AIN SHAMS UNIVERSITY
FACULTY OF ENGINEERING

Computational Intelligence CSE473s
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Final Project

[Neural Network Library]

– Team – 18

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Introduction

This project implements a neural network library **from scratch** using NumPy. Part 1 focuses on developing the **core training pipeline**, including:

- Fully Connected (`Dense`) layers
- Nonlinear Activation functions (ReLU, Sigmoid, Tanh, Softmax)
- Loss computation using **Mean Squared Error** (`MSELoss`)
- Gradient-based weight updates using **Stochastic Gradient Descent** (`SGDOptimizer`)
- A `Sequential` model class to combine all components
- Experimental validation using the **XOR problem**

This implementation provides a foundational understanding of forward propagation, backward propagation, and parameter updates — without relying on deep learning frameworks.

System Architecture & Design

Overall Workflow

```
Input → Sequential.forward → MSELoss → MSELoss.backward → Sequential.backward
→ SGDOptimizer(step)
```

Modular Design Strategy

Component	Responsibility
`Sequential`	Manages layers, full training loop (`fit`)
`Dense`	Trainable linear transformation (stores `W`, `b`, `dW`, `db`)
Activation Functions	Apply nonlinearity, no trainable parameters
`MSELoss`	Computes loss and its gradient w.r.t model output
`SGDOptimizer`	Updates parameters using gradients

The separation allows future extension:

- More optimizers (Momentum, Adam)
- Additional loss functions
- Regularization
- More layer types

Implemented Components

Dense Layer

- Trainable weights: `W` and `b`
- Uses scaled random initialization: `np.random.randn() * scale`
- Stores gradients: `dW`, `db`

Forward [$Z = XW + b$]

Backward:

- $[dW = X^T * dZ]$
- $[db = \sum dZ]$
- $[dX = dZ * W^T]$

Activation Layers

Activation	Derivative
ReLU	$(1_{x>0})$
Sigmoid	$(y[1-y])$
Tanh	$(1 - y^2)$
Softmax	Used later with cross-entropy

- Non-trainable (only modify the gradient).

`MSELoss` class

Used for XOR regression-style learning.

- $[L = \frac{1}{2N} \sum (y - \hat{y})^2]$
- $[\frac{\partial L}{\partial \hat{y}} = \frac{1}{N}(\hat{y} - y)]$

`SGDOptimizer` class

Updates trainable parameters:

- $[W_{n+1} = W_n - \eta \cdot dW_n]$
- $[b_{n+1} = b_n - \eta \cdot db_n]$

Where (η) = learning rate.

`Sequential` class

Responsibilities:

- Store ordered layers
- `forward()` → inference
- `backward()` → propagate gradients
- `fit()` → complete training loop
    1. Forward pass
    2. Computing loss
    3. Backward pass
    4. Optimizer weight update

Result: **Simple high-level API** for training models.

Experiment: XOR Problem

Dataset

Input (x1, x2)	Target (y_true)
[0,0]	0
[0,1]	1
[1,0]	1
[1,1]	0

- XOR is **non-linearly separable**
- Validates backprop & nonlinear learning

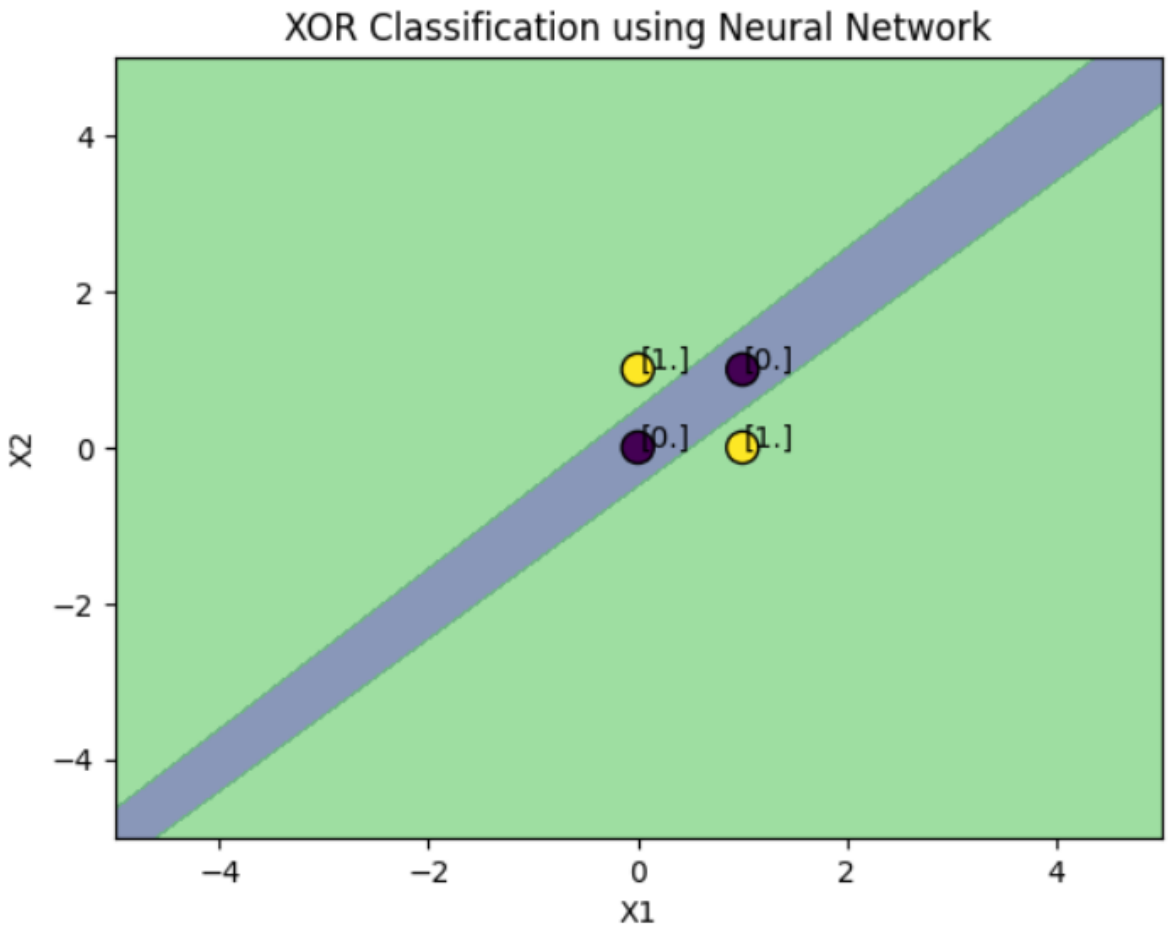
Model Architecture

Layer	Scaling factor (Parameters initialization)	Details
Dense layer (2 -> 4)	1.0	Hidden layer
Tanh	–	Nonlinear activation
Dense layer (4 -> 1)	1.0	Output layer
Sigmoid	–	Output activation

- Loss function: [**MSELoss**].
- Optimizer: [**SGDOptimizer**] with learning rate (η) = 1.0, and epochs = 10,000.

Results

Boundary layers plotting



Final Predictions

Input	Target	Predicted	Rounded
[0,0]	0	0.00321	0
[0,1]	1	0.99170	1
[1,0]	1	0.99166	1
[1,1]	0	0.00996	0

The model successfully learned XOR mapping, achieving correct classification.

Observations & Notes

- With **MSE + Sigmoid**, learning can be slower due to saturation
- Increasing:

  - Hidden layer size
  - Learning rate Can improve convergence
- The pipeline correctly computes gradients and updates weights

This confirms our framework works end-to-end.

Conclusion

- Fully functional neural network training library implemented
- Verified using XOR experiment
- Solid foundation for Part 2 improvements:
  - Softmax + Cross-Entropy for classification
  - More optimizers
  - Model evaluation metrics
  - Better weight initialization
  - Saving/loading models

The implementation demonstrates fundamental understanding of neural networks and backpropagation.

Appendix

GitHub Repository

https://github.com/CSE473s-Course-Project-Fall25/neural-network-lib.git