Week 4: Hyperparameter Tuning, Model Interpretation, and Deployment

Tasks Completed:

1. **Hyperparameter Tuning**:

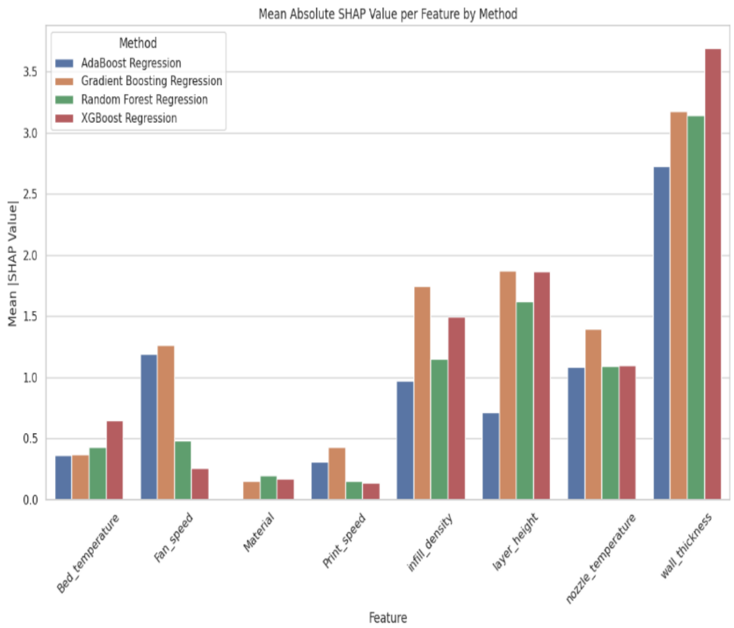
   Random Forest tuned via RandomizedSearchCV:

   - Best parameters: `max_depth=20`, `n_estimators=124`.
   - Improved test R^2 to **0.88** (from 0.81).

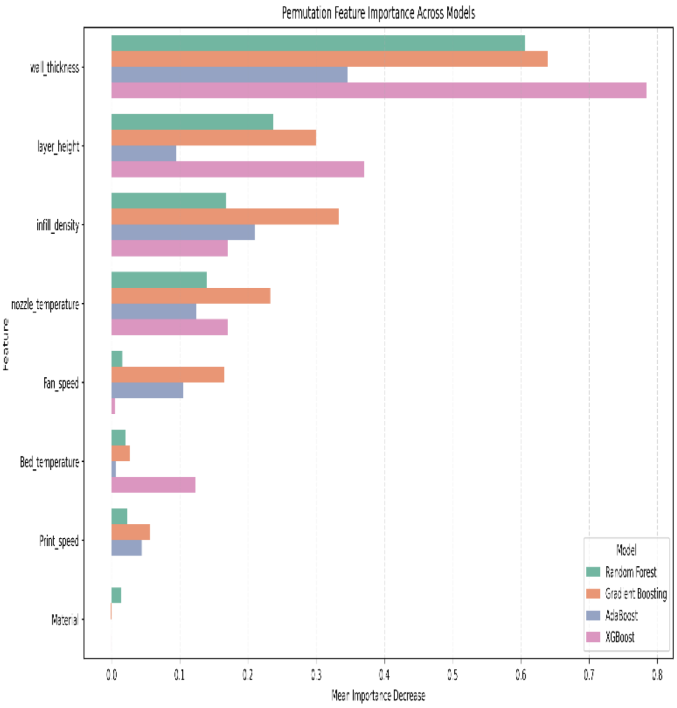
- **Gradient Boosting** optimized with GridSearchCV:
  - Best parameters: `learning_rate=0.2`, `max_depth=3`.
  - Achieved R^2 = **0.91** (highest among all models).

2. **Model Interpretation**:

- **SHAP Analysis**:
  - Wall thickness (SHAP = 3.7) and layer height (SHAP = 2.1) identified as top predictors

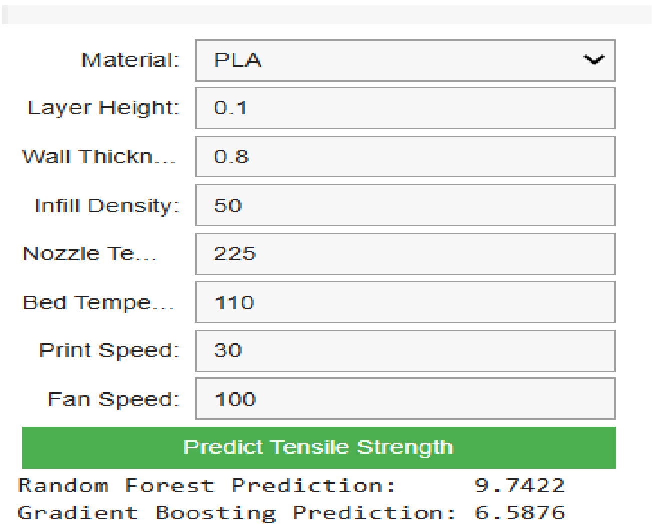


- **Permutation Importance**:
  - Wall thickness contributed 32% to prediction accuracy



3. **UI Development**:

- Built an interactive widget using `ipywidgets`



- Inputs: Material type, layer height, nozzle temperature, wall thickness.
- Output: Predicted tensile strength (MPa) using Random Forest.
- Integrated with Jupyter Notebook for real-time use.

Challenges Faced:

- Long tuning times for GridSearchCV (4+ hours for Gradient Boosting).
- SHAP analysis required high memory usage for large datasets.

Outcomes:

- Finalized tuned models with improved accuracy.
- Published **Results and Discussion** section with SHAP visualizations.
- Deployed UI for practical use by 3D printing engineers.

Tasks Planned for Finalization:

- Validate UI predictions with experimental 3D-printed samples.
- Prepare manuscript for submission to *Additive Manufacturing* journal.

Key Achievements

1. **Best Model**: Tuned Gradient Boosting (R^2 = 0.91, MSE = 5.1).
2. **Critical Insights**:
   - Wall thickness and layer height are the most influential parameters.
   - Higher nozzle temperatures reduce tensile strength (negative correlation).
   - **Tool Delivered**: Interactive UI for optimizing 3D printing parameters.