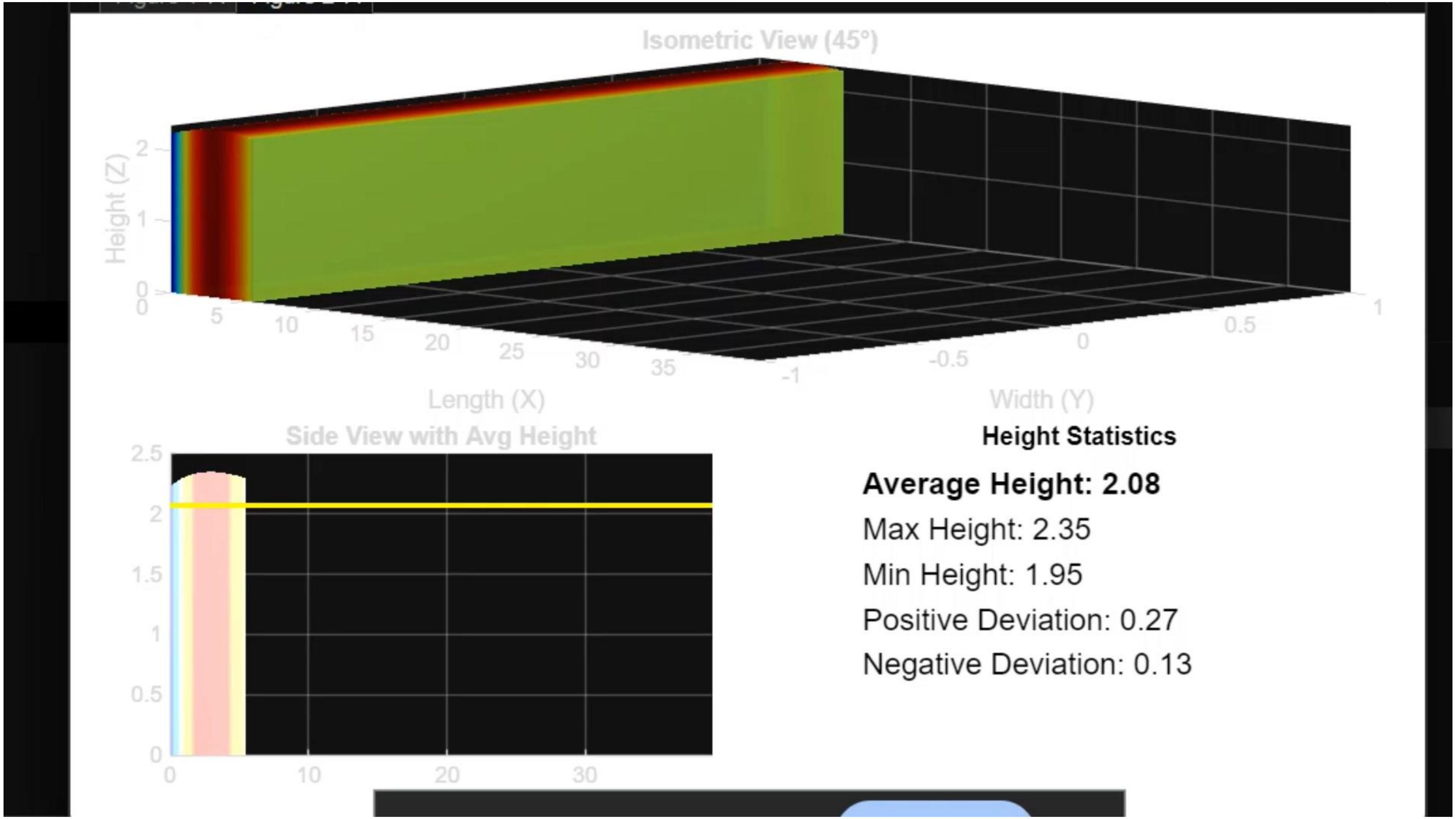


Provided advanced tabs for constant height control. User will input height ---->output is powder feed rate and microplasma current .

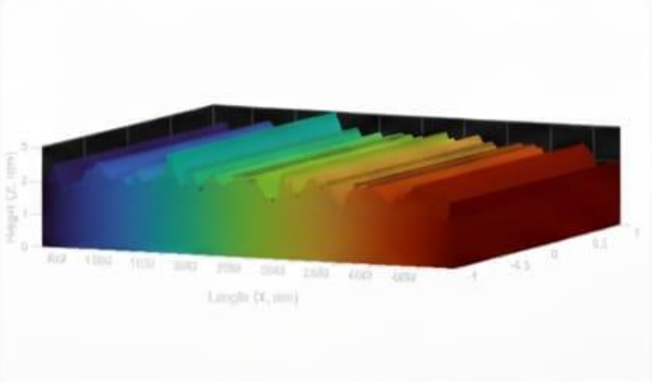
Video Animation (MATLAB)



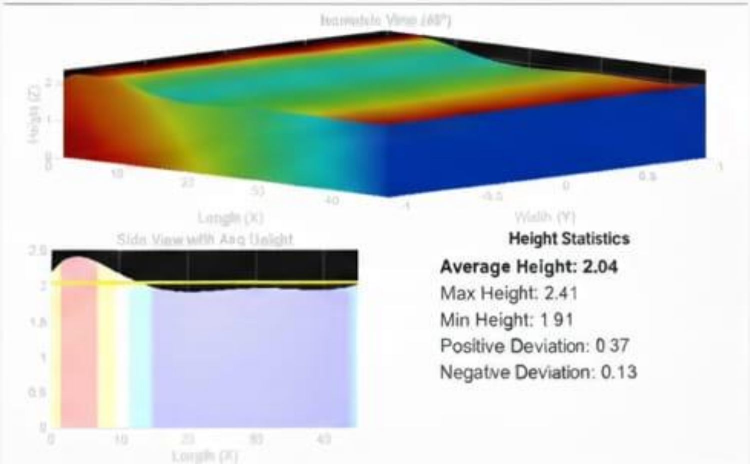
Video Animation (MATLAB)



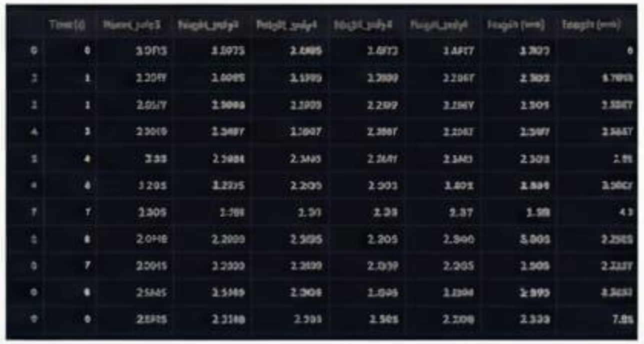
Work Done Till Now



Real time height deposition with respect time



Uniform height deposition with diffrent voltage current using py tourch



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0	0	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0
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[illegible]	4	2.33	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	7	2.305	[illegible]	2.31	[illegible]	2.37	[illegible]	[illegible]
[illegible]	8	[illegible]	[illegible]	[illegible]	2.205	[illegible]	[illegible]	[illegible]
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[illegible]	0	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	7.85

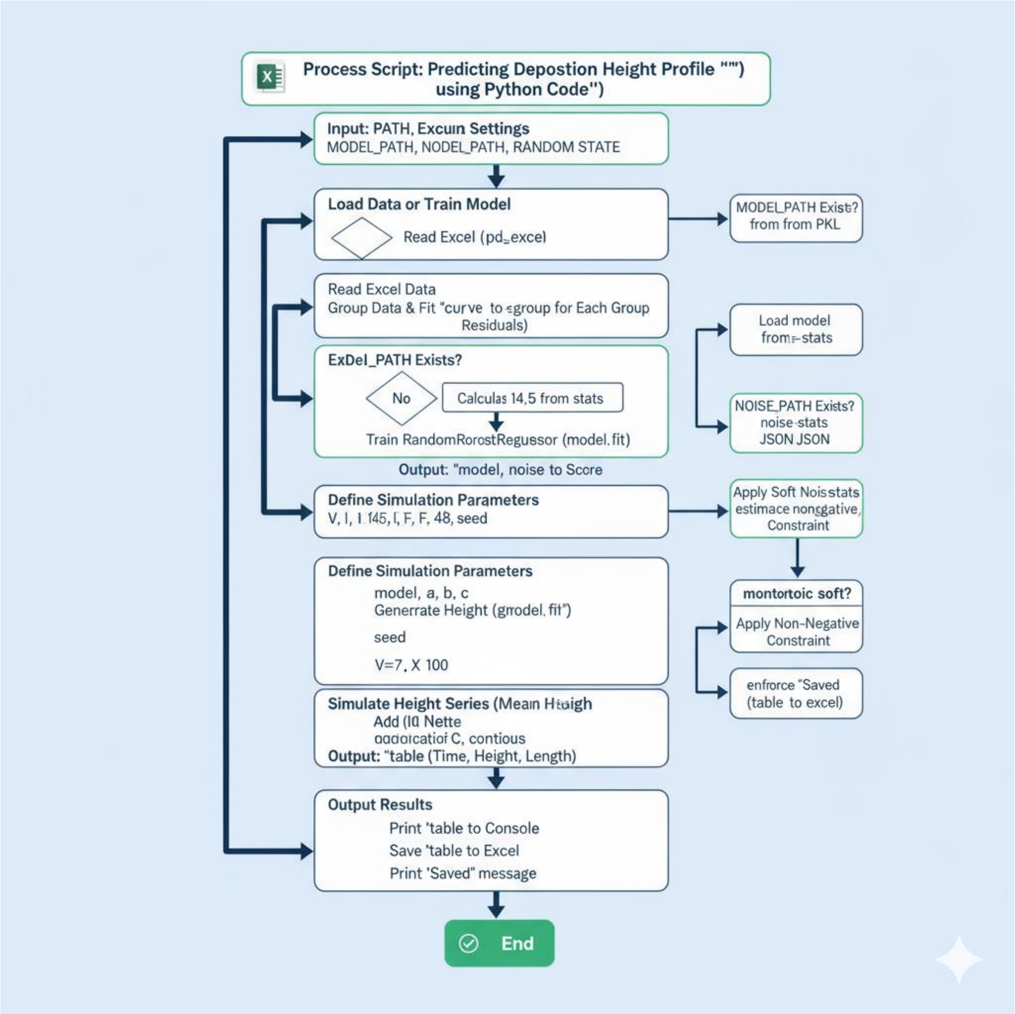
Table of 2-6 degree polıymial fits for constant height deposition

Work Done Till Now

METHOD USED FOR TRAINING MODEL

Predictive Modelling 1 - Input to output

0.3 <= R2 <= 0.4



$$H_{\text{mean}}(t) = a\left(1 - e^{-bt}\right) + c$$

This is an *exponential approach-to-asymptote* model

At $t = 0$: $H_{\text{mean}}(0) = a(1-1) + c = c.$

As $t \to \infty$: $H_{\text{mean}}(\infty) = a + c.$

$$r_t = H_{\text{observed}}(t) - H_{\text{mean}}(t).$$

Pointwise Residual, capture measurement noise, process variability, and model mismatch

$$\sigma = \text{std}(\text{all residuals}), \quad (\text{population std})$$

Deviations from the mean curve

$$\rho^{(i)} = \frac{\sum_t (r_t - \bar{r})(r_{t+1} - \bar{r})}{\sqrt{\sum_t (r_t - \bar{r})^2}\sqrt{\sum_t (r_{t+1} - \bar{r})^2}}$$

Lag 1 correlation , Residuals often show temporal correlation — successive errors are not independent

$$R^2_{\text{multi}} = \frac{1}{m}\sum_{j=1}^{m}\left(1 - \frac{\sum_i (y_{ij} - \hat{y}_{ij})^2}{\sum_i (y_{ij} - \bar{y}_j)^2}\right)$$

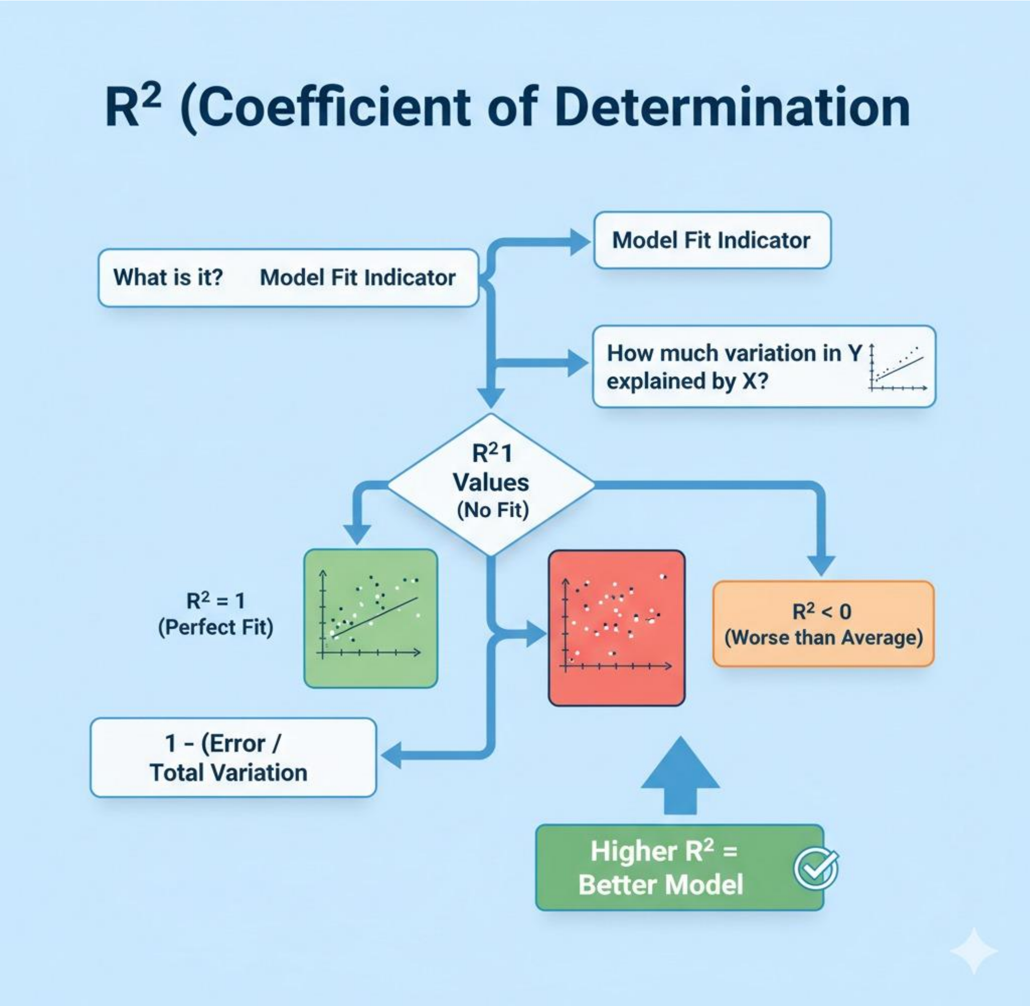
$$\text{Length}_t = \frac{\text{TraversalRate}}{60} \cdot t$$

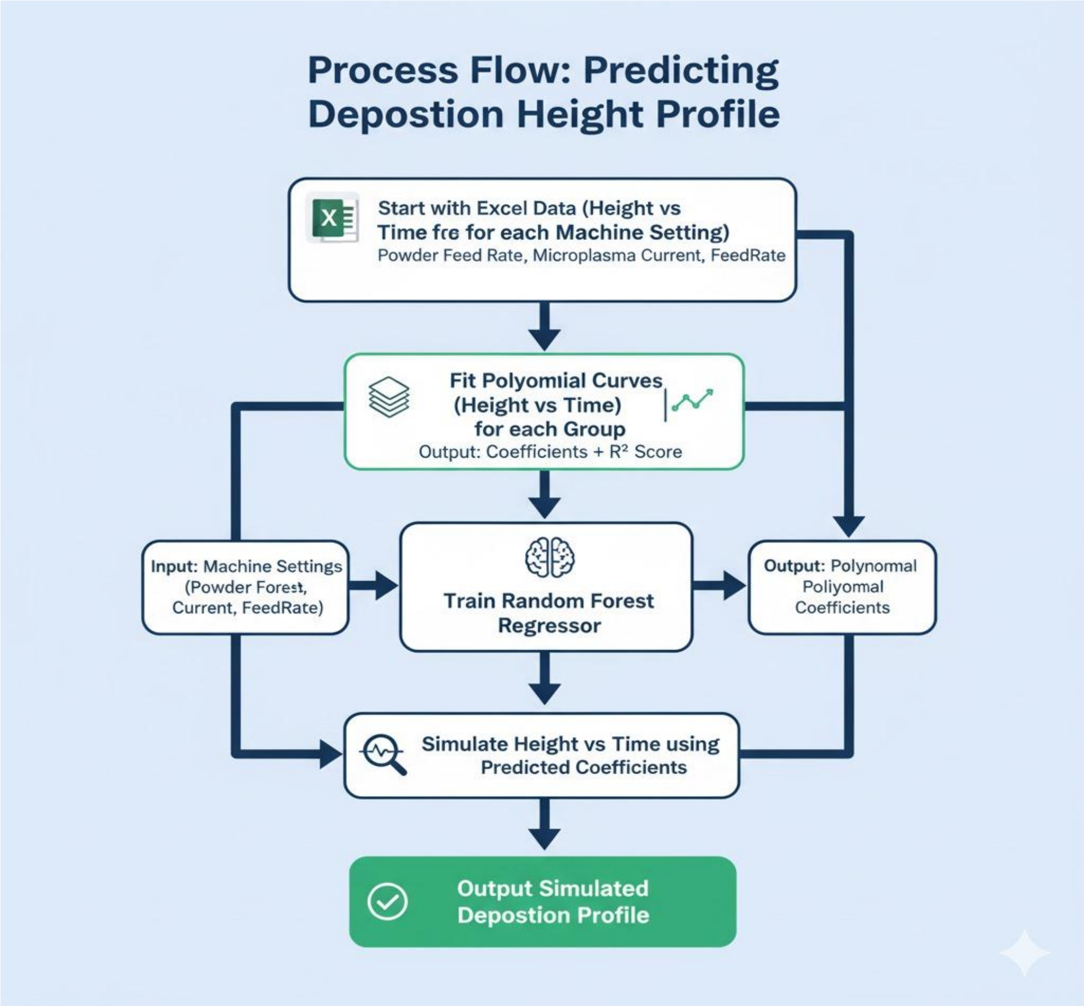
Work Done Till Now

METHOD USED FOR TRAINING MODEL

Predictive Modelling 2 - Input to output

0.6 <= R2 <= 0.7



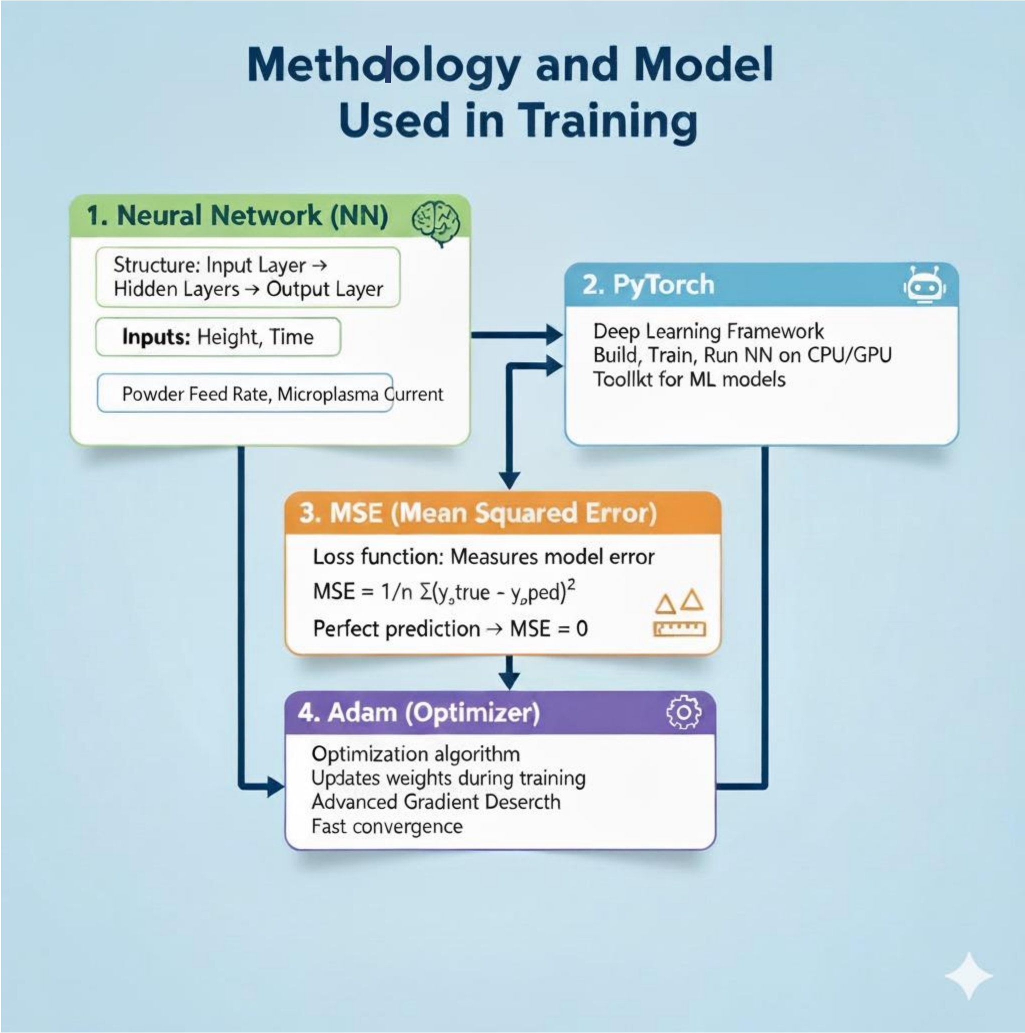


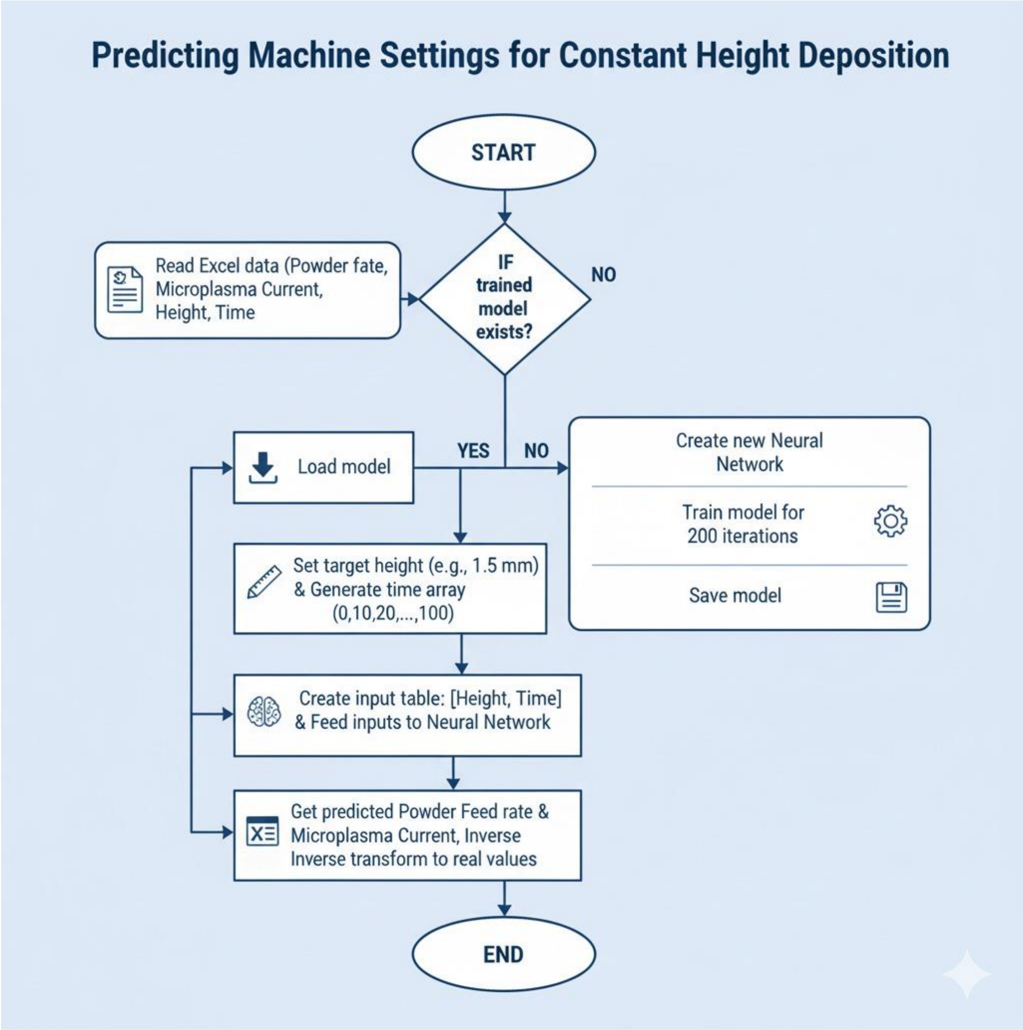
Mathematics

$(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$	where x = Time (s), y = Height (mm).
$y \approx a_d x^d + a_{d-1} x^{d-1} + \cdots + a_1 x + a_0$	approximated by a polynomial of degree ddd
$x_{\text{norm}} = \frac{x}{x_{\max}}$	Normalization
$\text{minimize} \sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)^2$	np.polyfit finds the coefficients that minimize the least squares error
$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$	compute R^2 score to measure how well the polynomial fits
$\hat{y} = \frac{1}{N} \sum_{i=1}^{N} T_i(x)$	Ti(x) is the prediction of tree i, and N is the number of trees
$\hat{y}(t) = a_d \left(\frac{t}{x_{\max}} \right)^d + a_{d-1} \left(\frac{t}{x_{\max}} \right)^{d-1} + \cdots + a_0$	**Final Equation**

Work Done Till Now

Reverse Modelling 2 – Output to input





Work To Be Done

- ❖Incorporate sensors and control into the machine for real-time monitoring.
- ❖ Vary microplasma current and powder feed rate to maintain constant Deposition height.
- ❖Test on the machine and update the digital twin for improved control.

THANK YOU