Convolutional Neural Networks for Phase Retrieval in Speckle-based Imaging

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Contents

Why do we need to use Deep Learning?

MIST [1,2]:

Needs priori information about the sample.

Originally written for monochromatic energy.

Needs at least two [1] or four [2] sample images to retrieve multimodal information.

UMPA [3]:

Iterative minimization of a cost function.

It requires several images (20) to retrieve signals with high quality and spatial resolution.

Why Deep Learning?

Limitations on traditional phase retrieval algorithms: Absorbed dose and priori information is needed.

A model could learn a function to retrieve speckle pattern displacements from one sample image only.

Deep Learning in a Nutshell

- Deep Learning is a subset of Machine Learning.
- Deep Neural Networks learn hierarchical representations of a dataset through multiple levels of abstraction [4].
- Mathematically: Optimization of $\Phi(x;\theta) \rightarrow y$. [5]
- Depending on data availability: Supervised or Unsupervised.

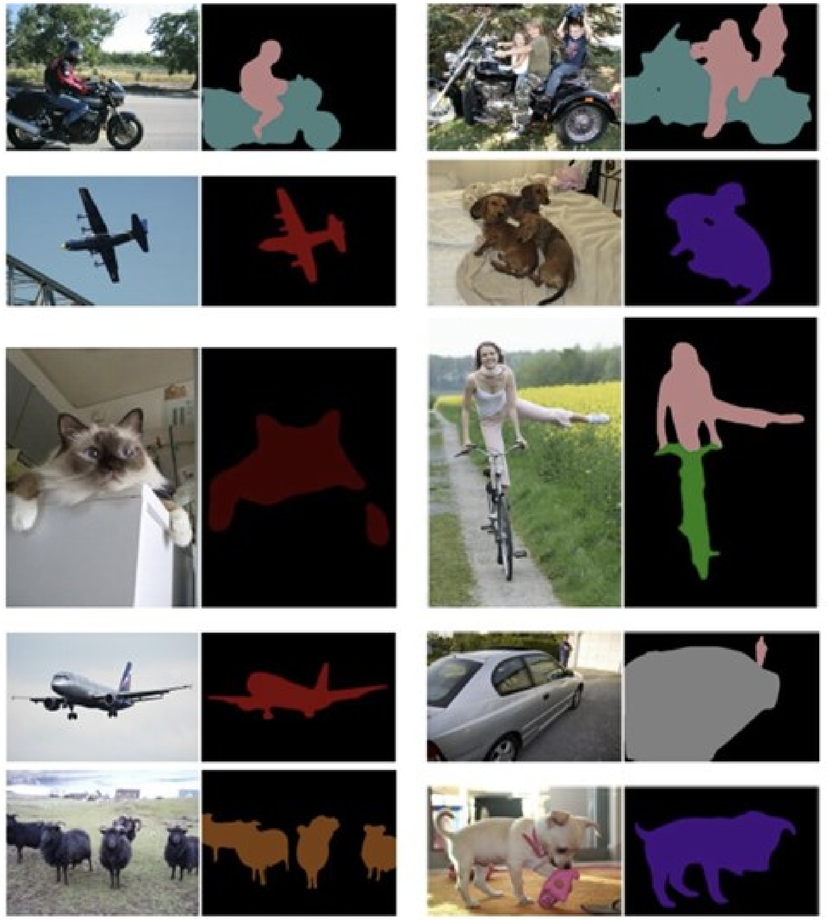
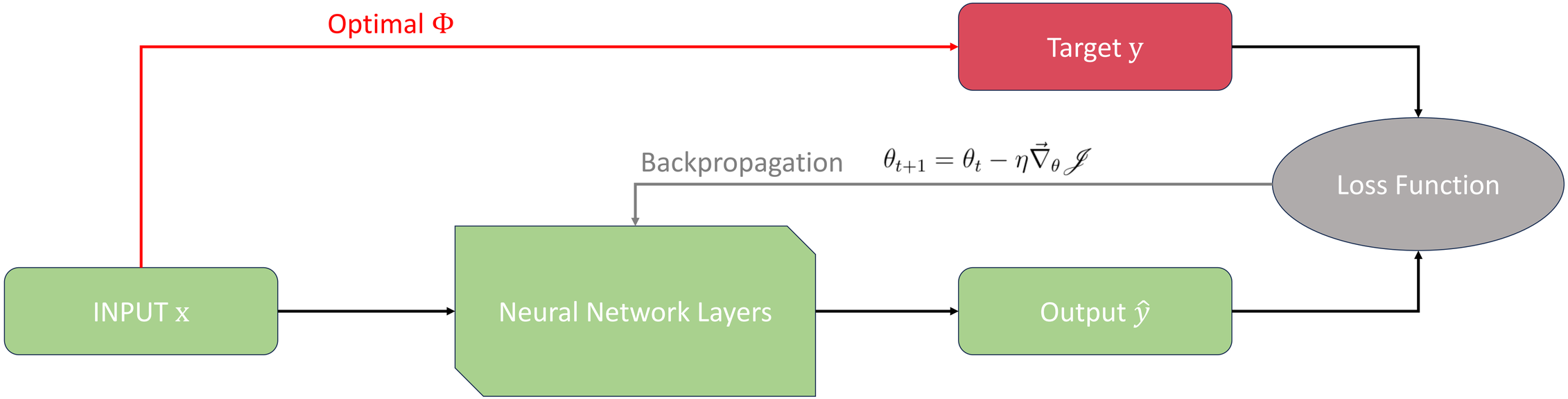
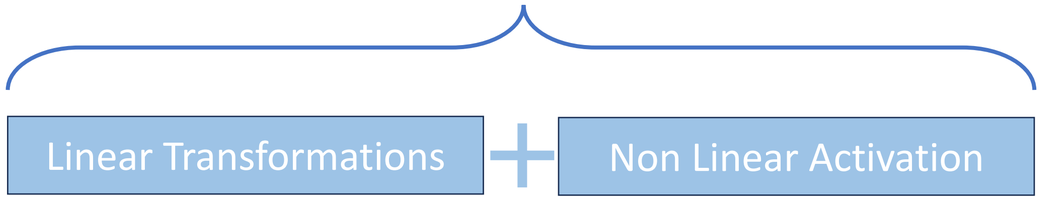


Fig1: Segmentation task performed by Deep Learning models. Taken from [6].

Deep Learning in a Nutshell





$$z = \vec{w}^{\,T}\vec{x} + b$$

$$\sigma(z) = \frac{1}{1+e^{-z}}$$

$$\sigma(z) = \tanh(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$

$$\sigma(z) = \max(0, z)$$

$$\sigma(z) = \begin{cases} z & \text{if } z > 0 \\ \alpha z & \text{if } z \leq 0 \end{cases}$$

Convolutional Neural Networks

- Image processing [5].
- Operates on high-dimensional tensors (H x W x C).
- Convolution for extracting hierarchical features [5] $(I * K)(i,j) = \sum\sum I(i-m, j-n)K(m,n)$
- Max Pooling to systematically reduce the dimensionality of input tensor [5].

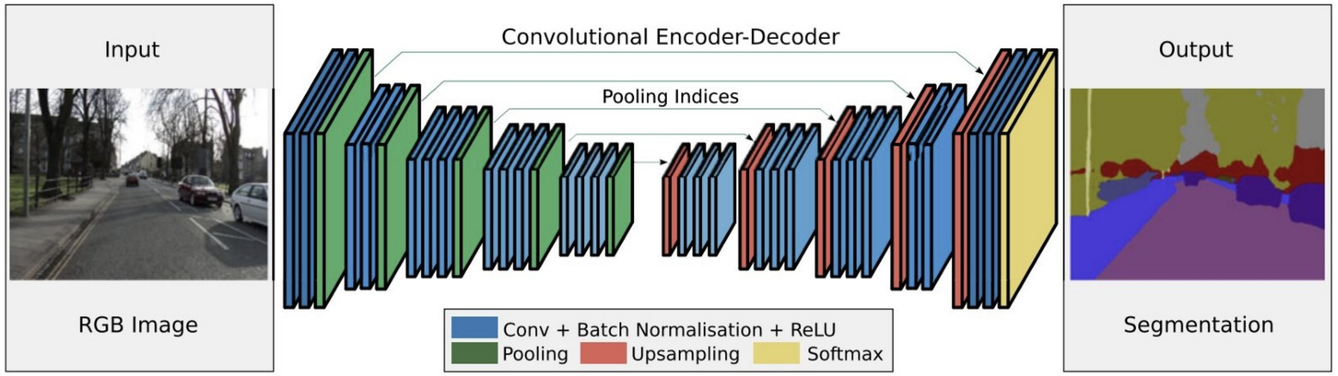


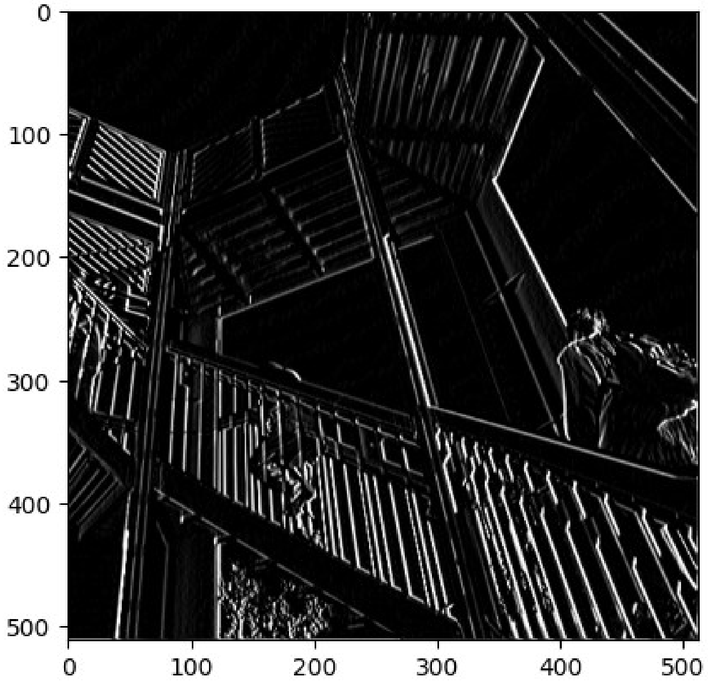
Fig2: Convolutional Neural Network. Taken from [6].

Convolutions: Practical Example

Input Image

$$* \quad \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \longrightarrow$$

Highlight vertical borders

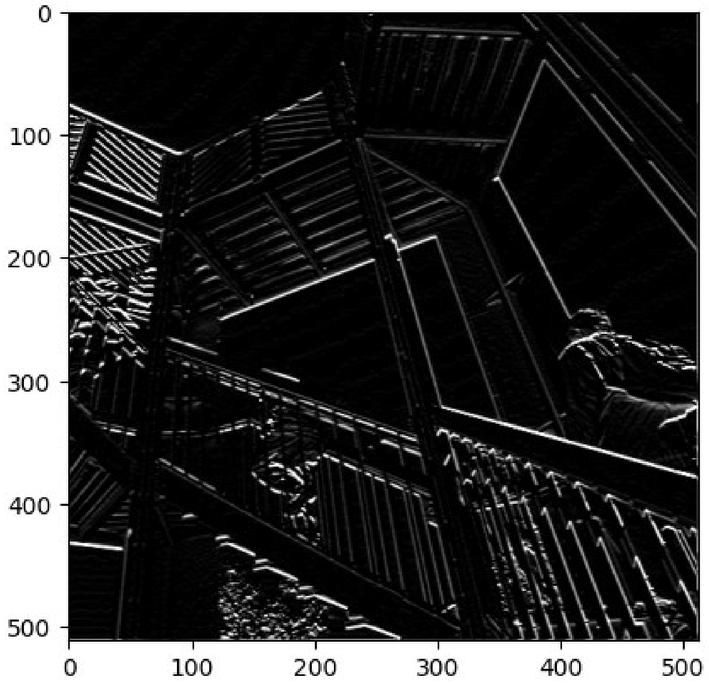


Convolutions: Practical Example

Input Image

$$* \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \longrightarrow$$

Highlight horizontal borders

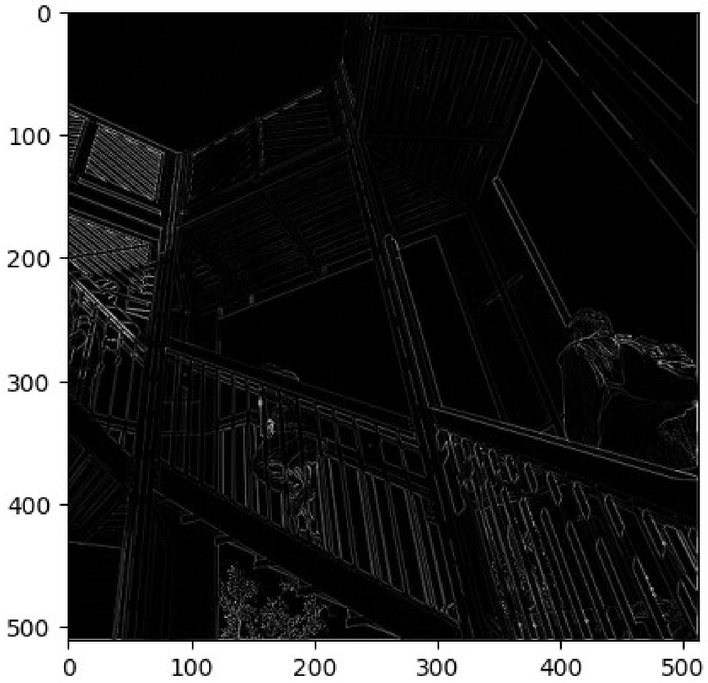


Convolutions: Practical Example

Input Image

$$* \quad \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \longrightarrow$$

Highlight all borders



UNet: Retrieving Speckle Displacements

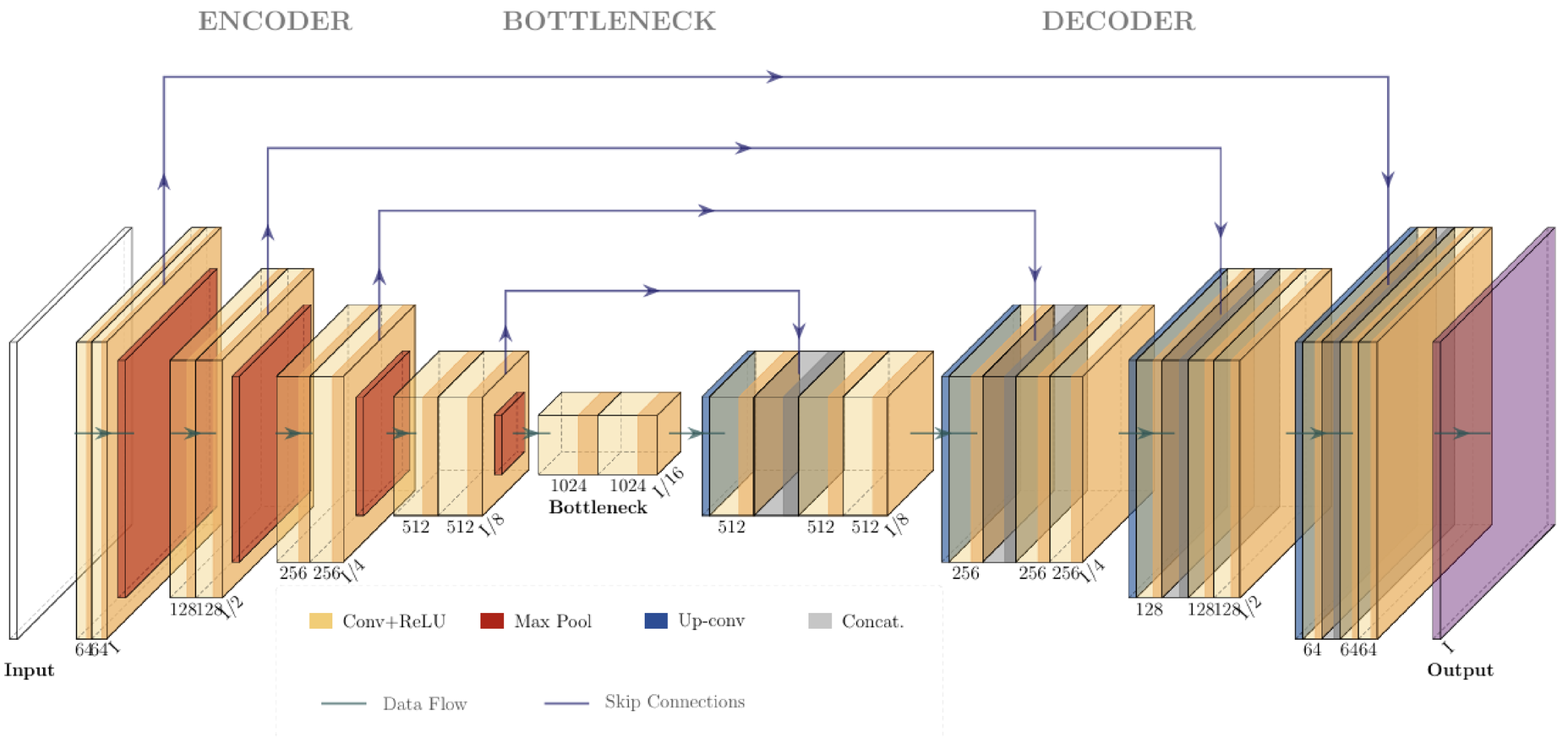
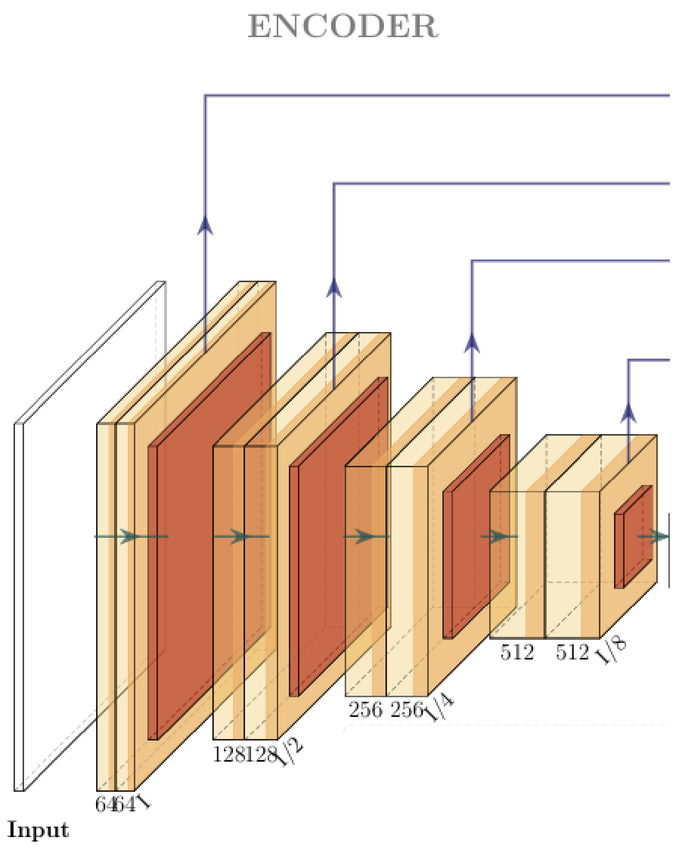


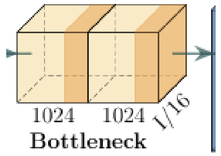
Fig3: UNet Architecture.

UNet: Retrieving Speckle Displacements



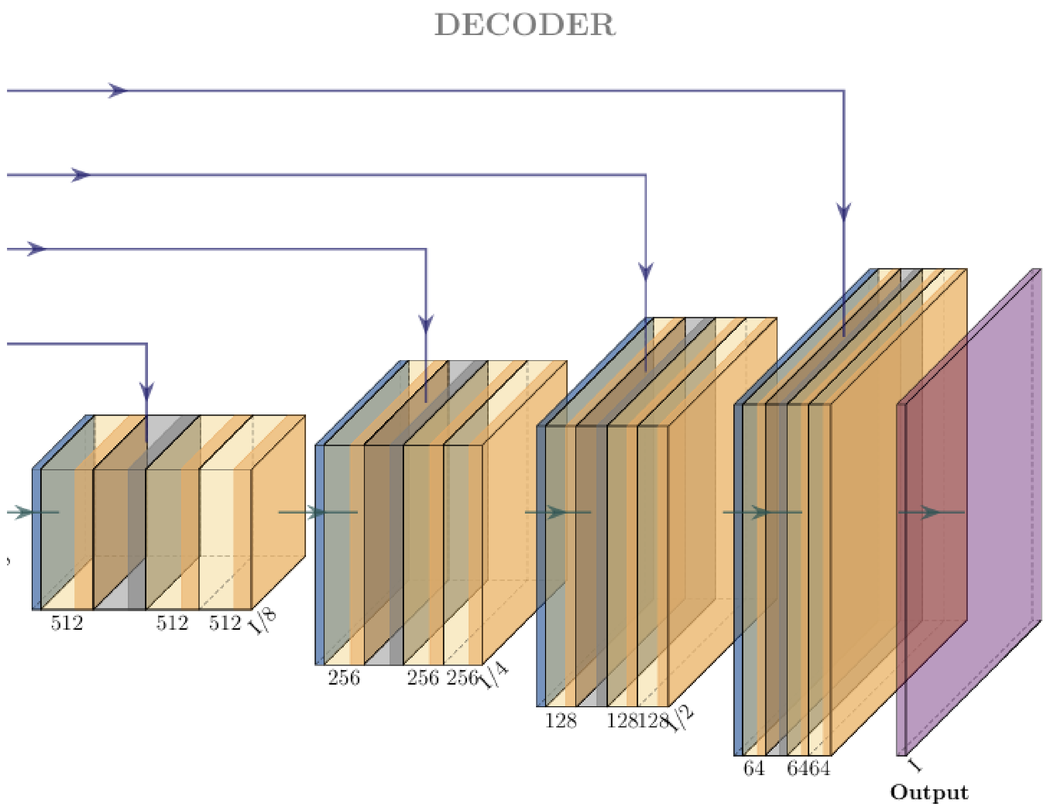

```python
def build_unet(input_shape=(256, 256, 2), num_classes=2):

    inputs = Input(input_shape)

    # Bloque 1 (64 filtros)
    c1 = Conv2D(64, (3, 3), activation='relu', padding='same')(inputs)
    c1 = Conv2D(64, (3, 3), activation='relu', padding='same')(c1)
    p1 = MaxPooling2D((2, 2))(c1)

    # Bloque 2 (128 filtros)
    c2 = Conv2D(128, (3, 3), activation='relu', padding='same')(p1)
    c2 = Conv2D(128, (3, 3), activation='relu', padding='same')(c2)
    p2 = MaxPooling2D((2, 2))(c2)

    # Bloque 3 (256 filtros)
    c3 = Conv2D(256, (3, 3), activation='relu', padding='same')(p2)
    c3 = Conv2D(256, (3, 3), activation='relu', padding='same')(c3)
    p3 = MaxPooling2D((2, 2))(c3)

    # Bloque 4 (512 filtros)
    c4 = Conv2D(512, (3, 3), activation='relu', padding='same')(p3)
    c4 = Conv2D(512, (3, 3), activation='relu', padding='same')(c4)
    p4 = MaxPooling2D((2, 2))(c4)
```

UNet: Retrieving Speckle Displacements




```
# Bloque Central (1024 filtros)
c5 = Conv2D(1024, (3, 3), activation='relu', padding='same')(p4)
c5 = Conv2D(1024, (3, 3), activation='relu', padding='same')(c5)
```

UNet: Retrieving Speckle Displacements




```python
# Bloque 4 (Expansión hacia 512 filtros)
u6 = Conv2DTranspose(512, (2, 2), strides=(2, 2), padding='same')(c5)
u6 = concatenate([u6, c4]) # Skip connection con Bloque 4
c6 = Conv2D(512, (3, 3), activation='relu', padding='same')(u6)
c6 = Conv2D(512, (3, 3), activation='relu', padding='same')(c6)

# Bloque 3 (Expansión hacia 256 filtros)
u7 = Conv2DTranspose(256, (2, 2), strides=(2, 2), padding='same')(c6)
u7 = concatenate([u7, c3]) # Skip connection con Bloque 3
c7 = Conv2D(256, (3, 3), activation='relu', padding='same')(u7)
c7 = Conv2D(256, (3, 3), activation='relu', padding='same')(c7)

# Bloque 2 (Expansión hacia 128 filtros)
u8 = Conv2DTranspose(128, (2, 2), strides=(2, 2), padding='same')(c7)
u8 = concatenate([u8, c2]) # Skip connection con Bloque 2
c8 = Conv2D(128, (3, 3), activation='relu', padding='same')(u8)
c8 = Conv2D(128, (3, 3), activation='relu', padding='same')(c8)

# Bloque 1 (Expansión hacia 64 filtros)
u9 = Conv2DTranspose(64, (2, 2), strides=(2, 2), padding='same')(c8)
u9 = concatenate([u9, c1]) # Skip connection con Bloque 1
c9 = Conv2D(64, (3, 3), activation='relu', padding='same')(u9)
c9 = Conv2D(64, (3, 3), activation='relu', padding='same')(c9)

outputs = Conv2D(num_classes, (1, 1), activation='linear')(c9)

model = Model(inputs=[inputs], outputs=[outputs])
return model
```

Training Dataset

$$\vec{d}_{\perp}(x,y) = \frac{z_d}{k}\vec{\nabla}_{\perp}\phi(x,y)$$

$$\phi(x,y,z) = -k\int_{z=0}^{z=z_0}\delta_{\omega}(x,y,z)dz$$

$$\phi(x,y,z) = -k\delta_{\omega}T(x,y)$$

- 600 images.
- 150 images per geometry.
- Three materials: Al_2O_3, PMMA, Nylon.
- 28keV, 4 sandpapers SiC 125um, source-detector distance 2m.

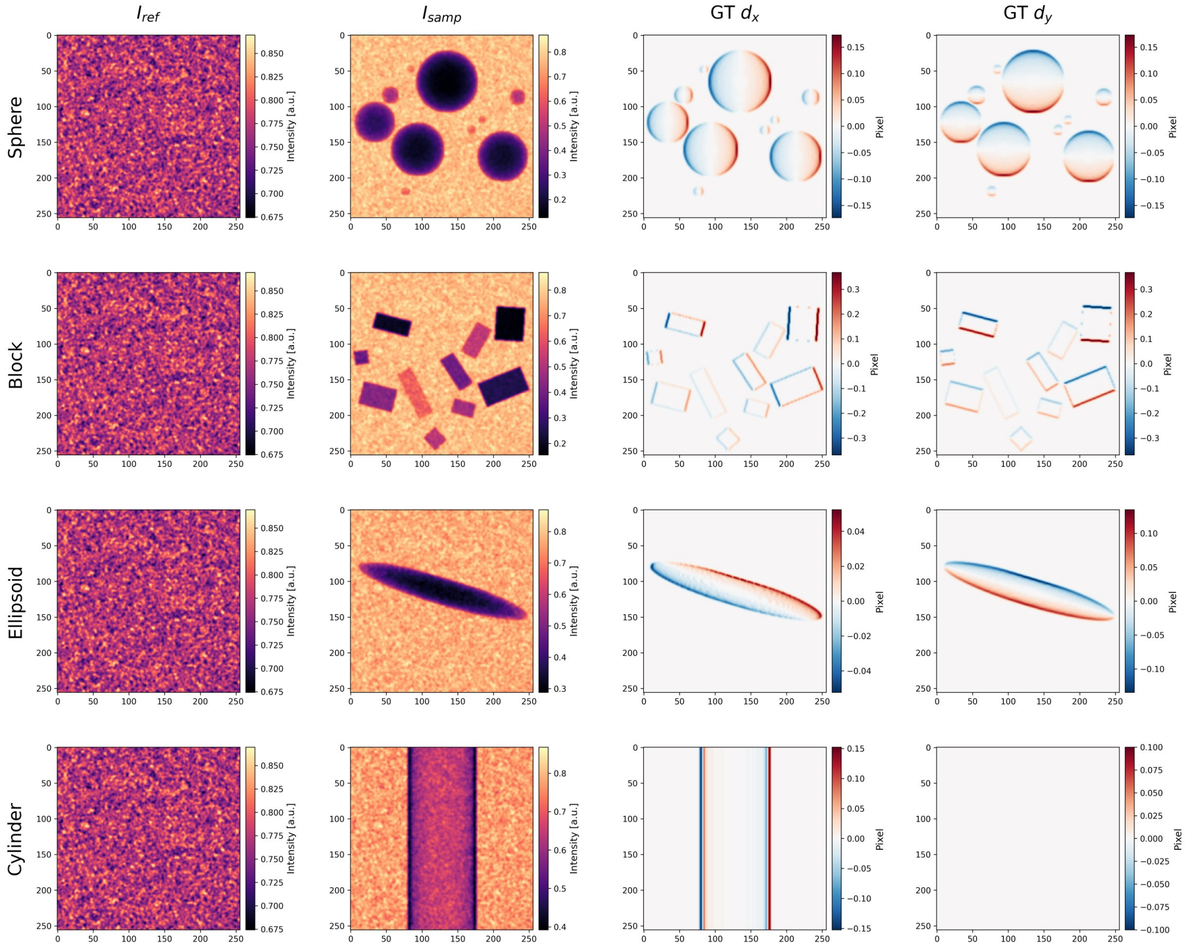


Fig4: Training dataset.

Validation Dataset

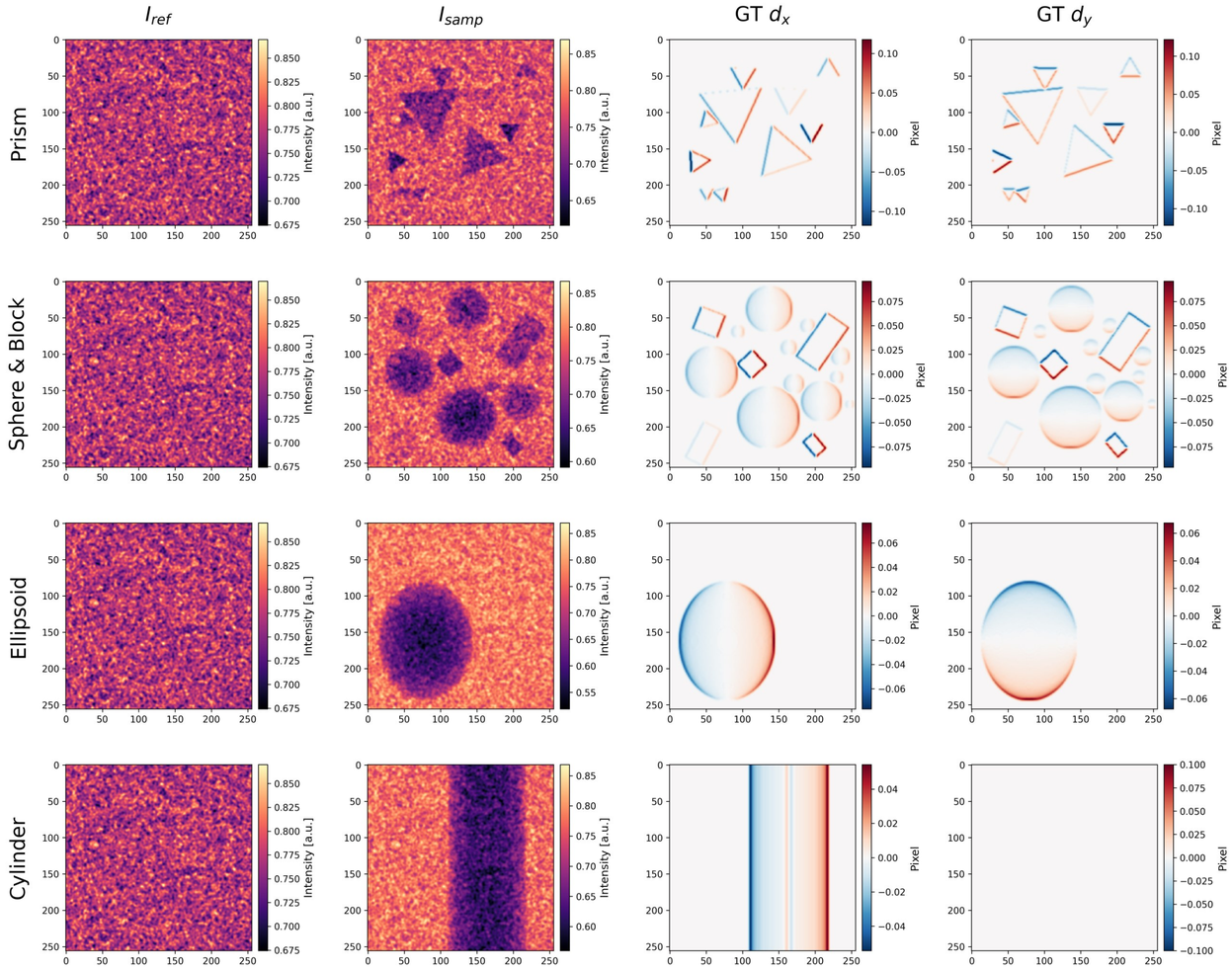


Fig5: Validation dataset.

Evaluation Dataset

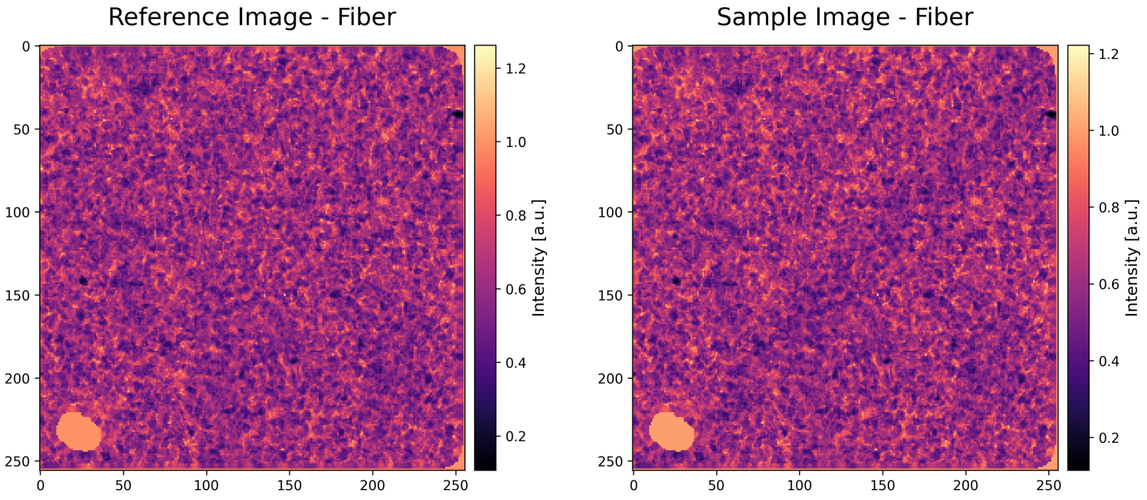


Fig6: Evaluation: Nylon fiber.

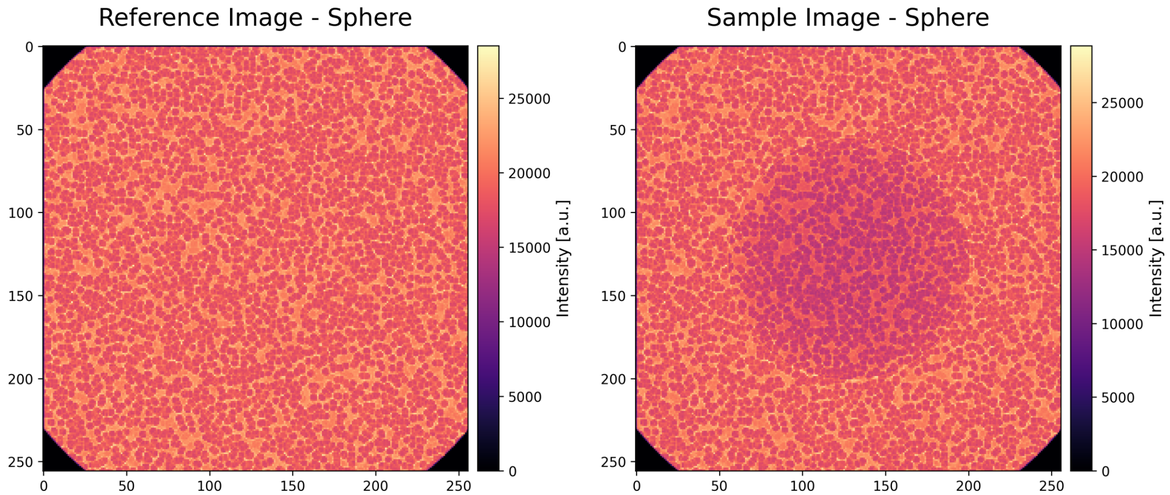


Fig7: Evaluation: Nylon sphere.

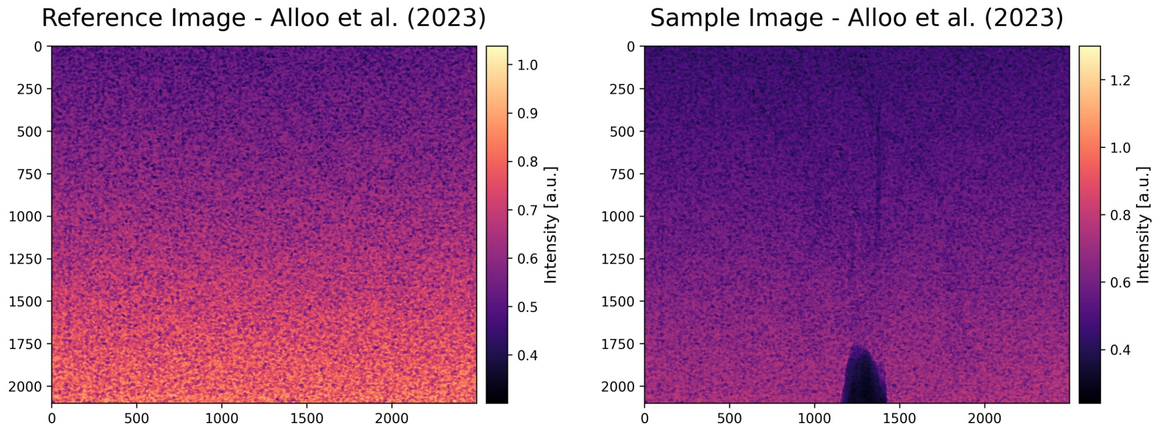


Fig8: Evaluation: Wattle flower [2].

Link to Google Drive

- Link: https://drive.google.com/drive/folders/1TFuEhGH6aF2DhmRQAdSwJm6O6c6zZ8FN?usp=sharing

References

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