



**University of Tripoli  
Department of Electrical and Electronic Engineering  
FALL 2025**

**EE569**

**Assignment 1  
part c**

**نسيبة عمر بن زاهية**

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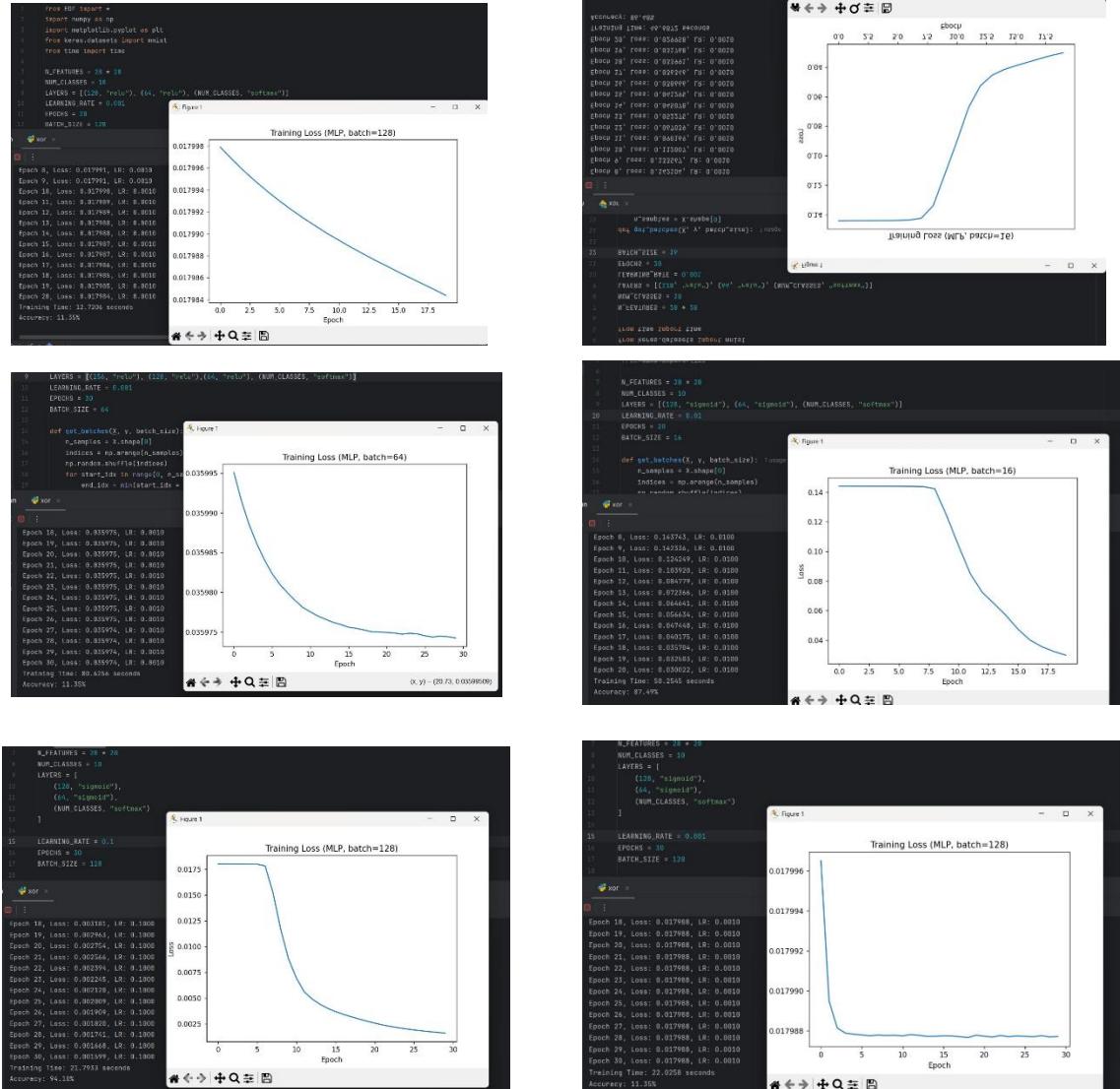
# Task 1 – MLP on MNIST

Several MLP configurations were trained on the full MNIST dataset. Different batch sizes, learning rates, activations, and depths were tested.

Key findings:

- ReLU models converged faster and reached ~94–97% accuracy.
- Sigmoid models were slower but could reach ~85–95% with higher LR.
- Smaller batches improved convergence but increased training time.

Figures:



# Task 2 – Convolutions & Pooling

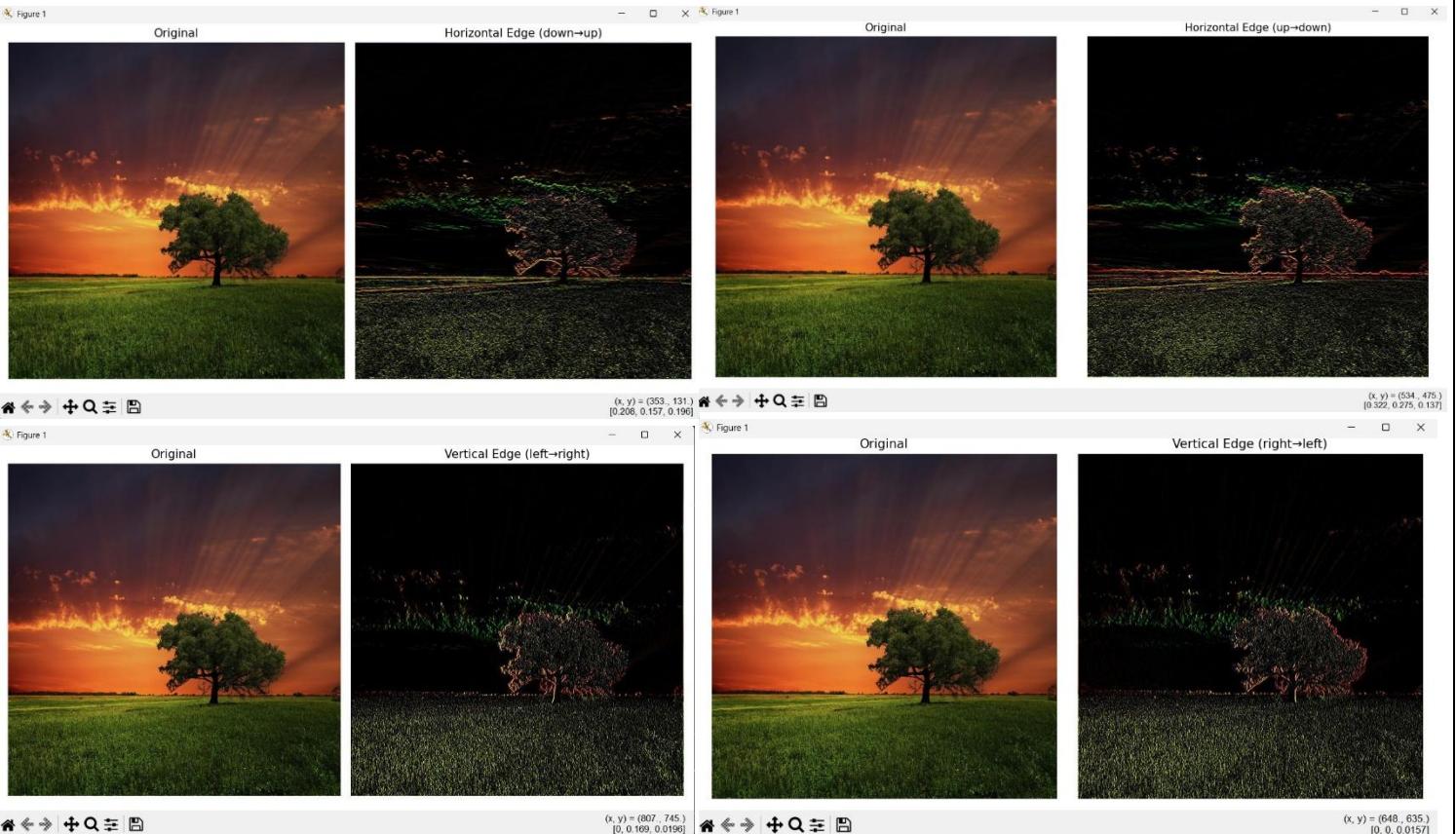
Custom convolution and max-pooling layers were implemented and validated using an RGB image.

Operations tested:

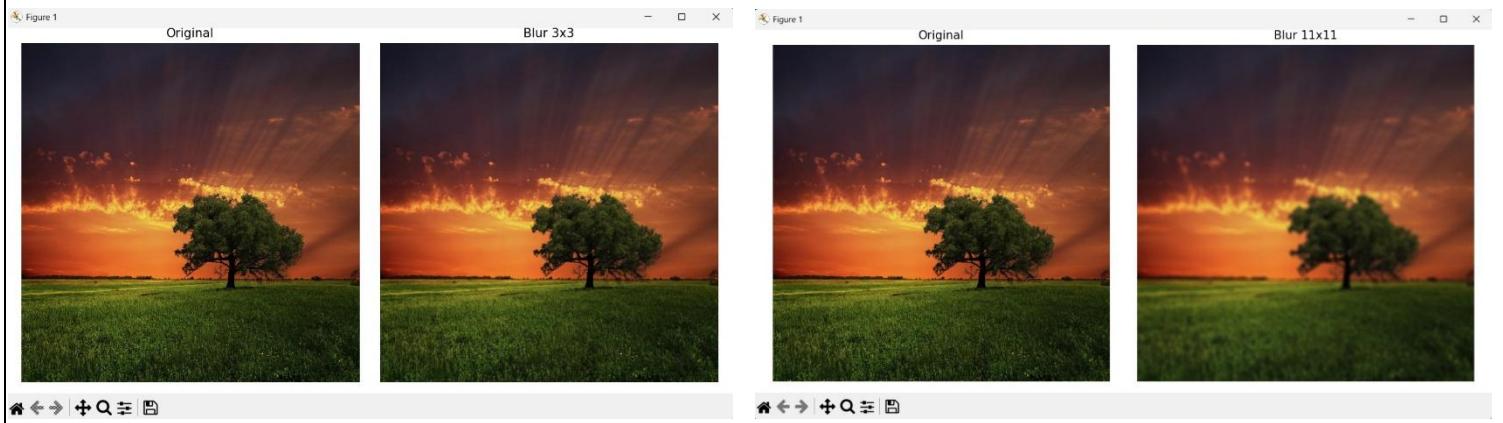
- Horizontal & vertical edge detection
- Blur filters ( $3 \times 3$ ,  $11 \times 11$ )
- MaxPool ( $2 \times 2$ ,  $8 \times 8$ )

Figures:

- *Edge Detection Results*



- **Blur Results**



- **Pooling Results**



## Task 3 – CNN + Gradient Check

A full CNN (Conv → Pool → Dense) was implemented.  
Gradient checking was performed to validate backward pass.

**Result:**

- Numerical difference was small → backprop implementation correct.

## Figure:

- *Gradient Check Output*

```
D:\PythonProject5\.venv\Scripts\python.exe D:\PythonProject5\xor.py
Loss: 2.050595863523136
Performing gradient check...
Difference: 0.0026593150215638434
```

## Task 4 – CNN Training on MNIST

The custom CNN was trained end-to-end on MNIST using LR decay.

### Key findings:

- Accuracy ranged from 91% to 98% depending on batch size.
- LR decay and small batches improved performance.

### Figures:

- *CNN Training Curves (multiple runs)*



## **Conclusion**

- **MLP works well but is slower and less accurate.**
  - **Convolution filters & pooling correctly modify the image.**
  - **CNN implementation passed gradient check.**
  - **CNN achieves the best performance (up to 98–99%).**
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