Single pixel imaging with optical phase arrays: a machine learning assisted approach

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INTRODUCTION

Speckle patterns are created and exploited for imaging applications using a single pixel detector working together with Optical Phased Arrays (OPAs). The methodology is based on the fact that light modulated by the OPA and then propagating through a multimode fiber or scattered by a diffraction grating creates complex speckle patterns as a result of several light paths [1,2]. After illuminating the target, the intensity distribution of these speckle patterns can be detected by a bucket detector in single pixel imaging, and the image is then reconstructed using Compressed Sensing (CS) computational techniques according with the sketch in Fig. 1 [1].

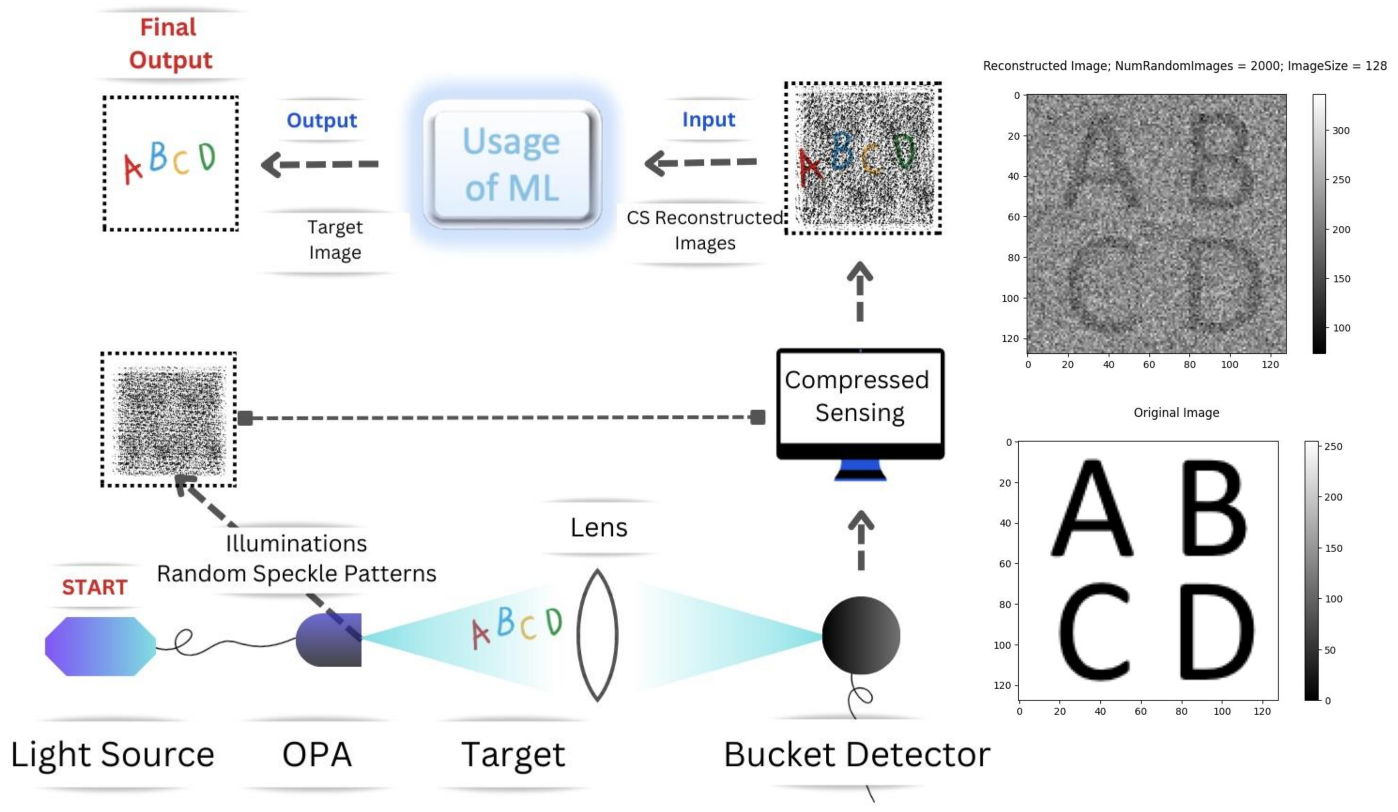

Fig 1. Concept drawing of the proposed ML model to process noisy or poorly resolved CS patterns and reconstruct the original target images.

In this study, the effectiveness of a Convolutional Neural Network (CNN) [3] and a U-Net [4] architecture for denoising target images is compared.

Combining CS and OPA illumination with a single pixel detector minimizes the need for complex hardware while still capturing the necessary data for image reconstruction. Additionally, we show that <u>**ML integration enhances the quality of CS reconstructed images, making the final image much more accurate**</u>**, thus improving upon the limitations of traditional CS techniques.**

This approach is particularly advantageous for MIR where detector technology is less advanced and the detectors are more bulky and more expensive with respect to those available in the visible and near infrared region of the electromagnetic spectrum.

METHODS

<u>**Dataset Preparation:**</u> In our work, a dataset consisting of couples of clean target images and their corresponding noisy CS reconstructions are simulated using a MATLAB algorithm. The training set size of 750 and the validation set that includes 250 noisy-clean image pairs were used to evaluate the performances of CNN Fig. 1 and U-Net Fig. 3 models. <u>The U-Net demonstrates a smooth denoising effect but struggles to reconstruct fine details.</u>

<u>**CNN Architecture:**</u> The CNN model was created using the basic encoder-decoder configuration. The decoder uses a single convolutional layer with a sigmoid activation function to reconstruct the image, while the encoder uses a series of convolutional layers with decreasing filter sizes (32 → 16 → 8 → 4).

<u>**U-Net Architecture:**</u> The U-Net model uses bypass connections between corresponding layers and a symmetric encoder-decoder structure. Convolutional layers (64 → 128 → 256 → 512 → 1024 filters) are set up with max-pooling layers to extract hierarchical features.

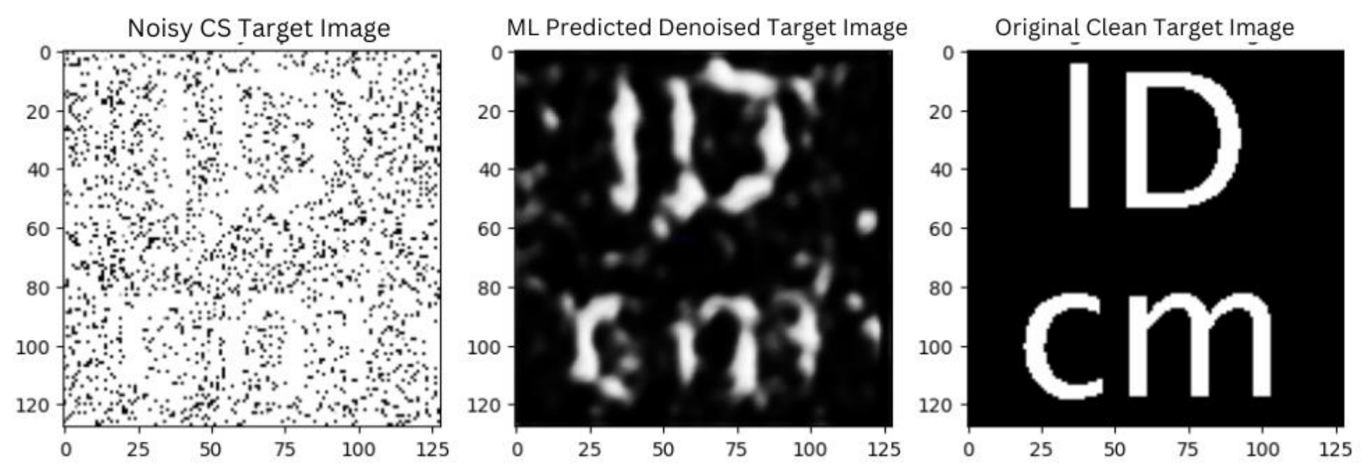

Fig 2. Illustrated results of the CNN model showing noisy inputs, predicted clean images, and the original clean ground truth.

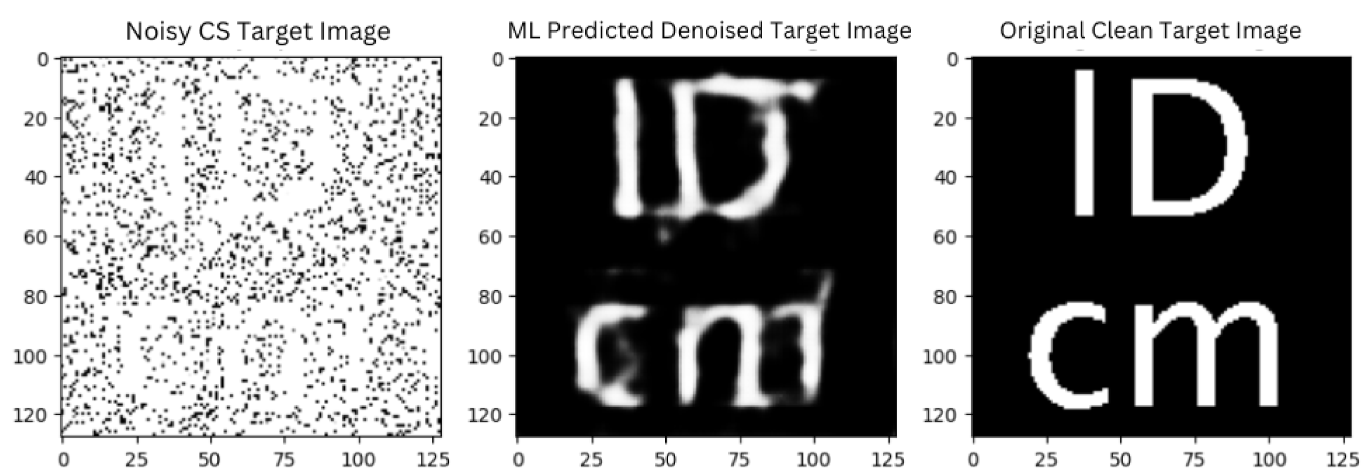

Fig 3. Illustrated results of the U-Net model showing noisy inputs, predicted clean images, and the original clean ground truth.

RESULTS

As seen by its lower SSIM and PSNR values, the CNN struggled to preserve small details despite demonstrating faster training and inference durations. But because **the U-Net** was able to preserve spatial features through skip connections, it **performed better on all criteria.**

Metric	CNN	U-Net
MSE	0.055	0.025
SSIM	0.32	0.75
PSNR (dB)	12.6	15.9

Table 1. Comparison of Performance Metrics for CNN and U-Net Architectures

CONCLUSIONS

1. **CNN vs. U-Net Performance:** While the CNN model offers computational efficiency with its simple encoder-decoder design, it struggles to reconstruct fine details in images. In contrast, the U-Net architecture outperforms the CNN, delivering superior structural integrity and achieving higher SSIM and PSNR values.
2. **Scalable Solutions for Photonic Systems:** The study highlights the growing role of ML in photonics, showcasing U-Net as a scalable and effective approach for advancing imaging techniques in future photonic systems [4].
3. **U-Net's Potential in Photonics:** The U-Net demonstrates significant promise for photonics applications, such as optical imaging, where high quality image reconstruction is essential [5]. U-Net performs in preserving fine grained details, whereas the CNN offers simplicity and faster training.

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