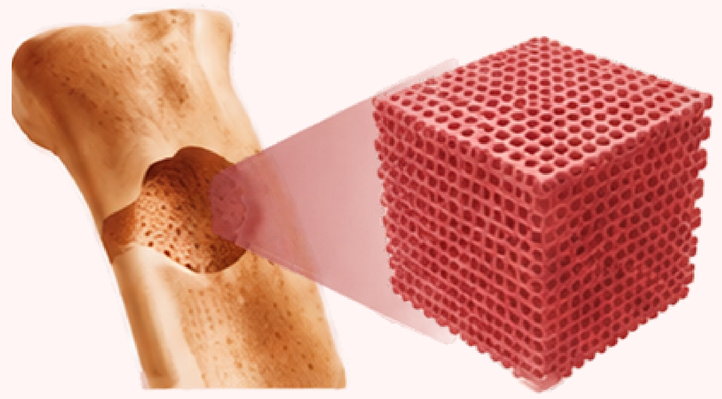
STEM CELL INNOVATION CONTEST 2026
11TH EDITION | THEME: STEM CELLS & AI
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GAUSSIAN PROCESS REGRESSION (GPR) AND CONSTRAINED BAYESIAN OPTIMIZATION (CBO) FOR OPTIMIZING MSC VIABILITY IN 3D-PRINTED BONE SCAFFOLDS

BACKGROUND



Critical-sized bone defects have limited self-healing capacity, while conventional bone grafting faces significant limitations. **Extrusion-based 3D bioprinting** enables the fabrication of **cell-laden scaffolds** that mimic bone ECM and support regeneration. **GelMA** provides a biocompatible matrix, while **nHA** enhances osteoconductivity. **MSCs** contribute to bone formation through osteogenic differentiation. However, **optimizing bioink composition** and **printing parameters** is essential to **balance MSC viability** and **printability**.

Research Rationale

Researchers often need to **test many combinations** of bioink composition and printing parameters to find the best conditions.

→ **Time and money consuming**

Research objectives

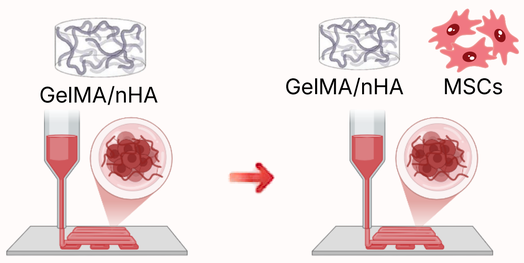
To identify the **optimal combinations** that **maximize MSC viability**

↳ **Reduce** the number of **experiments**.

- **Evaluate key factors**: Assess the effects of GelMA, nHA, and printing pressure on MSC viability.
- **Build a predictive model**: Use GPR to predict MSC viability from experimental data.
- **Optimize conditions**: Apply CBO to maximize MSC viability with fewer experiments.
- **Validate results**: Compare optimized and initial formulations.

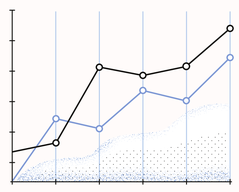
METHODOLOGY & EXPERIMENTAL DESIGN

Step 1. Experimental Design and Data Collection



Screen cell-free GelMA/nHA formulations

Validate representative formulations with encapsulated MSCs



Determine feasible parameters. **Select** 16 initial experimental configurations are measured MSC viability

INPUT

- X1: GelMA concentration
- X2: nHA concentration
- X3: Extrusion pressure

OUTPUT

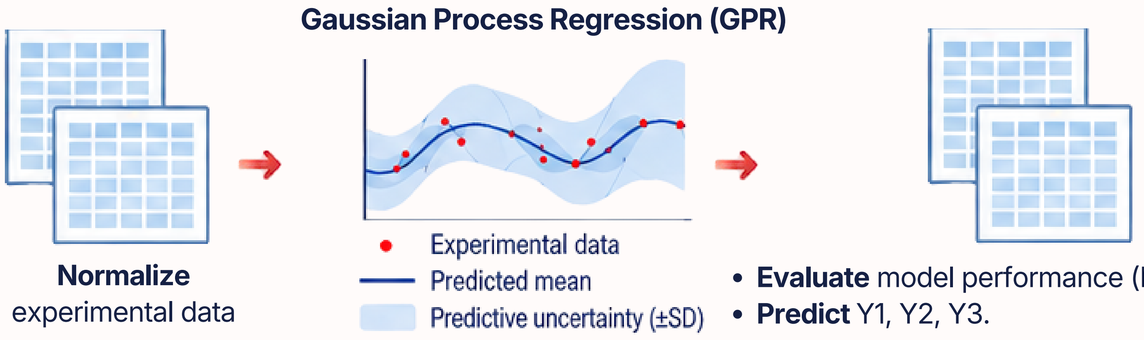


Y1 Geometric error

Y2 Compressive modulus

Y3 MSC viability on Day 7

Step 2. Gaussian Process Regression (GPR) Model Training

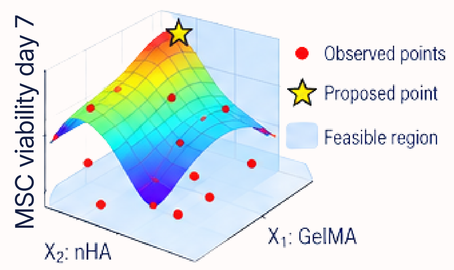


Normalize experimental data

- **Evaluate** model performance (MAE/RMSE).
- **Predict** Y1, Y2, Y3.

Step 3. Optimization by CBO

Constrained Bayesian Optimization (CBO)



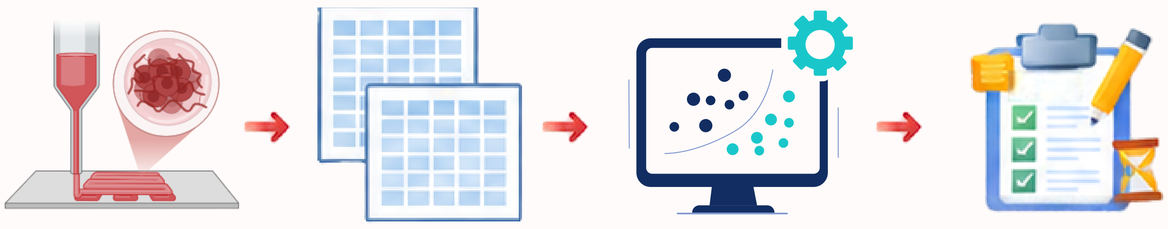
X1: GelMA concentration

X2: nHA concentration

X3: Extrusion pressure

Propose new configurations

Step 4. Experimental Validation and Iterative Model Updating



Fabricate and **evaluate the AI-suggested configurations**

Add new data to the training dataset

Retrain and **update** the GPR-CBO models

Experimentally validate the AI-selected formulation

EXPECTED RESULTS

Qualitative

1. Live/Dead assay demonstrates viable, spreading MSCs across scaffolds.
2. Extrusion pressure identified as the top sensitivity factor for cells.
3. GPR maps response surfaces with quantified prediction uncertainty bounds.

Quantitative

1. **MSC viability** on Day 7 achieves **≥80%**.
2. GPR model achieves high prediction accuracy with an **R-squared** over **0.80**.
3. Low prediction error was verified between machine learning and experiments.
4. **Active learning cuts** required physical experiments by **over 80%**.
5. **Compressive modulus** meets the bone scaffold target range of **50- 120 kPa**.
6. **Geometric pore area deviation** is successfully controlled within the limit (**10- 15%**).

CONCLUSION



Aim

Using AI to **identify** the **optimal combination** of three parameters to **maximize MSC viability** in 3D-printed bone scaffolds while **decreasing the number of experiments** required.

Limitation

The optimization **focuses mainly on MSC viability**. High cell viability alone does not guarantee the best scaffold for bone regeneration.

Future studies should **include mechanical strength** and **osteogenic differentiation** for more comprehensive scaffold optimization.

REFERENCES

Scan the QR for references

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