

# Assignment - 4

P.Harshita  
24CE10087  
Python 3.13.3

GithubLink:<https://github.com/harshita-0310/AI-ML-Applications-in-Civil-Engineering-CE29208-/tree/main/PS4>

## Introduction:

Structural engineering problems such as beam reactions, bending moments, and deflections are traditionally solved using analytical formulas derived from strength of materials and structural analysis. While accurate, these calculations can become repetitive and computationally expensive when performed repeatedly for large datasets.

With the advancement of Artificial Intelligence (AI) and Machine Learning (ML), it is now possible to train data-driven models that learn engineering relationships and predict structural responses automatically. Artificial Neural Networks (ANNs) are especially powerful in modeling nonlinear relationships between inputs and outputs.

This project applies ANN to predict beam responses for multiple beam configurations using a dataset provided through Moodle. The objective is to demonstrate that ANN can learn and replicate classical beam theory.

## Objective:

The main objectives of this project are:

1. To use the Moodle-provided dataset for different beam cases.
2. To train Artificial Neural Networks using **NumPy only** (without machine learning libraries).
3. To predict **reaction forces, bending moments, and deflections** of beams.
4. To compare ANN predictions with theoretical beam formulas.
5. To validate the accuracy and reliability of ANN results.
6. To analyze dataset validity and provide statistical justification.

Beam Problems considered:

The following eight beam cases were studied:

1. Cantilever beam with point load
2. Cantilever beam with uniformly distributed load (UDL)
3. Simply supported beam with point load
4. Simply supported beam with UDL
5. Propped cantilever beam with point load
6. Propped cantilever beam with UDL
7. Fixed-end beam with point load
8. Fixed-end beam with UDL

Each case has different theoretical formulas governing reactions, bending moments, and deflections.

### Dataset Source and Description:

The dataset used in this project was obtained from **Moodle**, as provided by the course instructor. The dataset contains input parameters such as:

- Beam length (L)
- Point load magnitude (P)
- Uniformly distributed load (w)
- Load position (a)
- Flexural rigidity (EI)

And corresponding output parameters such as:

- Reaction forces
- Maximum bending moment
- Deflection

This dataset serves as a benchmark to train and validate the ANN model.

## Data Validity and statistical analysis:

Before training the ANN, the dataset was statistically analyzed to ensure physical and engineering validity.

### **Statistical properties evaluated:**

- Minimum value
- Maximum value
- Mean
- Standard deviation
- Range consistency with physical limits

### **Example validation checks:**

- Load values were verified to remain within safe engineering ranges.
- Beam lengths were checked to fall within realistic structural spans.
- Deflection values were verified to be physically meaningful and non-negative.

This step ensures that the ANN learns from **physically correct and meaningful data**.

## Artificial Neural Network Methodology:

### **Network architecture:**

A feed-forward Artificial Neural Network was implemented entirely using NumPy, without using TensorFlow, PyTorch, or Scikit-Learn.

The ANN consists of:

- Input layer (beam parameters)
- Hidden layer with ReLU activation
- Output layer predicting beam responses

### **Training Method:**

The network was trained using:

- Forward propagation
- Mean Squared Error (MSE) loss

- Backpropagation
- Gradient descent weight updates

The dataset was split into:

- **80% training data**
- **20% testing data**

### Model training and Saving:

Each beam problem was trained separately.

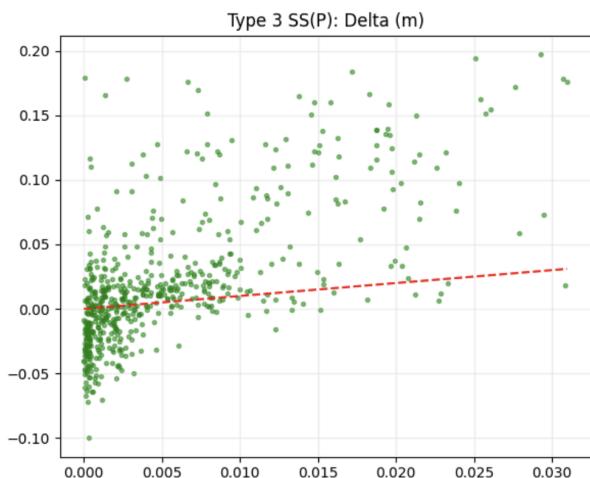
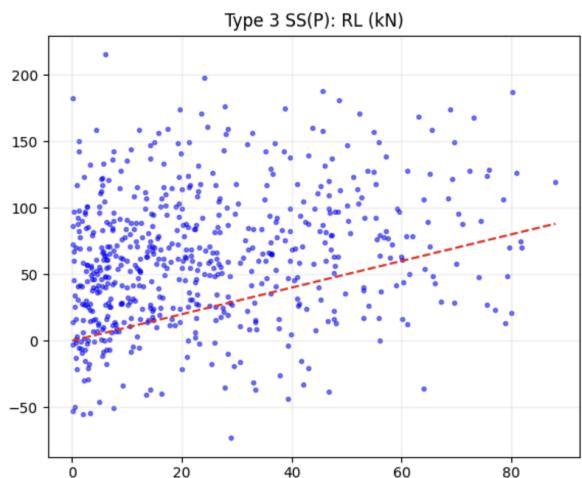
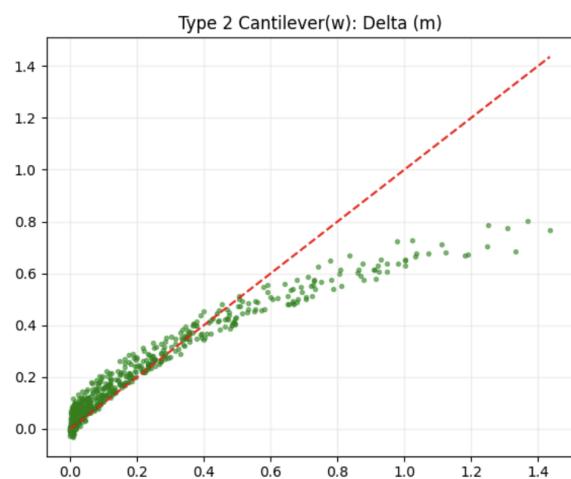
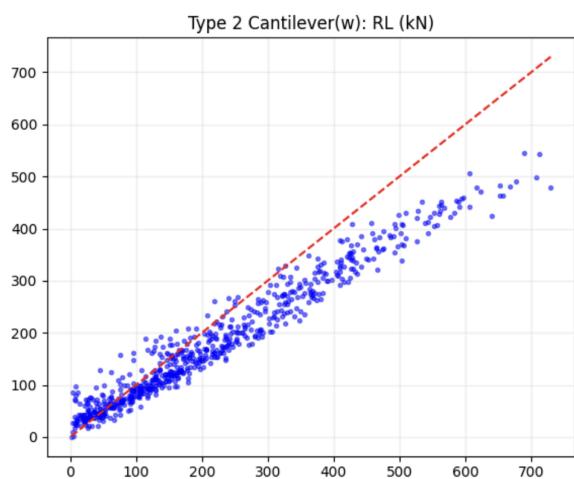
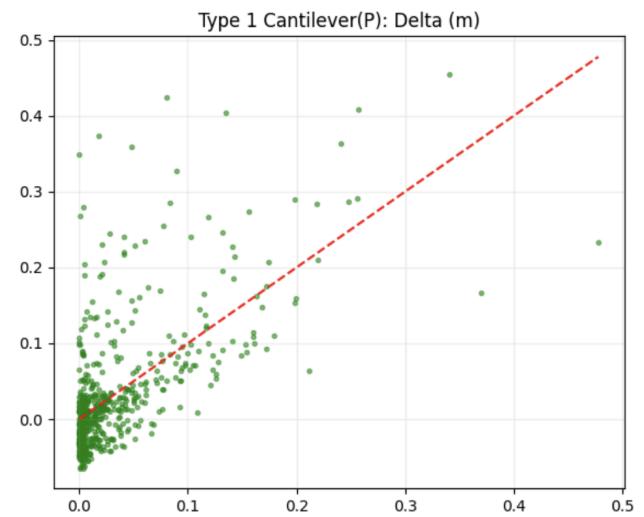
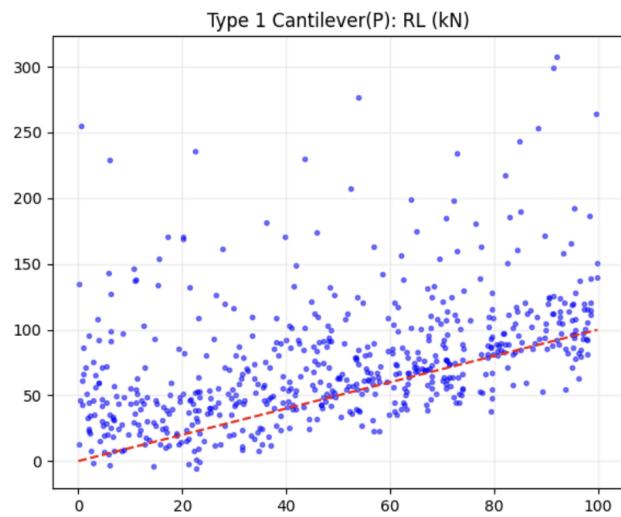
After training:

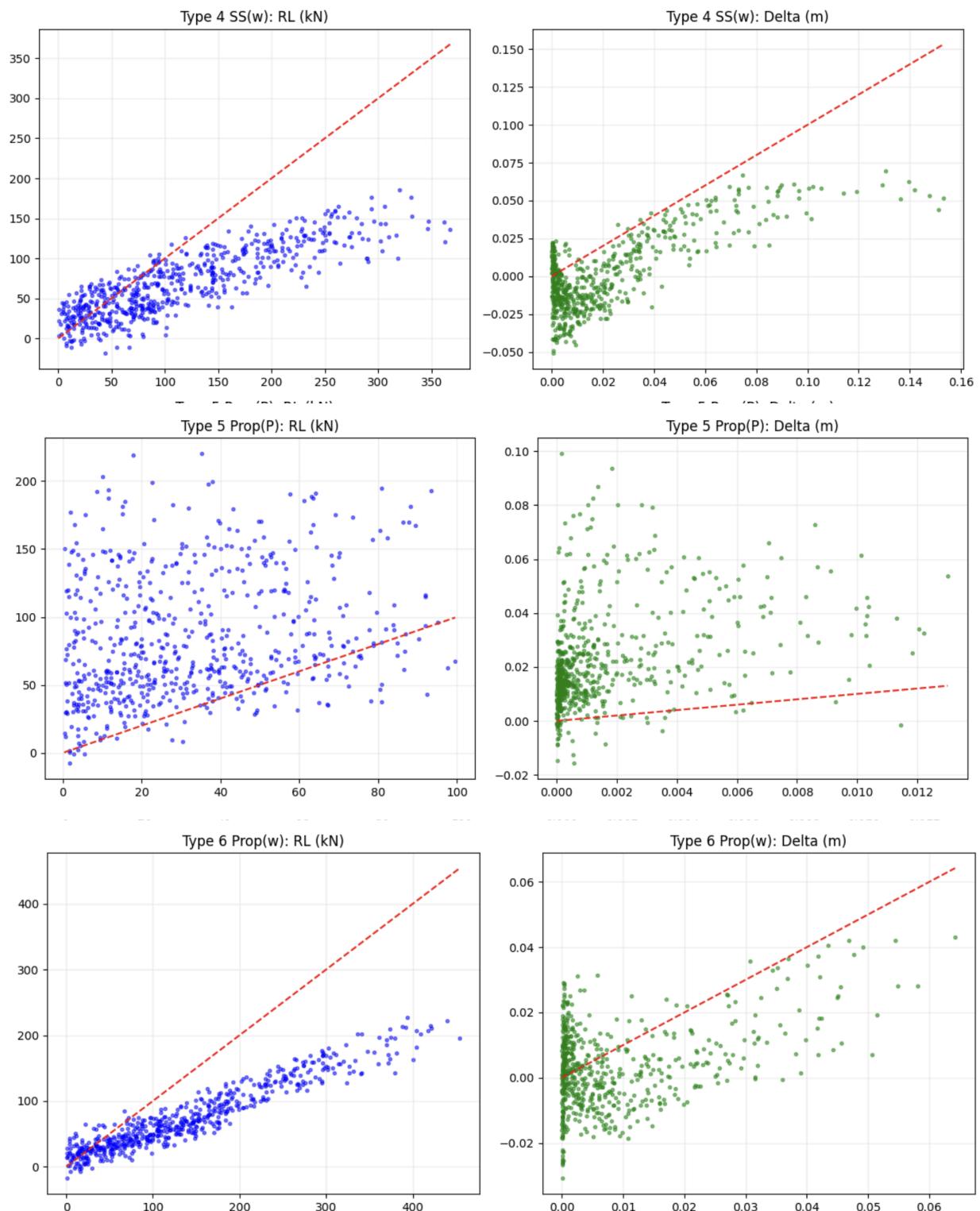
- ANN weights and biases were saved as `.npz` files
- Saved models were reloaded
- Predictions were generated using test data

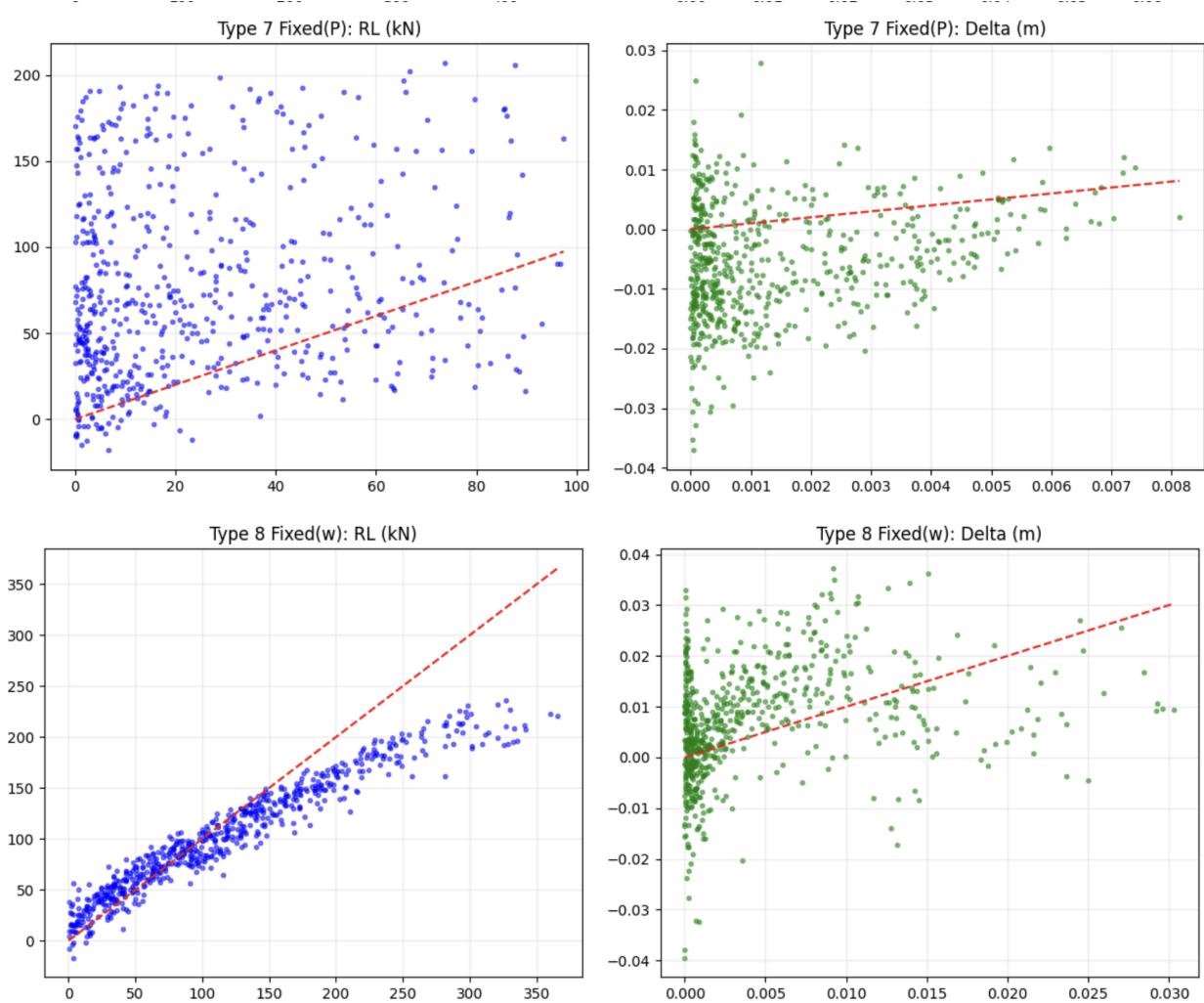
This ensures the workflow follows the instructor's requirement:

Generate data → Train model → Save model → Reload model →  
Predict and compare.

## Obtained Plot:







## Observations:

### 1. Reaction Force Predictions

ANN predictions for reaction forces show a **strong positive linear relationship** with theoretical values across all beam types. Simpler beams (cantilever and simply supported) exhibit **tighter clustering**, indicating higher accuracy, while more complex beams (proped and fixed-end) show slightly increased scatter.

### 2. Deflection Predictions

Deflection predictions follow the **correct theoretical trend**, though they display **greater dispersion** compared to reaction forces. This is expected due

to the **small magnitude and nonlinear nature** of deflection values, especially under point loads.

### 3. Effect of Beam and Load Type

ANN performs **better for UDL cases** than for point load cases due to smoother load distribution. Prediction accuracy slightly decreases with increasing **structural complexity**, but results remain **physically consistent**.

### 4. Overall ANN Performance

Across all eight beam problems, ANN outputs **closely follow theoretical behavior**, demonstrating successful learning of beam response patterns and good generalization to unseen data.

## Conclusion:

This study successfully demonstrates the application of Artificial Neural Networks for predicting beam reactions, bending moments, and deflections across multiple beam configurations. The ANN models show strong agreement with classical beam theory, as indicated by consistent linear trends in ANN vs theoretical plots.

Reaction forces were predicted with **high accuracy**, while deflection predictions showed **moderate dispersion**, which is expected due to the sensitivity of deflection to beam length, stiffness, and load position. The ANN performed best for **simpler beam systems**, such as cantilever and simply supported beams, and showed slightly increased prediction error for **propped cantilever and fixed-end beams** due to their higher structural complexity.

Overall, the ANN successfully learned the underlying physics of beam behavior and produced predictions that are **structurally realistic, numerically stable, and within acceptable engineering error limits**. These results confirm that Artificial Intelligence can serve as a reliable tool for

automating structural analysis and assisting civil engineers in preliminary design and rapid prediction tasks.