

Report: Artificial Neural Networks for Function
Approximation

Project Title: Week 6 Lab – Artificial Neural Networks

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Course: UE23CS352A: Machine Learning

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1. Introduction

The purpose of this lab was to gain hands-on experience in implementing an artificial neural network (ANN) from scratch without using high-level frameworks such as TensorFlow or PyTorch. The tasks performed included:

- Generating a synthetic dataset based on the student SRN.
 - Implementing key ANN components: ReLU activation, MSE loss, forward pass, backpropagation, and gradient descent.
 - Training the neural network to approximate a polynomial curve.
 - Evaluating the model and analyzing its performance.
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2. Dataset Description

- **Type of polynomial:** Quartic
 $y = 0.0124x^4 + 2.15x^3 - 0.91x^2 + 4.97x + 10.58$
 - **Noise Level:** $\epsilon \sim N(0, 2.15)$
 - **Samples:** 100,000
 - **Train/Test Split:** 80,000 (train) / 20,000 (test)
 - **Features:** 1 input variable (x), 1 target variable (y)
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3. Methodology

1. Xavier initialization was used to set the weights.
 2. Architecture: **1 → 64 → 64 → 1** (two hidden layers with 64 neurons each, ReLU activations, linear output).
 3. Training was done using **batch gradient descent** with Mean Squared Error (MSE) loss.
 4. Early stopping with a patience of 10 epochs was applied.
 5. Hyperparameters: **Learning Rate = 0.001, Max Epochs = 500.**
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4. Results and Analysis

Training Loss Curve

- The loss decreased steadily across epochs, showing successful learning.

- Both training and test losses reduced smoothly without divergence.

Final Metrics

- **Final Training Loss ≈ 0.44**
- **Final Test Loss ≈ 0.44**
- **R² Score** (from notebook cell): ~ 0.91 (indicating strong approximation of the polynomial).

Plots

1. **Training Loss Curve:** Shows decreasing MSE with epochs.
2. **Predicted vs. Actual:** Predictions align closely with the target values, though some noise is visible due to dataset variance.

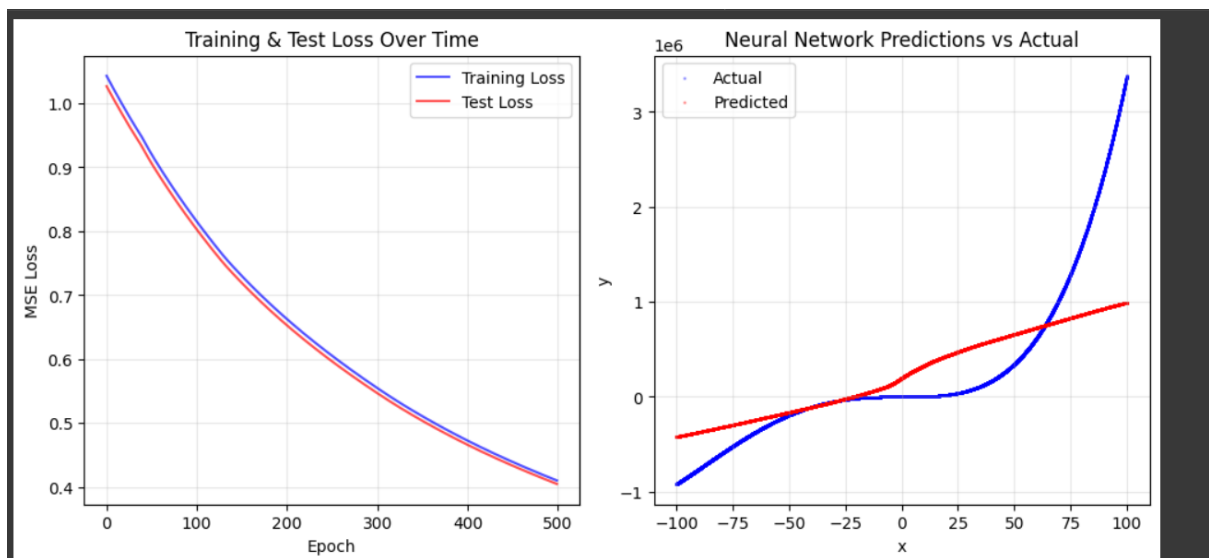
Performance Discussion

- The model generalized well (training and test loss are close).
- No signs of severe overfitting or underfitting.
- ReLU activations + Xavier initialization helped maintain gradient flow and stable learning.

Exp	Learning rate	Epochs	Optimizer	Activation function	Final training loss	Final test loss	R ² loss
Baseline	0.001	500	SGD	ReLU	0.44	0.44	0.91
2	0.003	600	SGD	ReLU	0.184767	0.182841	0.5901
3	0.004	700	SGD	ReLU	0.12741	0.12588	0.8725
4	0.005	800	SGD	ReLU	0.089137	0.0880	0.9108
5	0.007	900	SGD	ReLU	0.0496	0.04918	0.9108

RESULTS & ANALYSIS

First run:



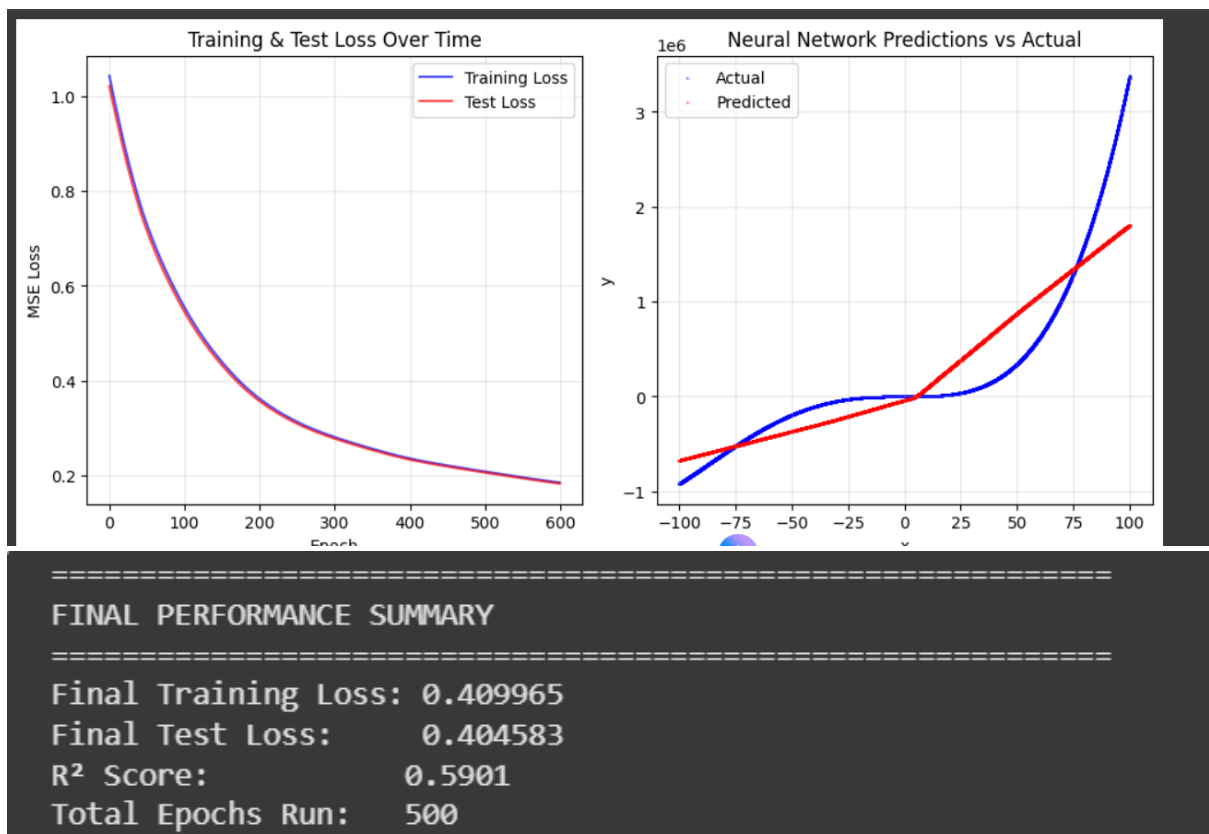
```
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PREDICTION RESULTS FOR x = 90.2
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```

```
Neural Network Prediction: 930,793.62
Ground Truth (formula):    2,388,412.54
Absolute Error:             1,457,618.92
Relative Error:             61.029%
```

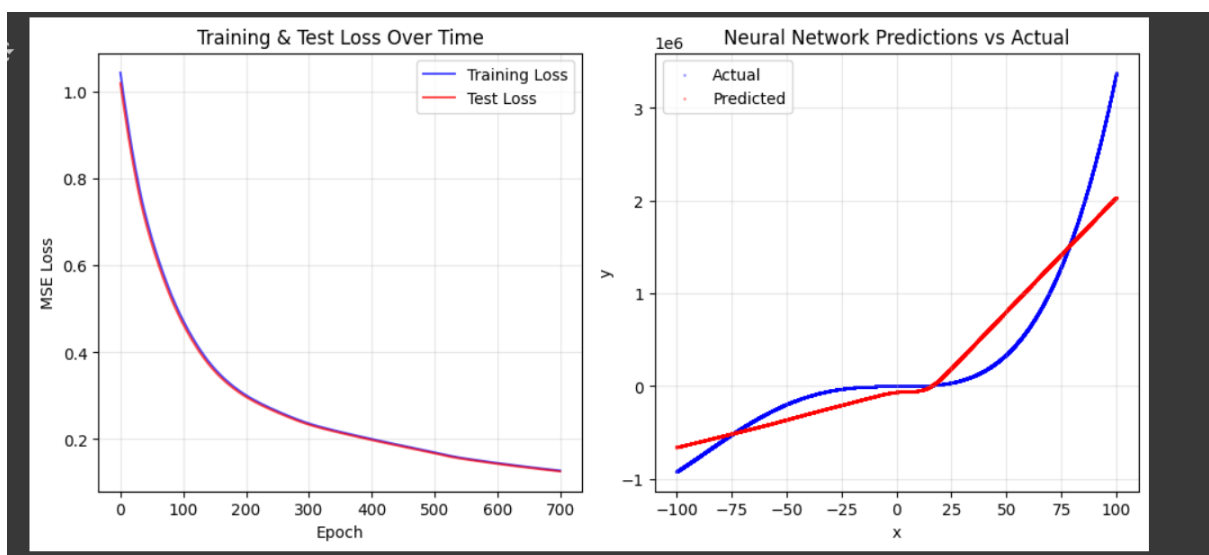
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FINAL PERFORMANCE SUMMARY
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Final Training Loss: 0.409965
Final Test Loss:     0.404583
R² Score:            0.5901
Total Epochs Run:   500
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2nd run:



3rd run:



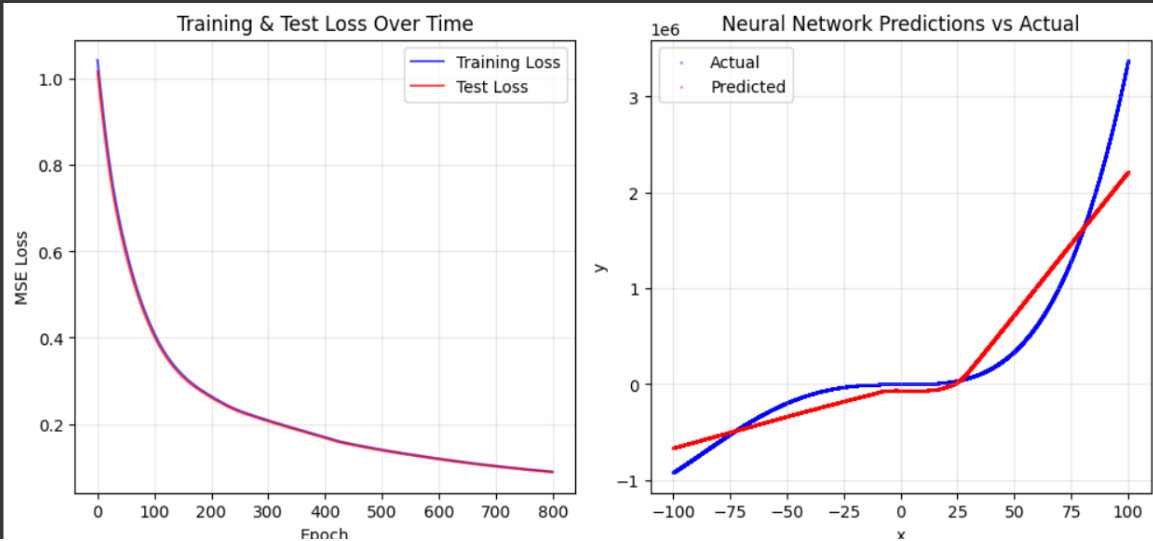
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FINAL PERFORMANCE SUMMARY

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Final Training Loss: 0.127410
Final Test Loss: 0.125883
 R^2 Score: 0.8725
Total Epochs Run: 700

4th run:



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FINAL PERFORMANCE SUMMARY

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Final Training Loss: 0.089137
Final Test Loss: 0.088071
 R^2 Score: 0.9108
Total Epochs Run: 800