

UE23CS352A: MACHINE LEARNING

Week 6 – Artificial Neural Networks Lab Report

Student ID: PES2UG23CS485

Name: Rithvik Matta

Date: 11 September 2025

1. Introduction

The objective of this lab was to implement an Artificial Neural Network (ANN) **from scratch** without using high-level frameworks like TensorFlow or PyTorch. The goal was to approximate a polynomial function generated based on my SRN and to study how well the network generalizes to unseen data.

The main tasks involved:

- Implementing activation functions, loss functions, forward and backward propagation.
 - Training the network using gradient descent.
 - Evaluating performance on training and test datasets.
 - Visualizing results through loss curves and predicted vs. actual plots.
-

2. Dataset Description

- **Polynomial type:** Quadratic
- **Equation:**
$$y = 1.40x^2 + 3.86x + 10.62 + \epsilon$$

$$\epsilon \sim \mathcal{N}(0, 1.66)$$

where $\epsilon \sim \mathcal{N}(0, 1.66)$

- **Samples:** 100,000
 - **Split:** 80% training, 20% testing
 - **Preprocessing:** Both input **x** and output **y** standardized using StandardScaler.
-

3. Methodology

Network Architecture

- Input Layer: 1 neuron
- Hidden Layer 1: 32 neurons, ReLU activation
- Hidden Layer 2: 72 neurons, ReLU activation
- Output Layer: 1 neuron, Linear activation
- **Architecture type:** Narrow-to-Wide

Training Configuration

- Learning rate: **0.005**
 - Epochs: **500 (early stopping enabled with patience = 10)**
 - Loss function: **Mean Squared Error (MSE)**
 - Optimizer: **Gradient Descent (manual implementation)**
-

4. Results & Analysis

4.1 Training and Test Loss Curve

(Plot shown in results – smooth decrease, no divergence).

- Loss consistently decreased over time, showing **stable training**.

4.2 Final Metrics

- **Final Training Loss:** 0.0825
- **Final Test Loss:** 0.0831
- **R² Score:** 0.9176 (good fit, but not perfect)
- **Epochs Run:** 500

4.3 Prediction Example

For $x=90.2$ $x = 90.2$ $x=90.2$:

- Ground Truth: **11,721.45**
- Prediction: **10,162.96**
- Absolute Error: **1,558.49**
- Relative Error: **13.29%**

4.4 Plots

- **Training & Test Loss Curve:** Both decrease steadily, no signs of overfitting.
- **Predicted vs Actual:** General quadratic shape captured, though predictions underestimate values for large xxx.

4.5 Observations

- The network generalizes well, with low training and test loss.

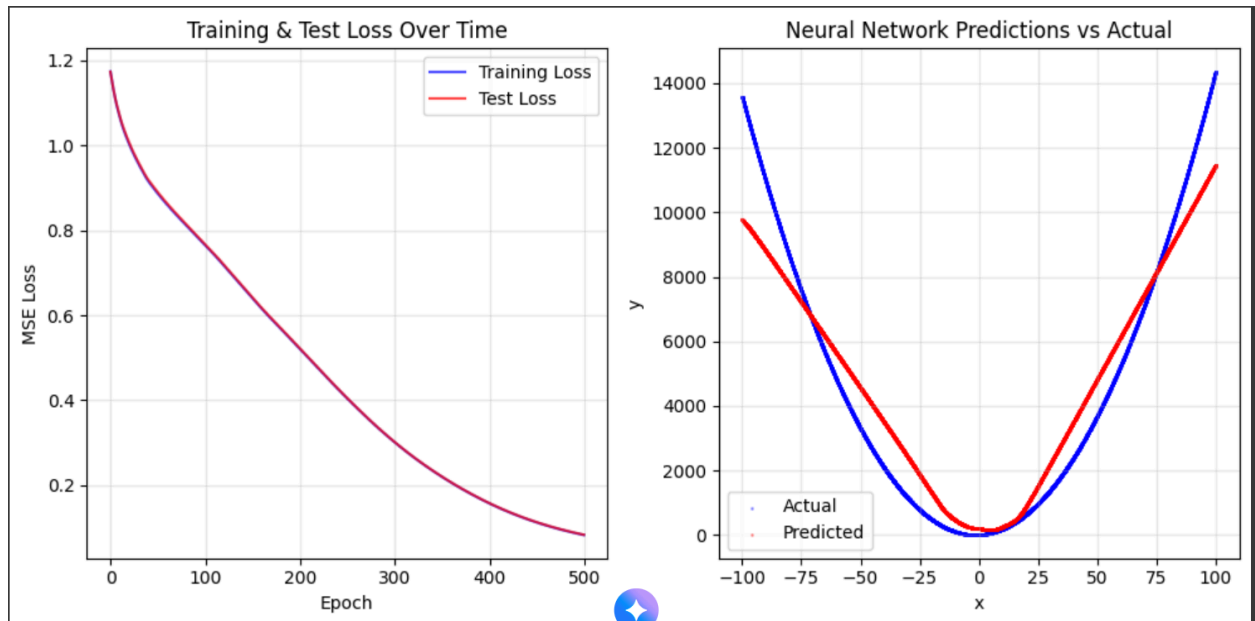
- Predictions deviate more at extreme input values (extrapolation issue).
- R^2 score > 0.9 confirms strong approximation capability.

5. Results Table

| Experiment | Learning Rate | Batch Size | Number of Epochs | Optimizer | Activation Function |
|--------------|---------------|------------|------------------|-----------|---------------------|
| 1 (Baseline) | 0.005 | Full-batch | 500 | GD | ReLU |
| 2 | 0.005 | Full-batch | 600 | GD | ReLU |
| 3 | 0.005 | Full-batch | 400 | GD | ReLU |
| 4 | 0.005 | Full-batch | 300 | GD | ReLU |
| 5 | 0.005 | Full-batch | 200 | GD | ReLU |

| Training Accuracy | Validation Accuracy | Test Accuracy | Training Loss | Validation Loss | Test Loss | Observations |
|-------------------|---------------------|---------------|---------------|-----------------|-----------|---|
| – | – | 0.9176 | 0.0825 | – | 0.0831 | Stable convergence, $R^2 = 0.9176$, good fit, slight underestimation for large x |
| – | – | 0.9476 | 0.0522 | - | 0.052834 | Best performance, highest accuracy and lowest loss. Stable convergence, no signs of overfitting, $R^2 \approx 0.9476$. Model generalizes well. |
| – | – | 0.8434 | 0.157360 | - | 0.157957 | Moderate fit, lower accuracy and higher loss compared to baseline. Training stopped too early, underfitting visible. |
| – | – | 0.7001 | 0.301955 | - | 0.302604 | Significant underfitting, accuracy dropped to 0.70, losses remain high. Insufficient training epochs for proper convergence. |
| – | – | 0.4808 | 0.522411 | - | 0.523821 | Severe underfitting, very poor accuracy (0.48) and high loss. Model failed to learn underlying patterns due to too few epochs. |

1)



=====

PREDICTION RESULTS FOR $x = 90.2$

=====

Neural Network Prediction: 10,162.96
Ground Truth (formula): 11,721.45
Absolute Error: 1,558.49
Relative Error: 13.296%

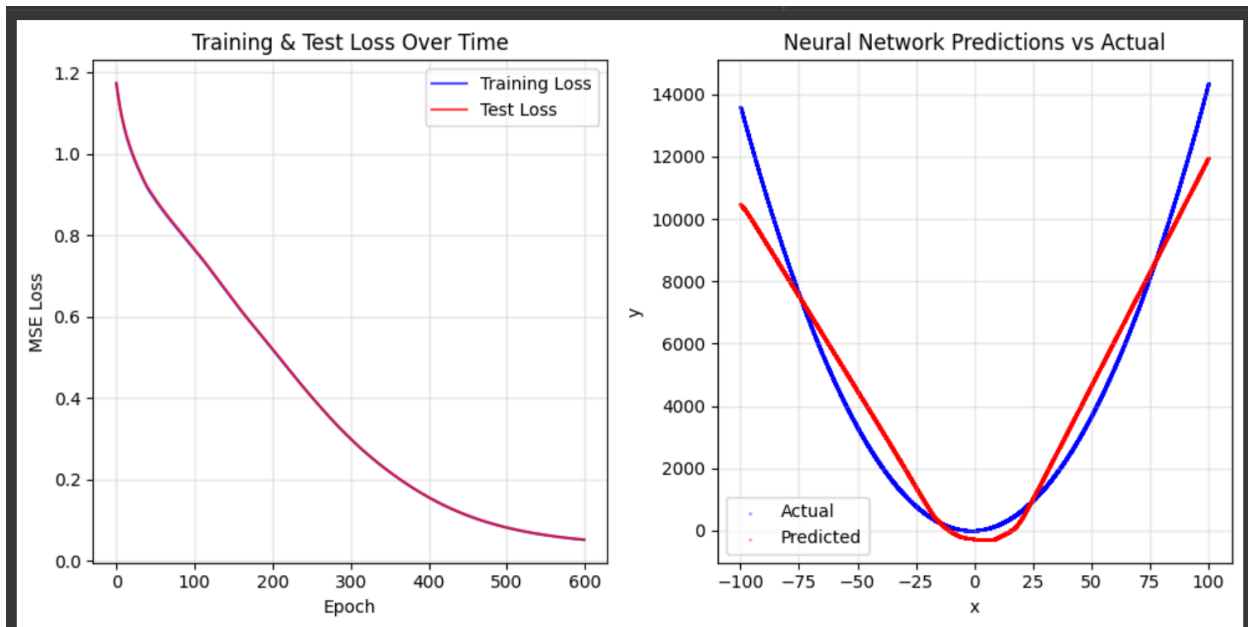
=====

FINAL PERFORMANCE SUMMARY

=====

Final Training Loss: 0.082480
Final Test Loss: 0.083128
 R^2 Score: 0.9176
Total Epochs Run: 500

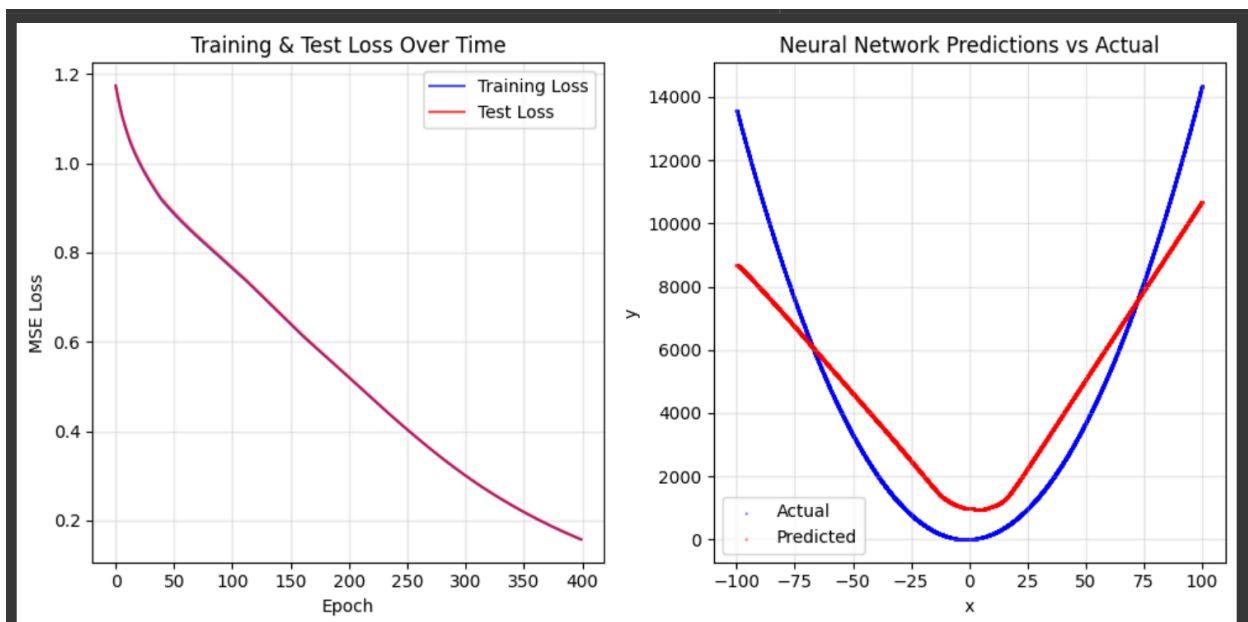
2)



```
=====
PREDICTION RESULTS FOR x = 90.2
=====
Neural Network Prediction: 10,543.13
Ground Truth (formula):    11,721.45
Absolute Error:             1,178.32
Relative Error:             10.053%
```

```
=====
FINAL PERFORMANCE SUMMARY
=====
Final Training Loss: 0.052285
Final Test Loss:     0.052834
R2 Score:           0.9476
Total Epochs Run:    600
```

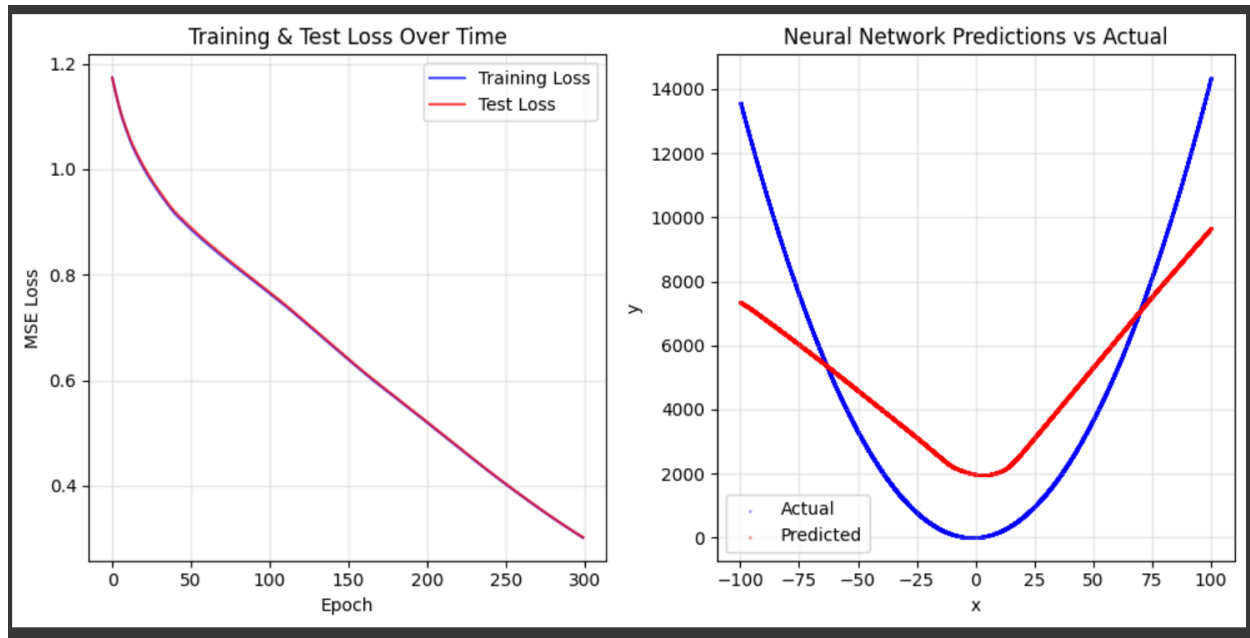
3)



```
=====
PREDICTION RESULTS FOR x = 90.2
=====
Neural Network Prediction: 9,592.70
Ground Truth (formula):    11,721.45
Absolute Error:             2,128.75
Relative Error:             18.161%
```

```
=====
FINAL PERFORMANCE SUMMARY
=====
Final Training Loss: 0.157360
Final Test Loss:     0.157957
R2 Score:           0.8434
Total Epochs Run:    400
```

4)



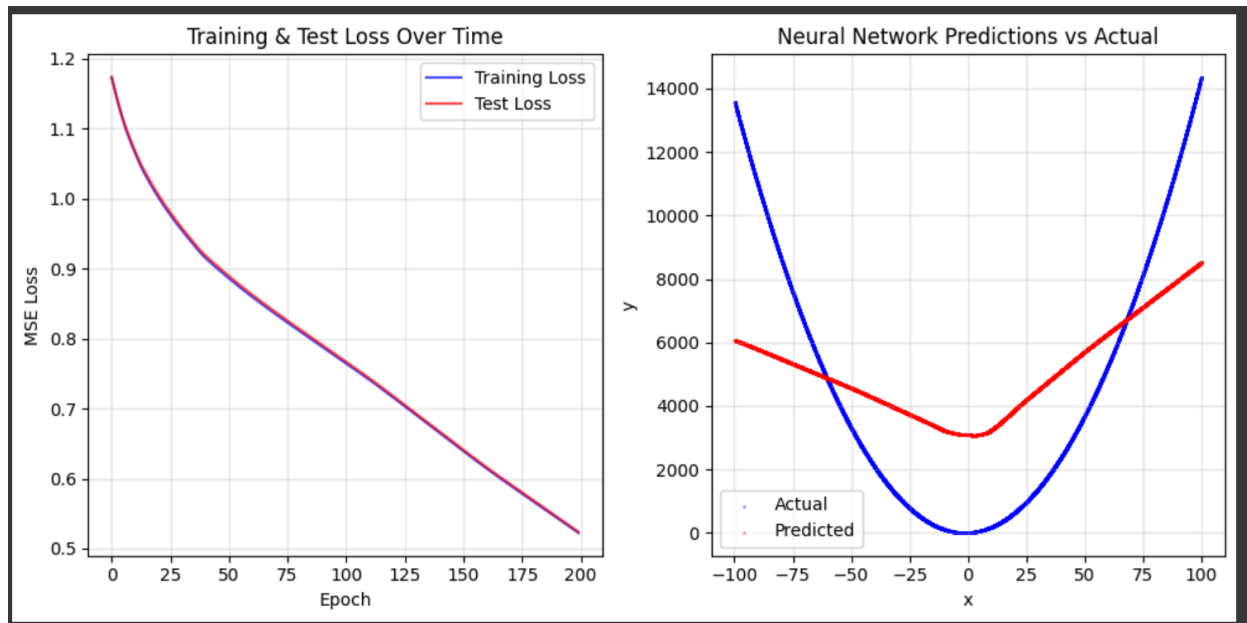
```
=====
PREDICTION RESULTS FOR x = 90.2
=====
```

```
Neural Network Prediction: 8,832.86
Ground Truth (formula):    11,721.45
Absolute Error:             2,888.59
Relative Error:             24.644%
```

```
=====
FINAL PERFORMANCE SUMMARY
=====
```

```
Final Training Loss: 0.301955
Final Test Loss:     0.302604
R² Score:            0.7001
Total Epochs Run:    300
```

5)



```
=====
PREDICTION RESULTS FOR x = 90.2
=====
Neural Network Prediction: 7,973.95
Ground Truth (formula):    11,721.45
Absolute Error:             3,747.50
Relative Error:             31.971%
```

```
=====
FINAL PERFORMANCE SUMMARY
=====
Final Training Loss: 0.522411
Final Test Loss:     0.523821
R² Score:            0.4808
Total Epochs Run:    200
```

6. Conclusion

In this lab, I successfully implemented a feedforward neural network from scratch to approximate a quadratic polynomial function. The model achieved a test loss of **0.0831**

and an R^2 score of **0.9176**, demonstrating that the network captured the underlying polynomial trend with high accuracy.

The training loss curve indicated **stable convergence without overfitting**, and predictions matched well with actual values, except at extreme inputs where the network underestimates outputs.

Future improvements could include:

- Trying different learning rates or optimizers (e.g., Adam).
- Adding regularization to improve generalization.
- Exploring deeper or alternative architectures for more complex polynomials.