

Image Classification from Coded Aperture

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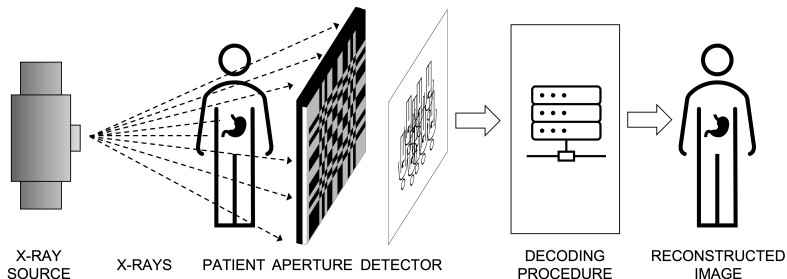
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In medical imaging, radiography typically uses apertures to modulate the radiation emitted by an x-ray source.

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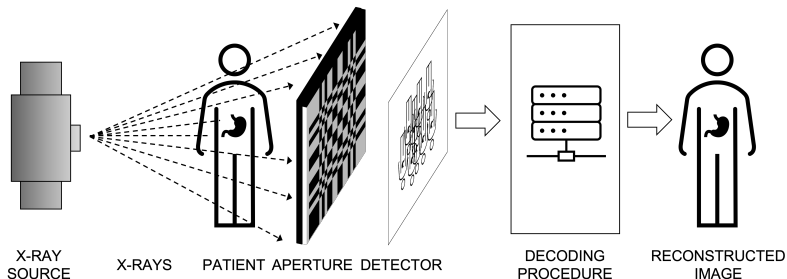
Problem: With more complicated apertures, a decoding procedure is necessary to reconstruct the image.



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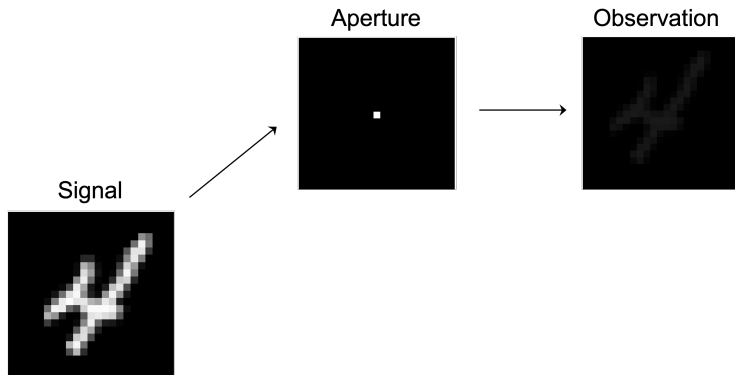
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Problem: With more complicated apertures, a decoding procedure is necessary to reconstruct the image.



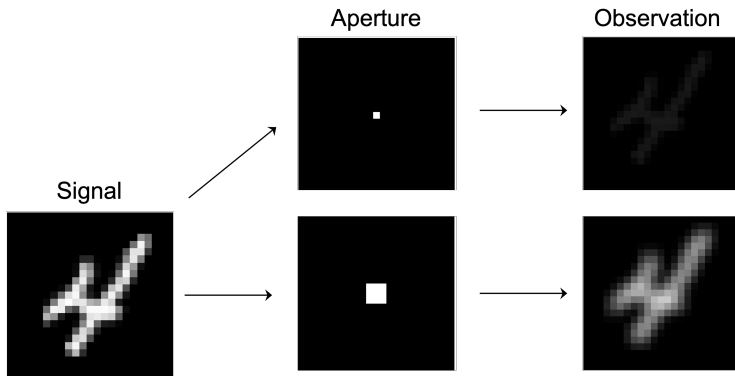
Goal: Classify images from coded observations without reconstructing the image.

Aperture Imaging



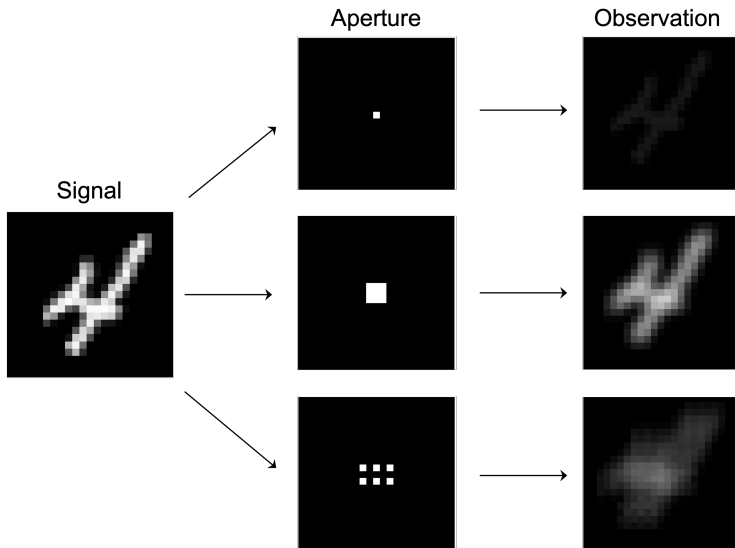
Small pinholes allow little light \implies **faint** observations

Aperture Imaging



Larger pinholes allow more light, but decrease resolution \Rightarrow **blurry** observations

Aperture Imaging



Multiple small pinholes \implies **overlapping** observations

Modified Uniformly Redundant Array (MURA)

A MURA pattern A consists of specified openings that has a corresponding decoding pattern G^1 .

¹Gottesman and Fenimore (1989)

Modified Uniformly Redundant Array (MURA)

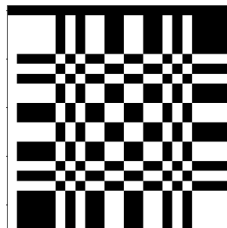
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Let p be a prime number and $A = \{A_{ij}\}_{i,j=0}^{p-1}$ be the binary aperture array. Set

$$A_{ij} = \begin{cases} 0 & \text{if } i = 0 \\ 1 & \text{if } j = 0, i \neq 0 \\ 1 & \text{if } C_i C_j = +1 \\ 0 & \text{otherwise} \end{cases}$$

where

$$C_i = \begin{cases} +1 & \text{if } i \text{ is a quadratic residue modulo } p \\ -1 & \text{otherwise} \end{cases}$$



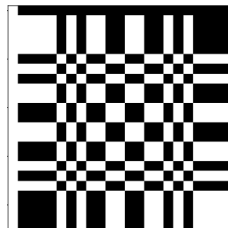
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The decoding function G is constructed as follows:

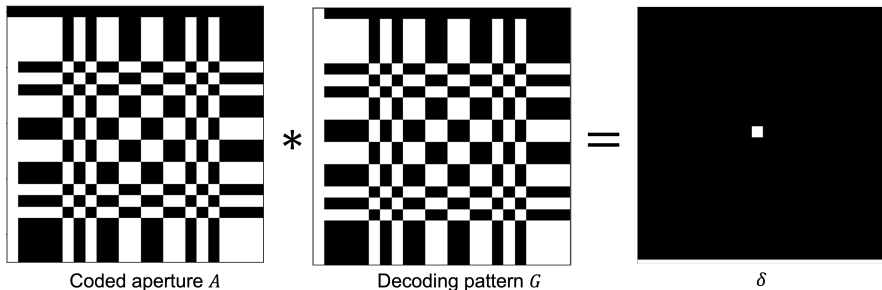
$$G_{ij} = \begin{cases} +1 & \text{if } i + j = 0 \\ +1 & \text{if } A_{ij} = 1, i + j \neq 0 \\ -1 & \text{if } A_{ij} = 1, i + j \neq 0 \end{cases}$$



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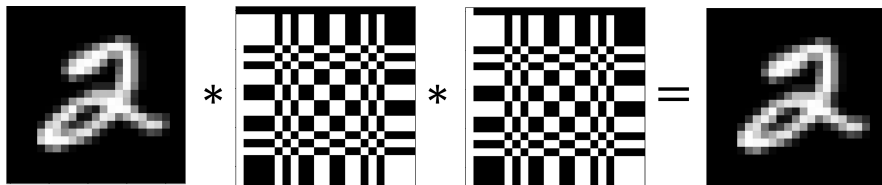
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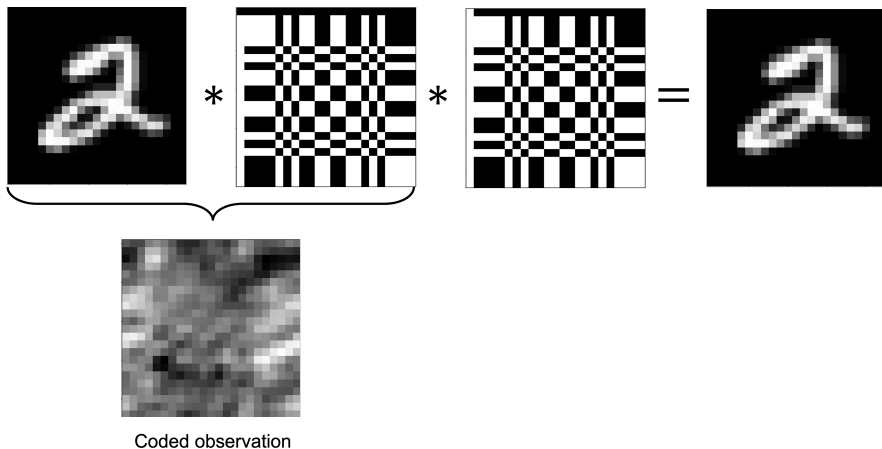


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Modified Uniformly Redundant Array (MURA)



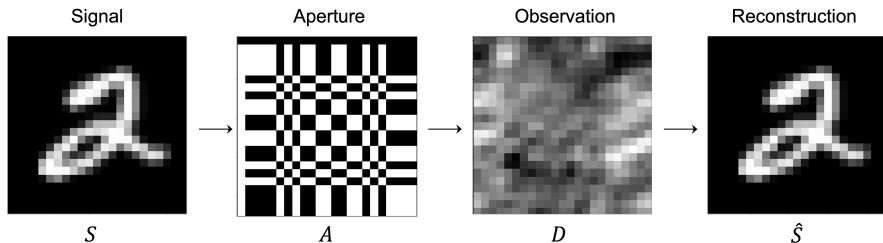
Modified Uniformly Redundant Array (MURA)



Coded observations appear unrecognizable, but MURAs are 50% open patterns¹
⇒ decoded observations are much brighter than those from small pinhole cameras.

¹Gottesman and Fenimore (1989)

MURA aperture imaging



The observation D is given by

$$D = S * A + B$$

where B is background noise. The MURA reconstruction is given by

$$\hat{S} = D * G$$

where G is the decoding pattern.

Training pipeline

Dataset: MNIST Handwritten Digits

- 28×28 pixels (grayscale)
- 60,000 training images
- 10,000 testing images

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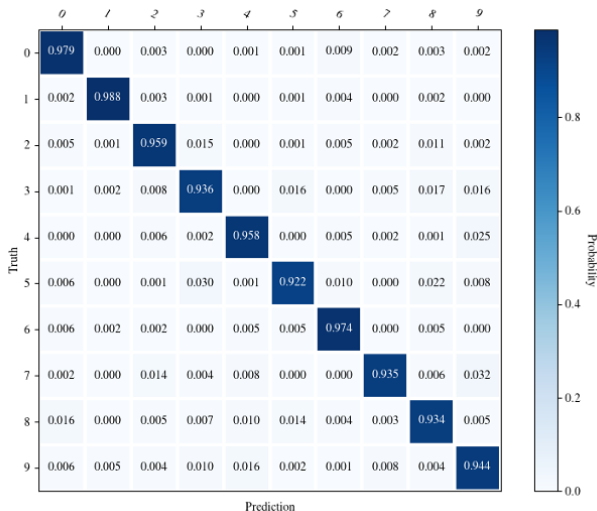
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- 4 Train a 2-layer CNN

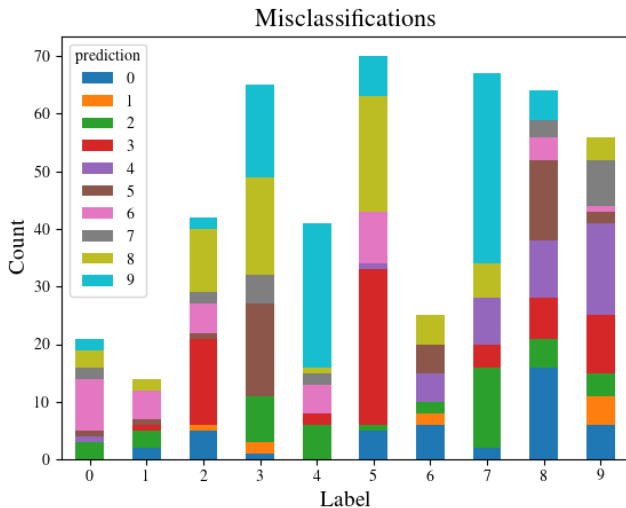
Results

CNN performance on coded observations test set.

Accuracy: **95.35%**



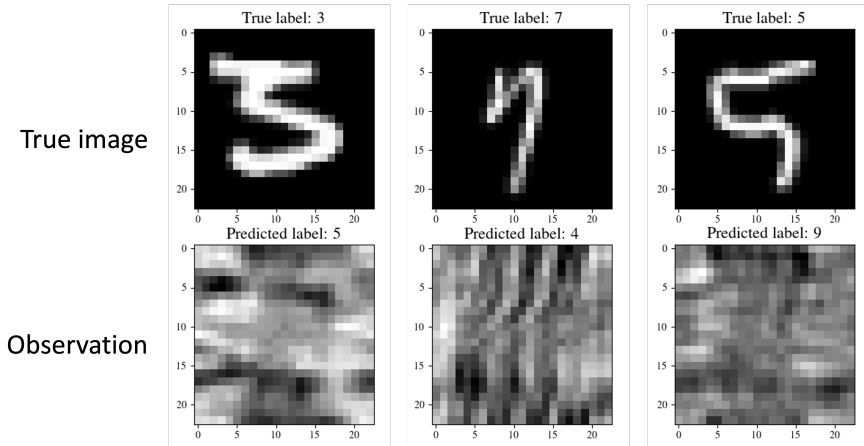
Results



Digits 3, 5 and 7 were the most common misclassifications.

Results

Most common misclassifications:



Gracias!