

# EXPERIMENT 1

## EXPERIMENT OBJECTIVE

To implement a Fully Connected Neural Network (FCNN) for classifying handwritten digits from the MNIST Dataset using NumPy.

## DATA PREPROCESSING

### Loading the MNIST Dataset

- The dataset is loaded from binary files containing images and labels.
- The images are 28x28 grayscale images, reshaped into a (784,) vector.
- The labels are converted into one-hot encoded vectors.

### Data Augmentation

- **Random Rotation:** Images are rotated within a range of  $-15^{\circ}$  to  $15^{\circ}$  with a 50% probability.
- **Horizontal Flip:** Images have a 50% chance of being flipped horizontally.

### Splitting the Dataset

- The dataset is divided into training, validation, and test sets.
- The training set is further split into 80% training and 20% validation.

## NEURAL NETWORK IMPLEMENTATION

### Architecture

- **Input Layer:** 784 neurons (28x28 pixels flattened)
- **Hidden Layer 1:** 256 neurons, ReLU activation
- **Hidden Layer 2:** 128 neurons, ReLU activation
- **Output Layer:** 10 neurons (digits 0-9), softmax activation

### Weight Initialization

- Weights are initialized using He (Kaiming) initialization.
- Biases are initialized to zeros.

### Activation Functions

- **ReLU (Rectified Linear Unit):** Used in hidden layers.
- **Softmax:** Applied to the output layer for probability distribution.

## Regularization

- **Dropout:** Randomly drops activations during training to prevent overfitting.
- **Gradient Clipping:** Limits gradient values to avoid exploding gradients.

## TRAINING CONFIGURATION

### Training the Model

- **Loss Function:** Cross-entropy loss is used.
- **Optimizer:** The model updates weights using backpropagation and gradient descent.
- **Learning Rate:** 0.2 (with decay over time)
- **Epochs:** Trained for 2500 epochs.
- **Batch Processing:** Mini-batch gradient descent is implemented.
- **Best Model Selection:** Saves weights of the best-performing model (lowest validation loss).

### Model Checkpointing

- The best model weights (based on validation loss) are saved periodically to `bestWeights.npy`.

## TRAINING AND VALIDATION RESULTS

### Key Performance Metrics from Training Output

| Epoch | Training Loss | Validation Loss | Accuracy (%) |
|-------|---------------|-----------------|--------------|
| 0     | 1.9218        | 1.9253          | 30.28%       |
| 8     | 1.5442        | 1.5684          | 52.47%       |
| 31    | 1.1557        | 1.1522          | 66.05%       |
| 122   | 0.6481        | 0.6511          | 81.34%       |
| 249   | 0.4502        | 0.4500          | 87.50%       |
| 604   | 0.2744        | 0.2625          | 93.67%       |
| 1017  | 0.1331        | 0.1327          | 96.69%       |
| 1506  | 0.0542        | 0.0508          | 98.67%       |
| 2293  | 0.0135        | 0.0132          | 99.57%       |
| 2368  | 0.0086        | 0.0081          | 99.69%       |

## **Evaluation Results**

- After training, the best model weights are loaded and tested on unseen test data.
- **Final Test Accuracy:** ~95.79%
- **Final Test Loss:** ~0.302

## **MODEL SAVING AND LOADING**

- **Saving Weights:** The best model weights (lowest validation loss) are saved to disk.
- **Loading Weights:** Enables reloading the best weights for inference or further training.

## **RESULTS AND CONCLUSIONS**

- The model achieves high accuracy using a simple fully connected architecture.
- Data augmentation and regularization significantly improve generalization.
- The saved best weights allow for consistent reproducibility of results.