

**UCL  
CEGE0004  
GROUP CHAOS  
PRESENTATION  
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# 25 years on: Is LeNet-5 still relevant?

The assignment paper says to “Start with a title that captures the essence of your project” - this is only a suggestion!

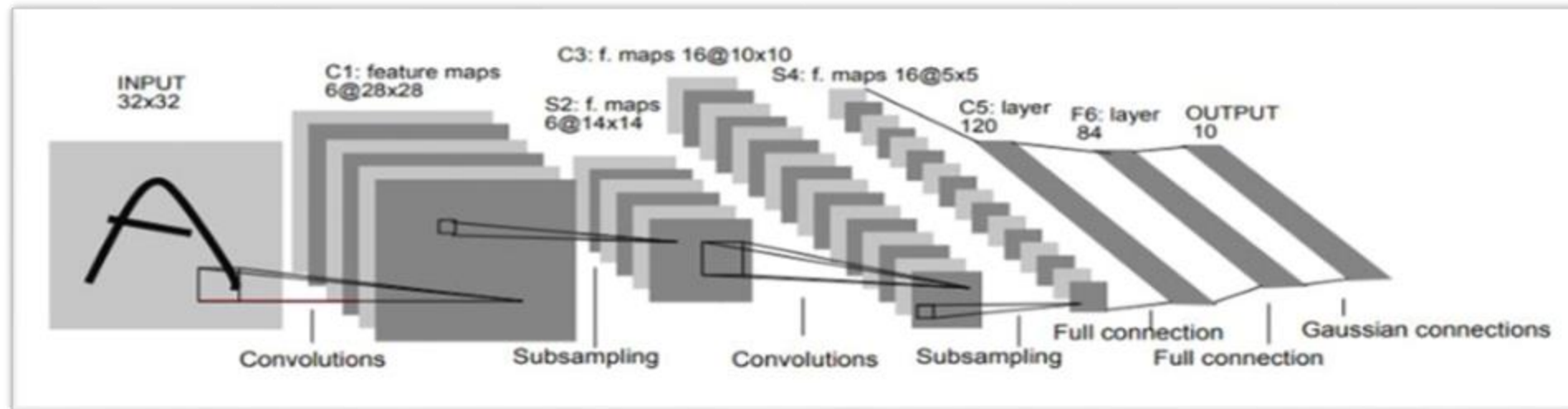
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# Background

- Connectionist revival after the second "AI Winter "
- Automatic ML > Heuristics-based algorithms with hardwired logics
- A good balance between performance and computational efficiency
- Foundational to the modern AI boom



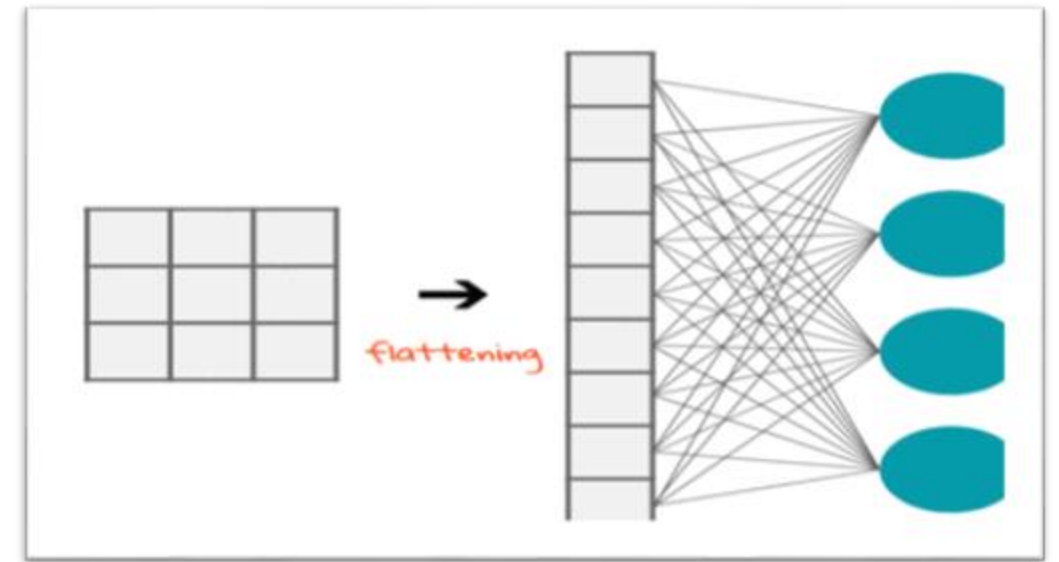
Yann LeCun, author of the paper and the father of modern AI



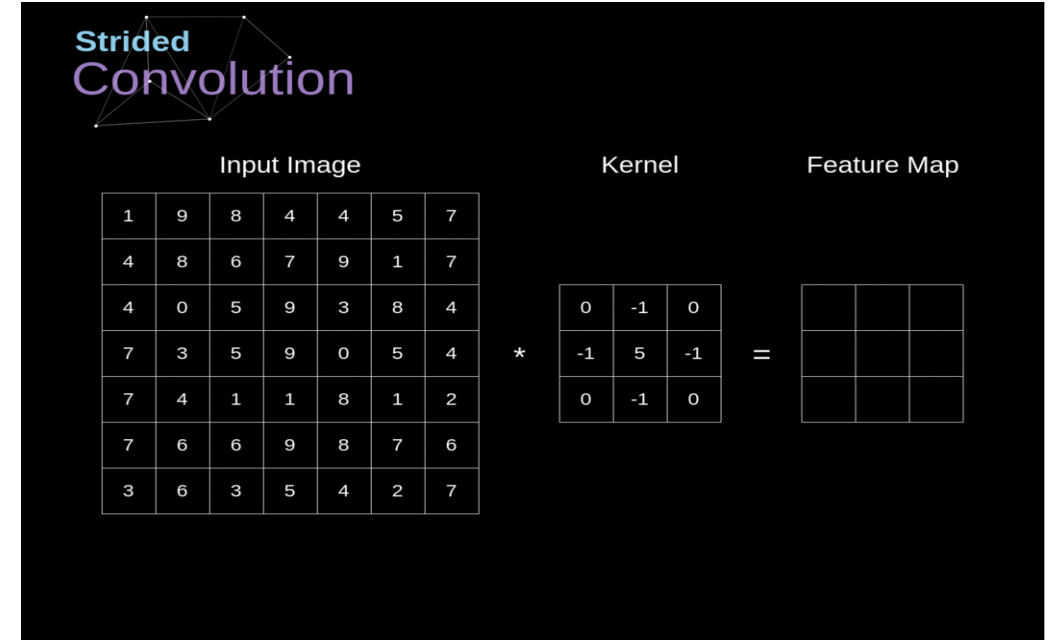
LeNet-5 model architecture

# Theory

- Weight sharing means more efficient than fully connected NNs.
- Takes the context and correlations inside an image itself into consideration. Inherently 2D.
- More tolerant to variabilities in the data than fully connected NNs.



2-layer FC network, 3x3 input (Up) One convolution layer (bottom))



# Objectives

- Reproduce the results from Yann LeCun's paper "Gradient-Based Learning Applied to Document Recognition"
- Apply the model to two additional datasets to examine the performance of the model in both datasets
- Doing hyperparameter tuning to enhance the performance of the model

# Dataset

## MNIST Database

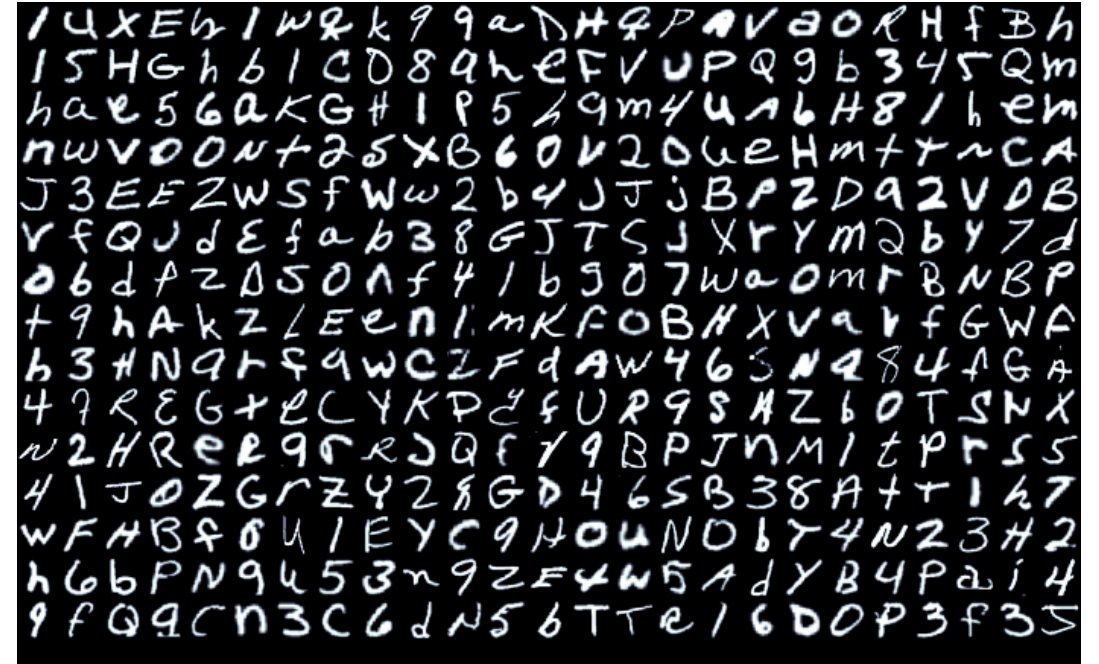
- A collection of handwritten digits from 0 to 9
- Contains 60,000 training images and 10,000 test images of handwritten digits
- Image format: 28x28 pixels
- Serves as a benchmark dataset for evaluating the performance of various machine learning algorithms, particularly for image classification tasks



Sample images from MNIST dataset

# EMNIST Database

- An extension of the MNIST dataset that includes handwritten characters from both digits (0-9) and uppercase and lowercase letters (A-Z, a-z)
- Contains approximately 2,255,710 characters in total, with 6 different categories of variant
- Image format: 28x28 pixels
- Increases the diversity of data for testing versatility of the algorithm



Sample images from Extended MNIST dataset

# FMNIST Database

- a dataset containing grayscale images of various clothing items, such as T-shirts, trousers, dresses, and shoes.
- consists of 60,000 training images and 10,000 test images
- Image format: 28x28 pixels
- One of a contemporary challenging dataset in modern days

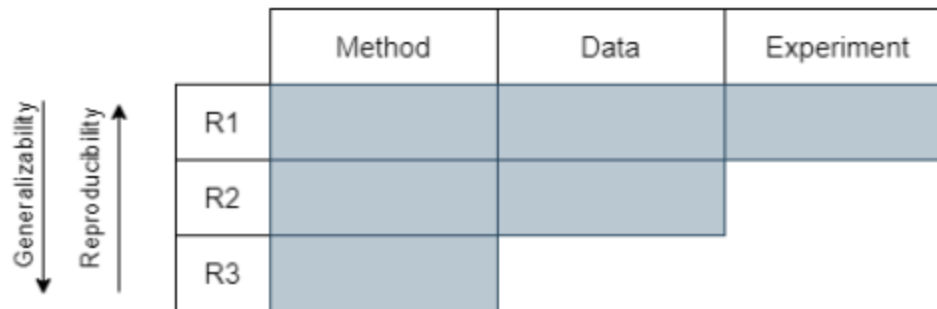


Sample images from Fashion MNIST dataset



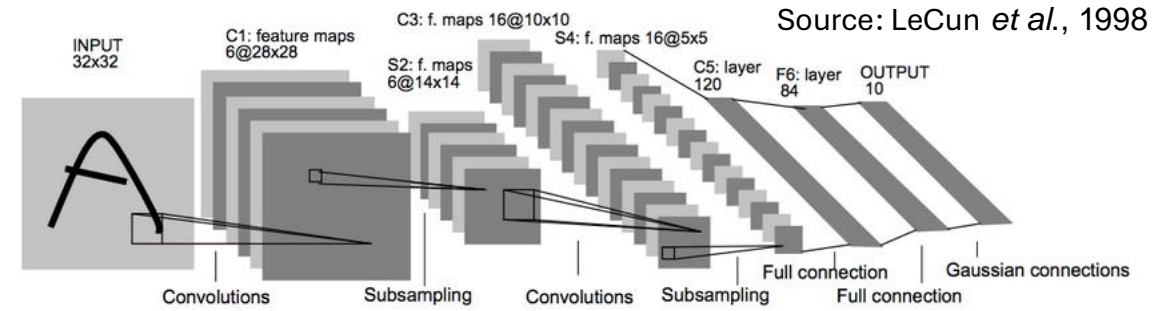
# Reproducibility

- Paper reproduced at 'R2' Level
- Aim to reproduce the results using the same data
  - Many hyperparameters listed in original paper
- R1 method not possible as exact implementation details not available
  - i.e., software versions, code



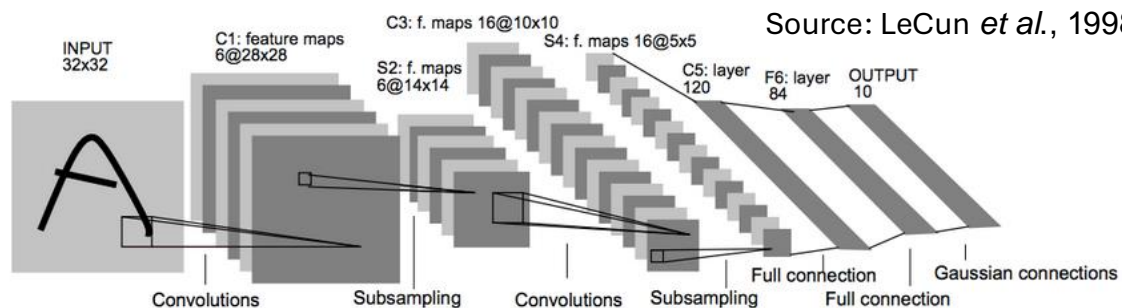
Source: Semmelrock *et al.*, 2023

# Methodology - steps



- Original dataset still available
  - Separate files for train/test split
- Detailed structure of LeNet-5 described in original paper
  - Includes number and types of layers, input image recognition and hyperparameters
- Keras chosen as replication tool
  - Allows developers to build (and fine-tune) all LeNet-5 layers using simple built-in functions

# Algorithm implementation



LeNet-5 Architecture (from paper [1])	Functionality Implemented/Parameters
20 training set iterations	Keras set to run for 20 epochs
<b>Convolution layer 1 (of 3) – C1</b> <ul style="list-style-type: none"> <li>6 feature maps (28x28 in size)</li> <li>5x5 kernel</li> </ul>	Keras Conv2D Layer <ul style="list-style-type: none"> <li>Filters=6</li> <li>Kernal size=5x5</li> </ul>
<b>Subsampling Layer 1 (of 2) – S2</b> <ul style="list-style-type: none"> <li>2x2 kernel</li> <li>Non overlapping</li> </ul>	Keras AveragePooling2D Layer <ul style="list-style-type: none"> <li>pool_size=(2, 2)</li> <li>strides=(2, 2)</li> </ul>
<b>Convolution layer 2 (of 3) – C3</b> <ul style="list-style-type: none"> <li>16 feature maps (28x28 in size)</li> <li>5x5 kernel</li> </ul>	Keras Conv2D Layer <ul style="list-style-type: none"> <li>Filters=16</li> <li>Kernal size=5x5</li> </ul>
<b>Subsampling Layer 2 (of 2) – S4</b> <ul style="list-style-type: none"> <li>6 feature maps (5x5 in size)</li> <li>2x2 kernel</li> </ul>	Keras AveragePooling2D Layer <ul style="list-style-type: none"> <li>pool_size=(2, 2)</li> <li>strides=(2, 2)</li> </ul>
<b>Convolution layer 3 (of 3) – C5</b> <ul style="list-style-type: none"> <li>120 feature maps (1x1 in size)</li> </ul>	Keras Dense Layer <ul style="list-style-type: none"> <li>units=120</li> </ul>
<b>Fully-Connected Layer – F6</b> <ul style="list-style-type: none"> <li>84 units</li> </ul>	Keras Dense Layer <ul style="list-style-type: none"> <li>units=84</li> </ul>
<b>Output Layer – OUTPUT</b> <ul style="list-style-type: none"> <li>10</li> </ul>	Keras Dense Layer <ul style="list-style-type: none"> <li>units=10</li> </ul>
<b>Layers C1 -&gt; F6</b> <ul style="list-style-type: none"> <li>Sigmoid squashing function (hyperbolic tangent)</li> </ul>	<pre>def custom_activation(x):     return (K.tanh(2/3 * x) * 1.7159)</pre>
<b>Learning rate scheduler</b> Global learning rate was scheduled as: <ul style="list-style-type: none"> <li>0.0005 for the first two passes</li> <li>0.0002 for the next three</li> <li>0.0001 for the next three</li> <li>0.00005 for the next 4</li> <li>0.00001 thereafter.</li> </ul> (20 training epochs in total)	<pre>def lr_schedule(epoch, lr):     if epoch &lt; 2:         return 0.0005     elif epoch &lt; 5:         return 0.0002     elif epoch &lt; 8:         return 0.0001     elif epoch &lt; 12:         return 0.00005     else:         return 0.00001</pre>

# Methodology - challenges

- Original implementation code not available
  - Need to create own as close to original as possible
- Original hardware not available (Single 200MHz processor!)
- Input image size for LeNet-5 is 32x32
  - MNIST image size 28x28. Padding added so that the size matched

# Result on MNIST

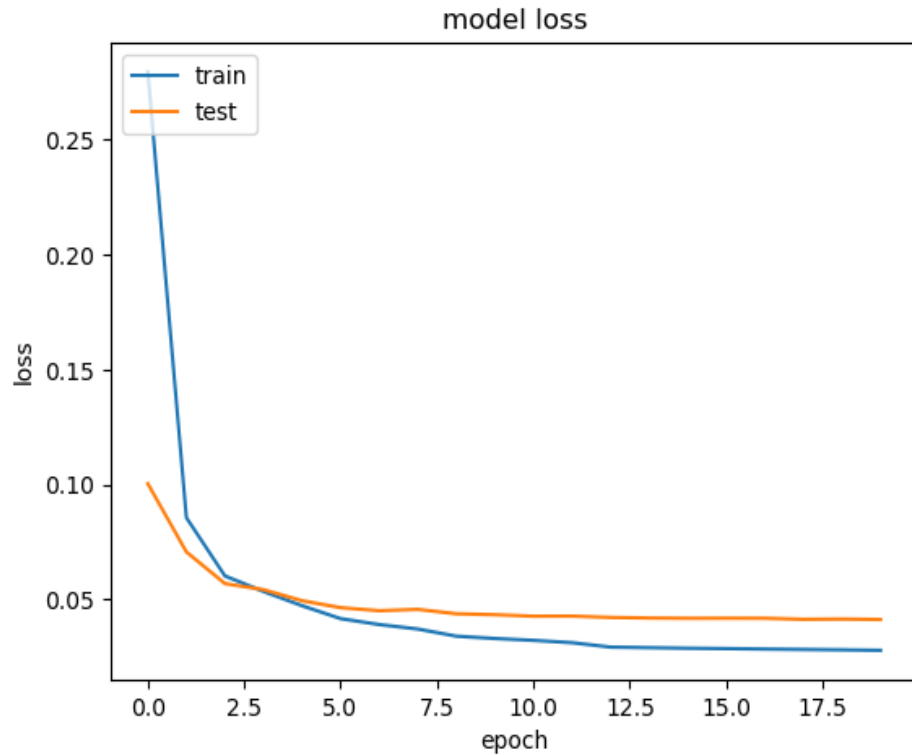


Figure.1. Training result on MNIST (20 epochs)

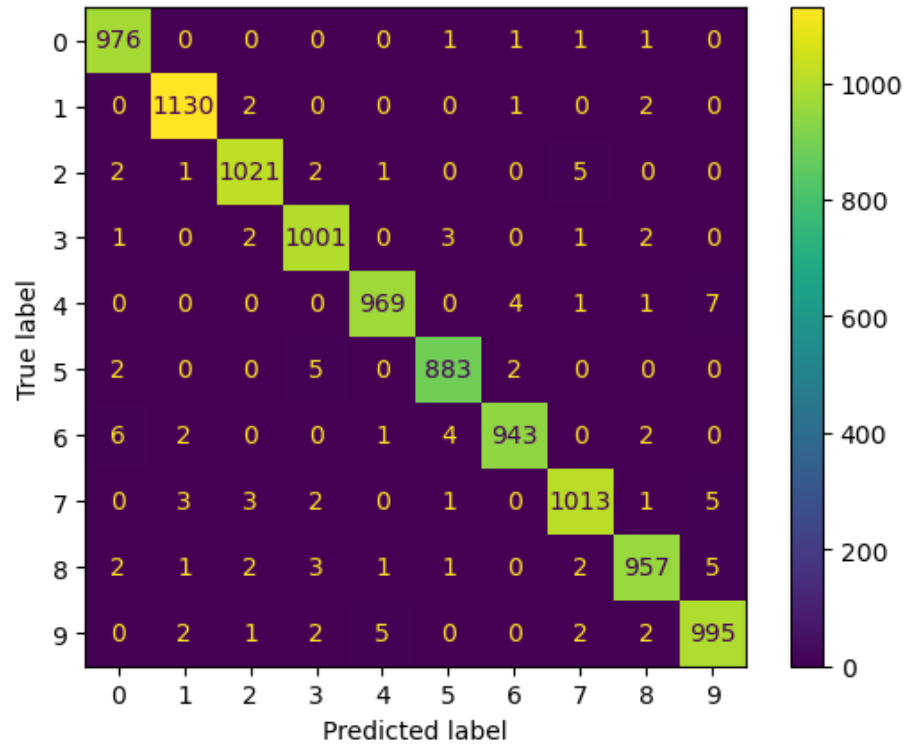


Figure.2. Confusion matrix on MNIST

Metrics	Value
Loss	0.0354
Accuracy	98.88%
Precision	98.88%
Recall	98.88%
F1	98.88%

# Compared with the original paper

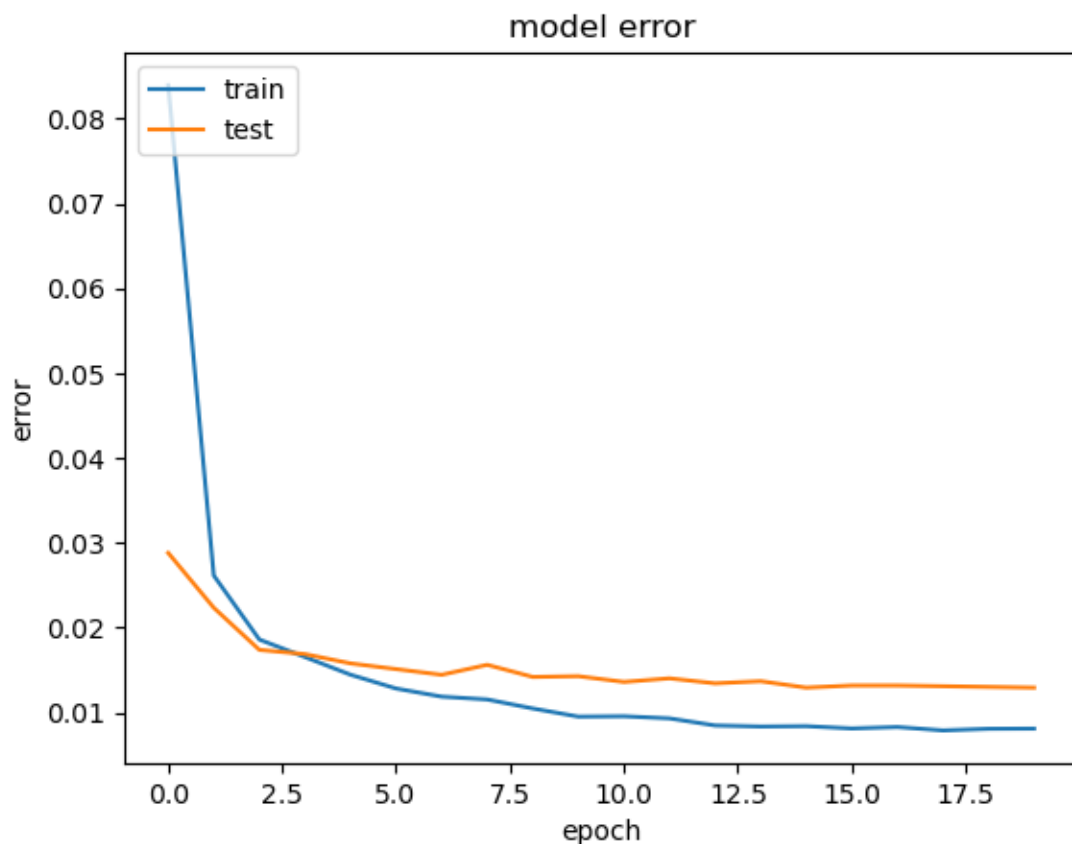


Figure.3. Training and test error from reproduced model

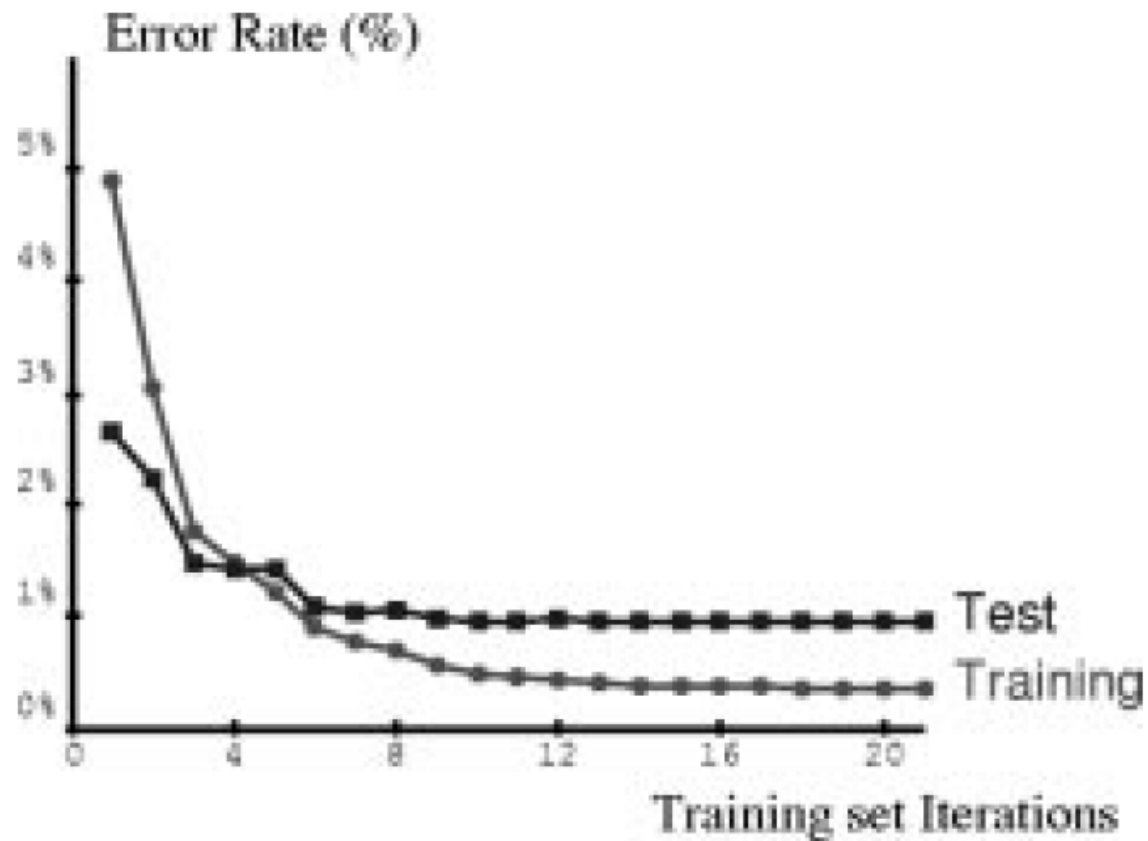


Figure.4. Training and test error from original paper

# Miss-classified examples

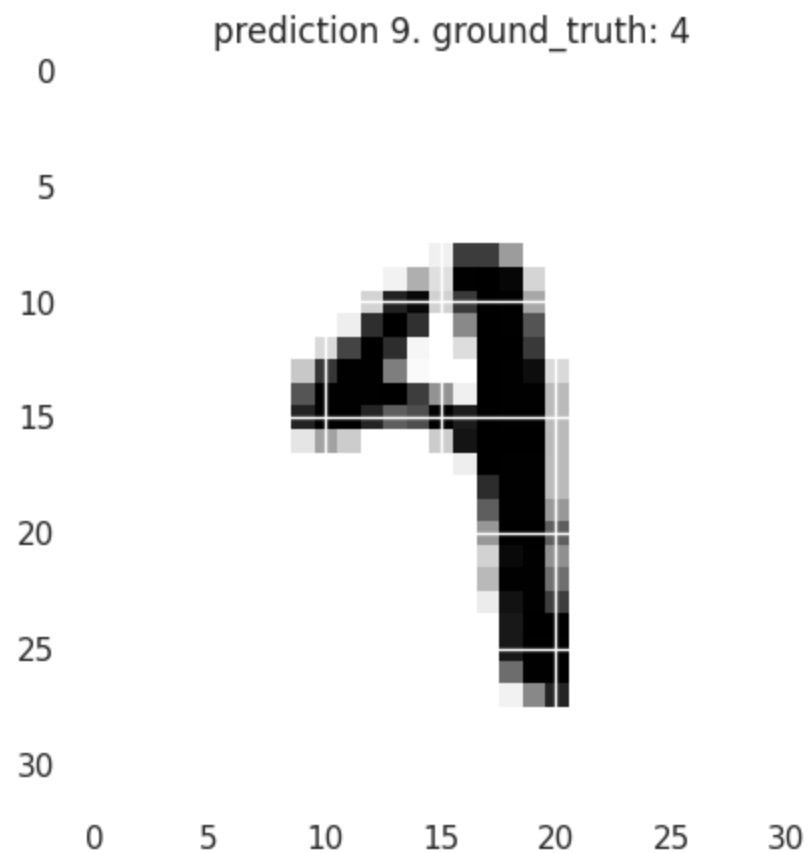


Figure.5. miss-classified example one

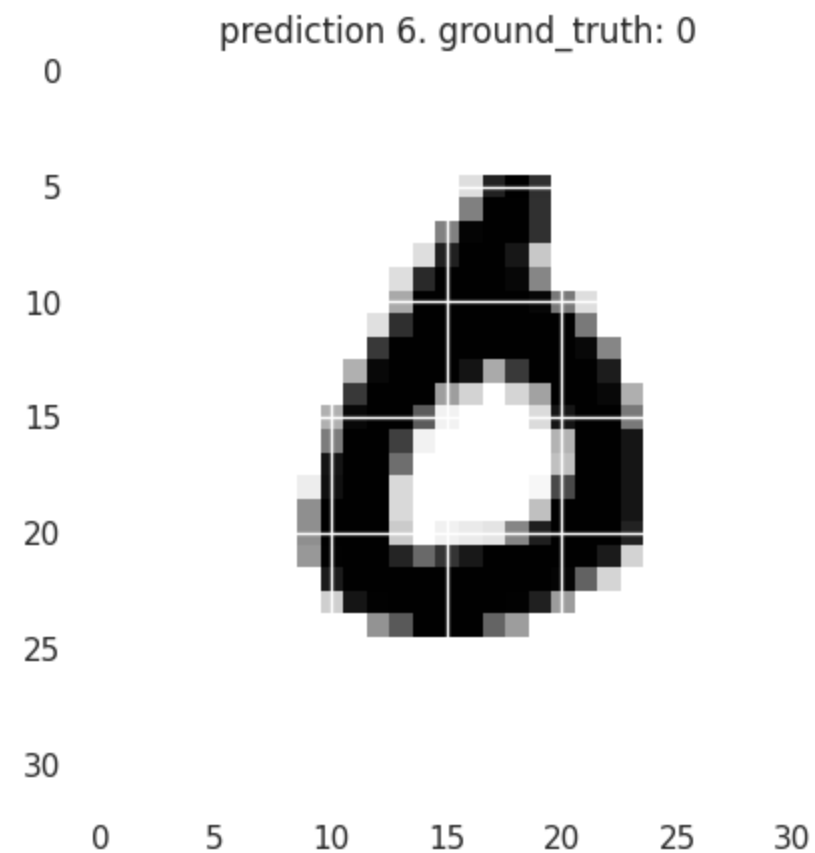


Figure.6. miss-classified example two

# Tuning Hyper-parameter

Figure. 7. MNIST model accuracy vs learning rate

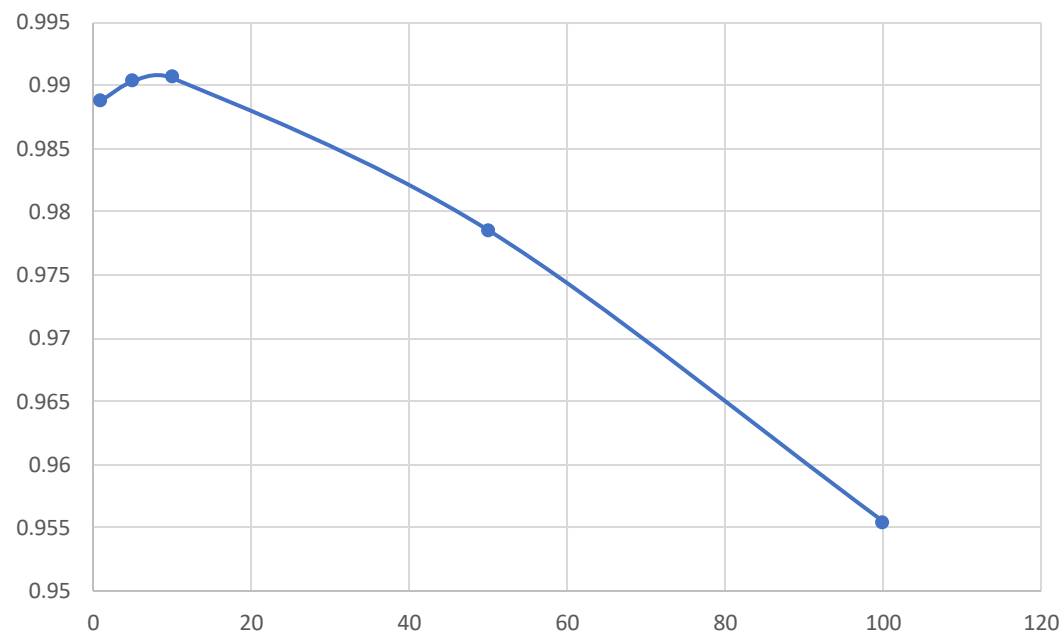
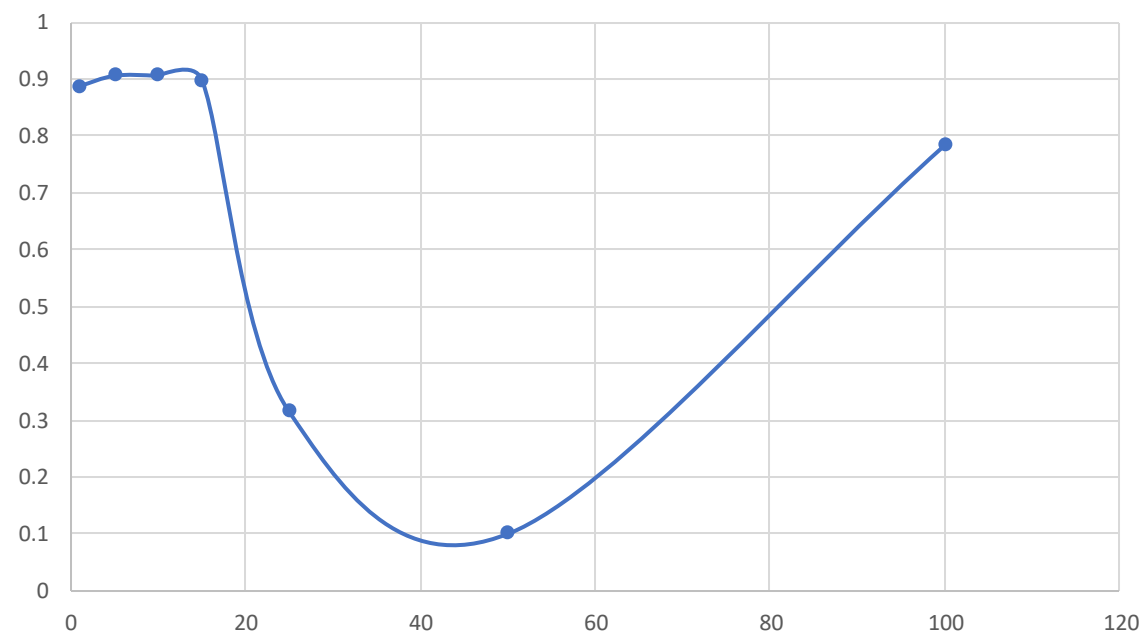


Figure. 8. FMNIST model accuracy vs learning rate





# Tuning Hyper-parameter

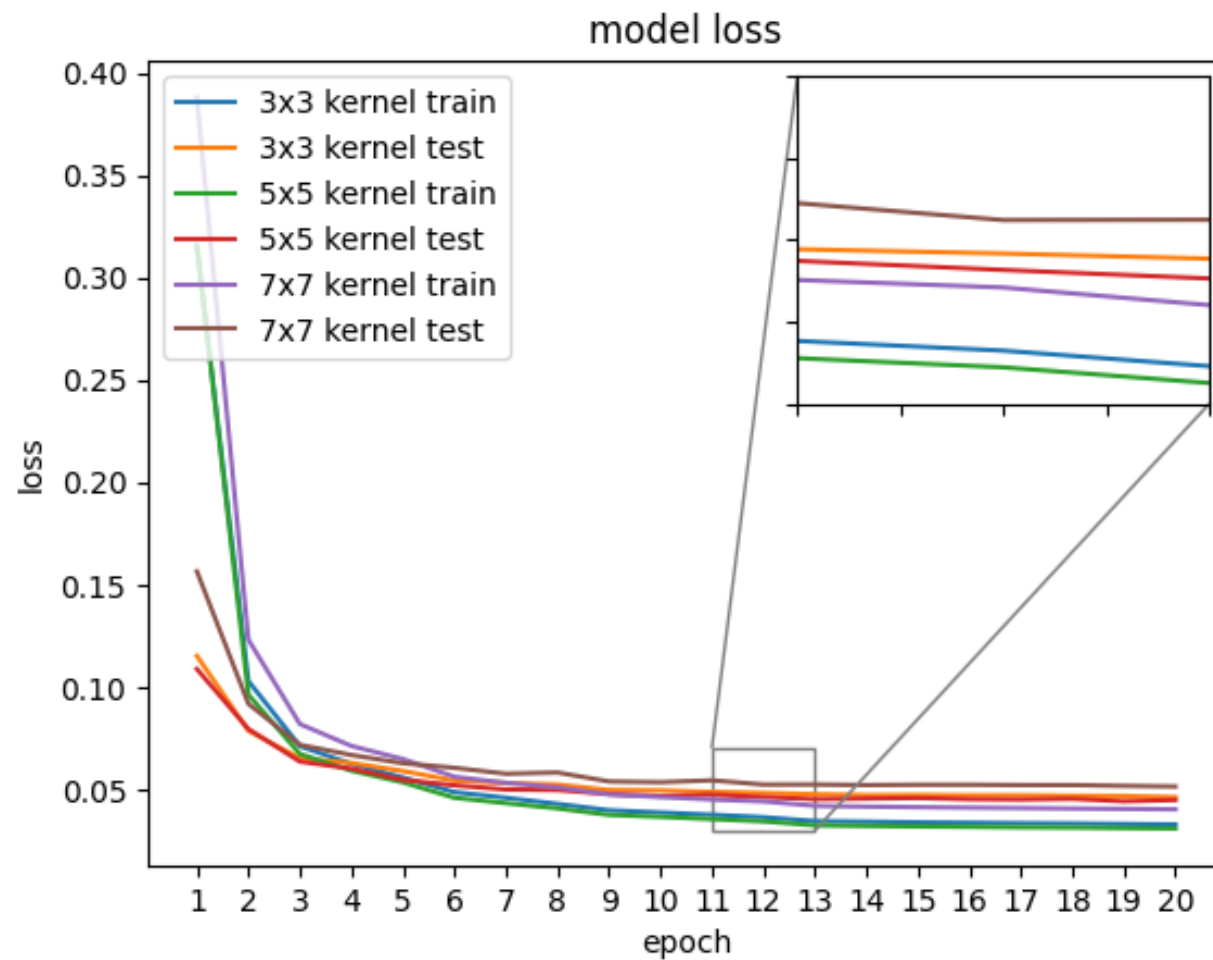


Figure.9. Model loss trained on MNIST with varying kernel sizes.

# Result on FMNIST

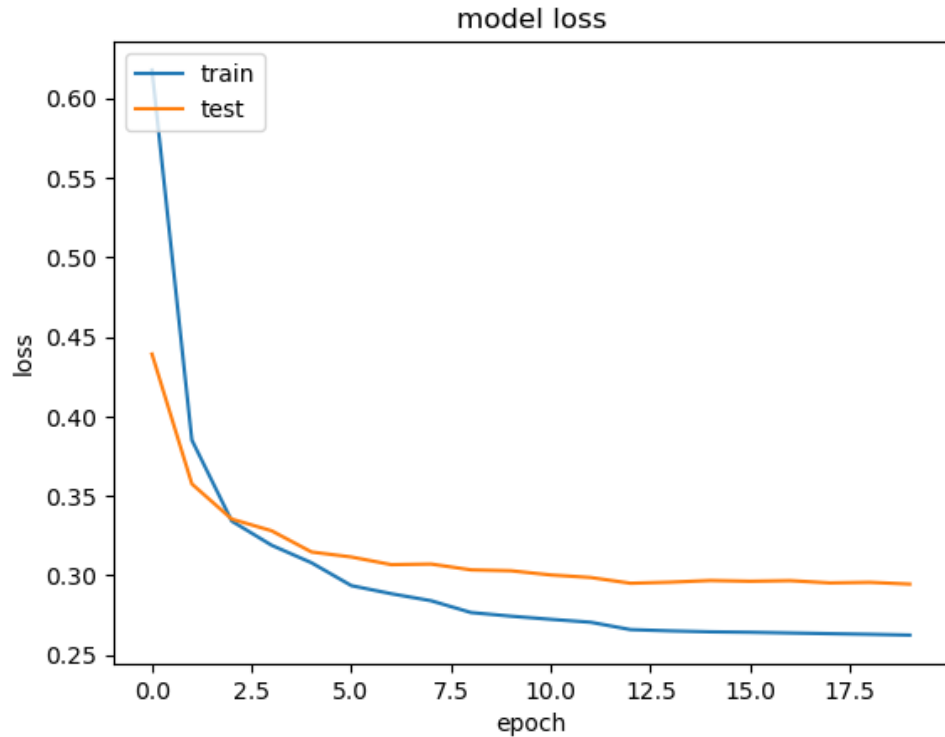


Figure.10. Training result on FMNIST (20 epochs)

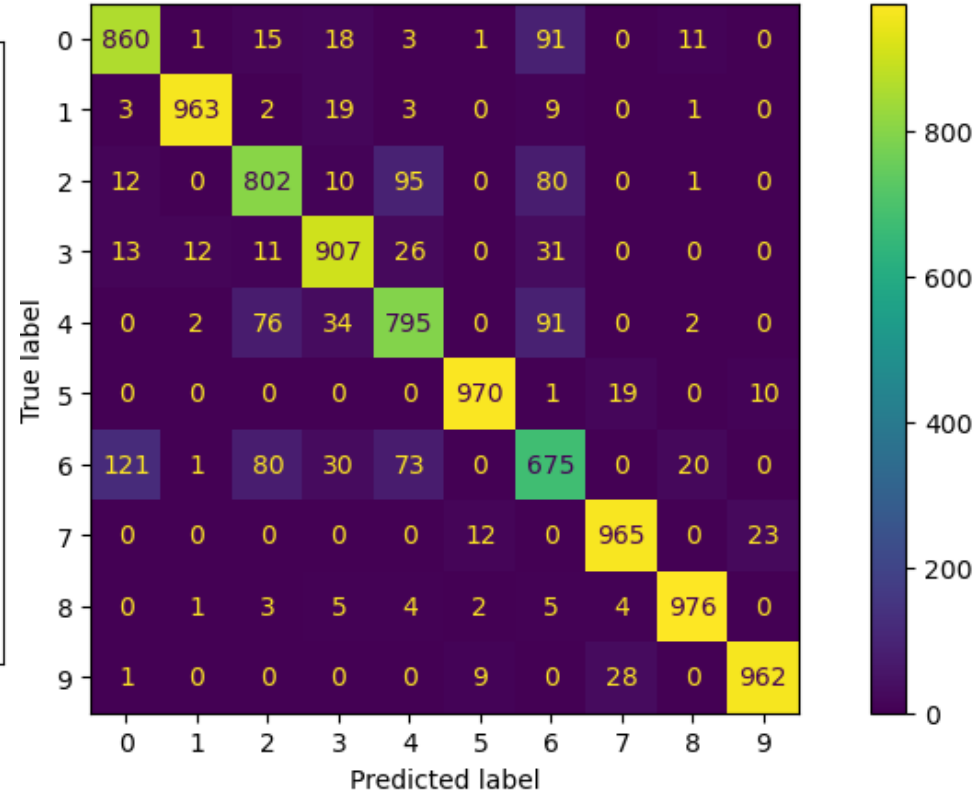


Figure.11. Confusion matrix on FMNIST

	Label		Label
0	T-shirt/top	5	Sandal
1	Trouser	6	Shirt
2	Pullover	7	Sneaker
3	Dress	8	Bag
4	Coat	9	Ankle boot

Metrics	Value
Loss	0.3093
Accuracy	88.75%
Precision	88.75%
Recall	88.75%
F1	88.75%

# Result on EMNIST

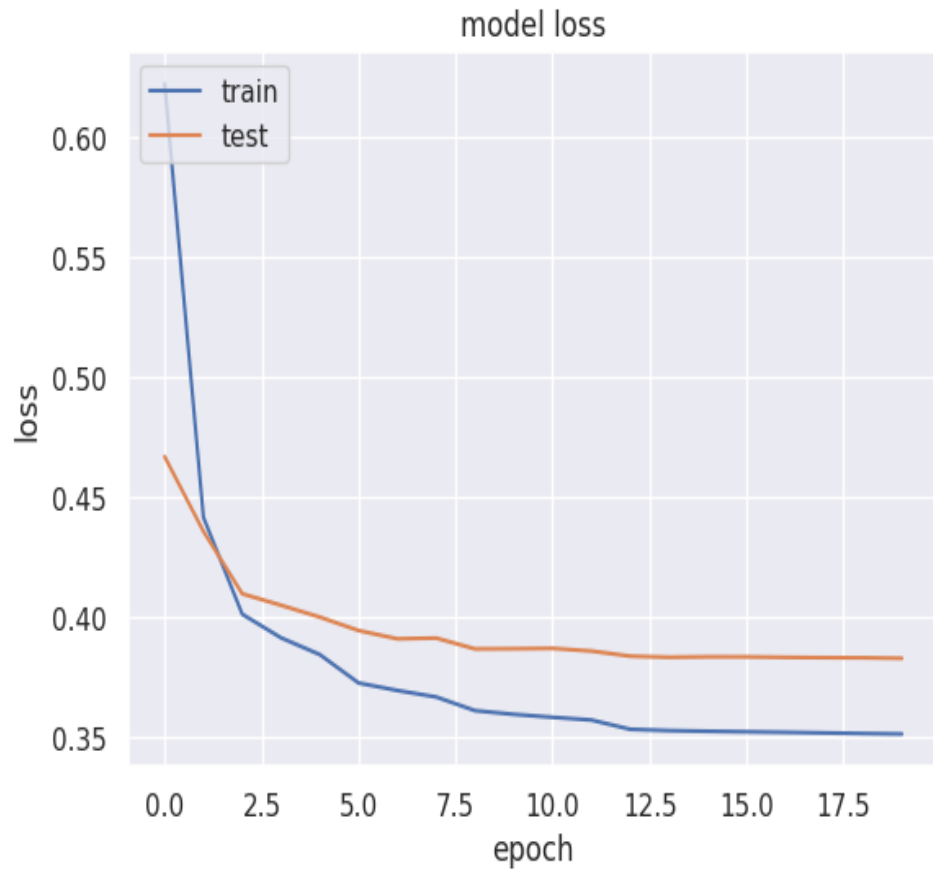


Figure.12. Training result on EMNIST (20 epochs)

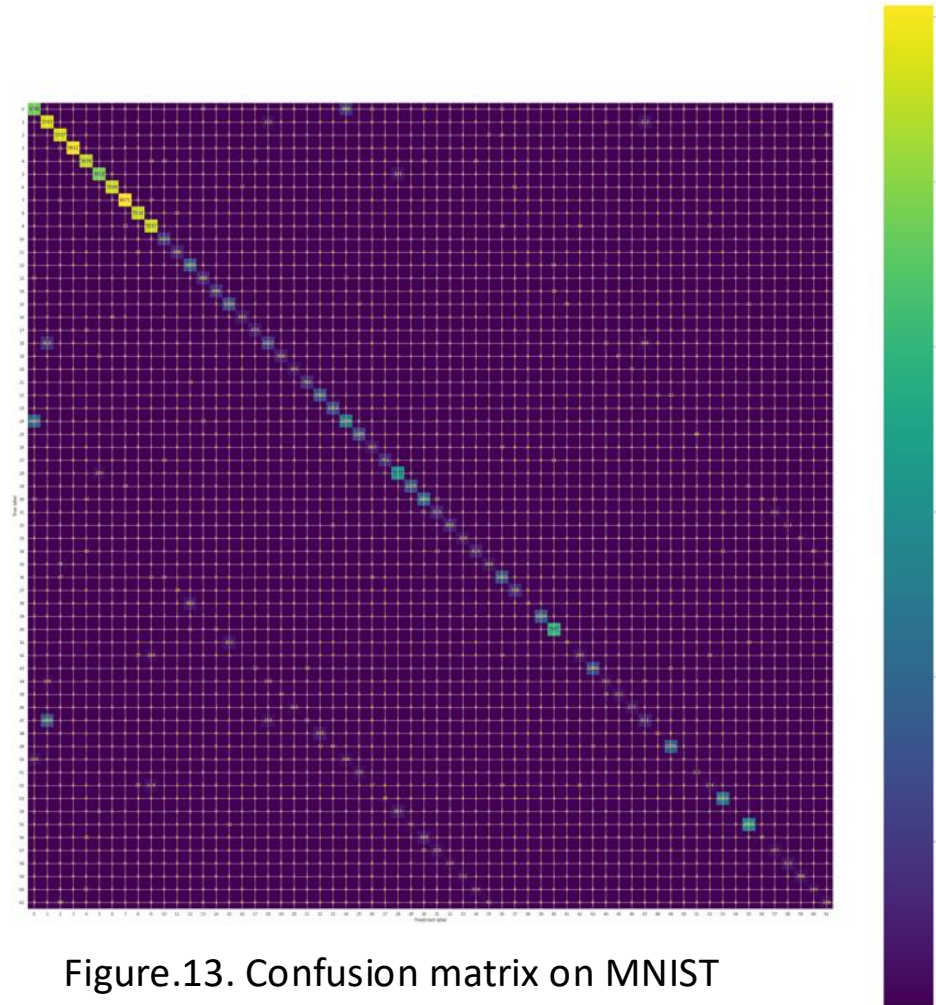


Figure.13. Confusion matrix on MNIST

Metrics	Value
Loss	0.3768
Accuracy	86.32%
Precision	86.32%
Recall	86.32%
F1	86.32%

# Limitations

- Some group members had access to GPUs while others did not. This could lead to inconsistent results.
- Hyperparameters were tuned independently due to limited time and resources.
- We do not have the original codes from 1998. The modern machine learning/ data science ecosystem did not exist back then.

- The paper is highly reproducible despite original codes missing.
- We reproduced nearly identical accuracy, error, speed of convergence as the original paper.
- The model performed less well on extra datasets due to increased complexities. (Mnist:98% ,Fmnist: 88%, Emnist: 86%)
- Increase learning rate by tenfold has a general positive impact on model performance, and 5x5 kernel size is optimal.
- If we had more time and computational resources, we would have benchmarked the performance of LeNet-5 against other models and increased the variabilities in hyper parameter tuning. And running everything with a GPU.

# References

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Hader. Gradient-Based Learning Applied to Document Recognition. 1998
- Harald Semmelrock, Simone Kopeinik, Dieter Theiler, Tony Ross-Hellauer, and Dominik Kowald. Reproducibility in machine learning-driven research. 2023.