

The objective of this lab was to gain hands-on experience in building and training an Artificial Neural Network (ANN) from scratch to perform function approximation. The core tasks involved implementing the fundamental components of a neural network, including activation functions, loss functions, forward propagation, and backpropagation. A synthetically generated dataset was used to train the network to approximate a polynomial curve, and various experiments were conducted by tuning hyperparameters to observe their impact on model performance.

## Dataset Description

The dataset used for this experiment was synthetically generated based on SRN.

- Total Samples: 100,000
- Training Set Size: 80,000 (80%)
- Testing Set Size: 20,000 (20%)

## Methodology

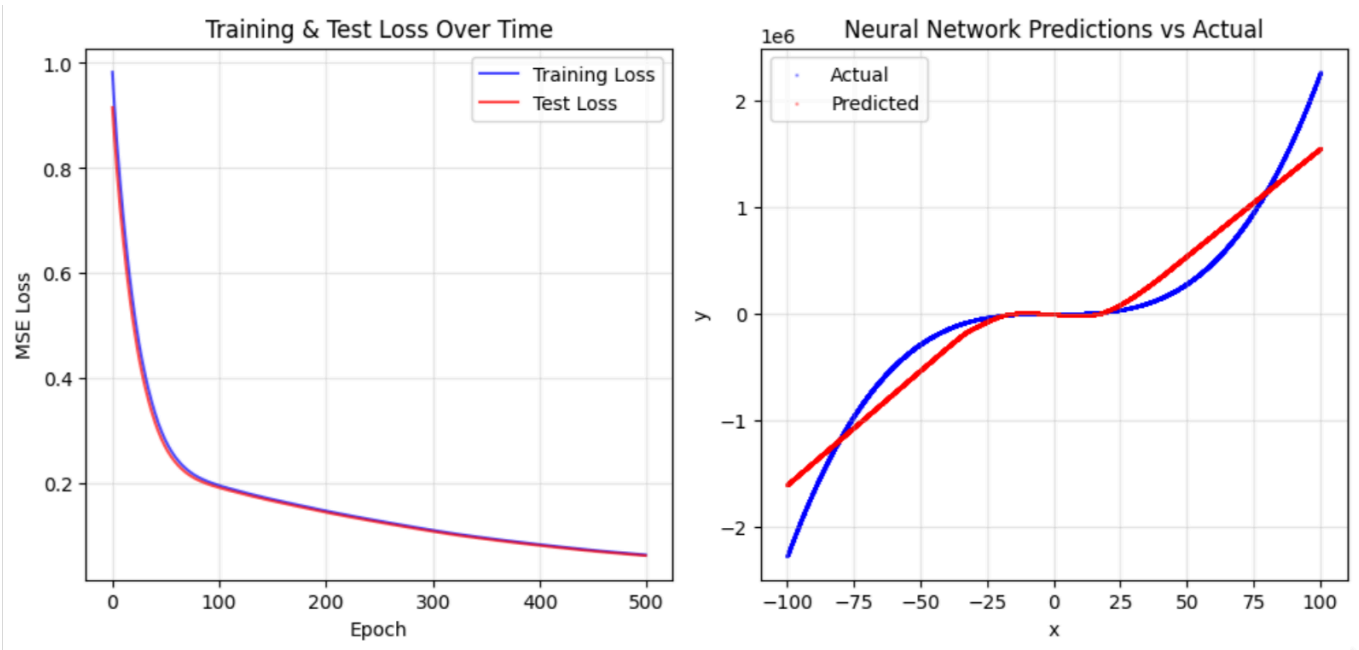
The neural network was implemented from the ground up without using high-level machine learning frameworks. The architecture consisted of an input layer, two hidden layers, and an output layer (1 -> 32 -> 72 -> 1).

The implementation steps were as follows:

1. Activation Function: The ReLU (Rectified Linear Unit) activation function and its derivative were implemented.
2. Loss Function: The Mean Squared Error (MSE) was implemented to quantify the model's prediction error.
3. Forward Propagation: A forward pass function was created to pass input data through the network and generate predictions.
4. Backpropagation: The backpropagation algorithm was implemented to calculate the gradients of the loss with respect to the network's weights and biases.
5. Training Loop: A training loop was established to iteratively update the model's parameters using gradient descent, minimizing the loss over a set number of epochs.

## Results & Analysis

The initial model was trained with a baseline set of hyperparameters to establish a performance benchmark. The model trained steadily, with both training and test loss decreasing consistently over 500 epochs.



Exp	Learning Rate	Batch Size	Epochs	Optimizer	Activation Function	Training Loss	Test Loss	R^2
Exp. 1	0.005	80000	500	Gradient Descent	ReLU	0.136520	0.134130	0.86
Exp. 2	0.007	80000	500	Gradient Descent	ReLU	0.104652	0.102595	0.89
Exp. 3	0.009	80000	500	Gradient Descent	ReLU	0.081343	0.079576	0.91
Exp. 4	0.011	80000	500	Gradient Descent	ReLU	0.063742	0.062231	0.93