# Estimation of Beam Transverse Parameters Through a Multimode Fiber Using Deep Learning

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## Abstract

To meet CERN's demand for alternative imaging solutions due to the discontinuation of rad-hard cameras, a **multimode fiber** (MMF) transmitting image to a CMOS camera away from high radiation zones is investigated[1]. Despite challenges with image distortion at the fiber's output, a machine learning approach using a deep **convolutional encoder-regressor network** was developed. This end-to-end model allows the direct estimation of key **transverse beam parameters** like centroids and sizes from the fiber output, bypassing the need for full image reconstruction and reducing the model size as well as training time, providing a robust and safe **imaging solution for high-radiation** settings.

## Methodology

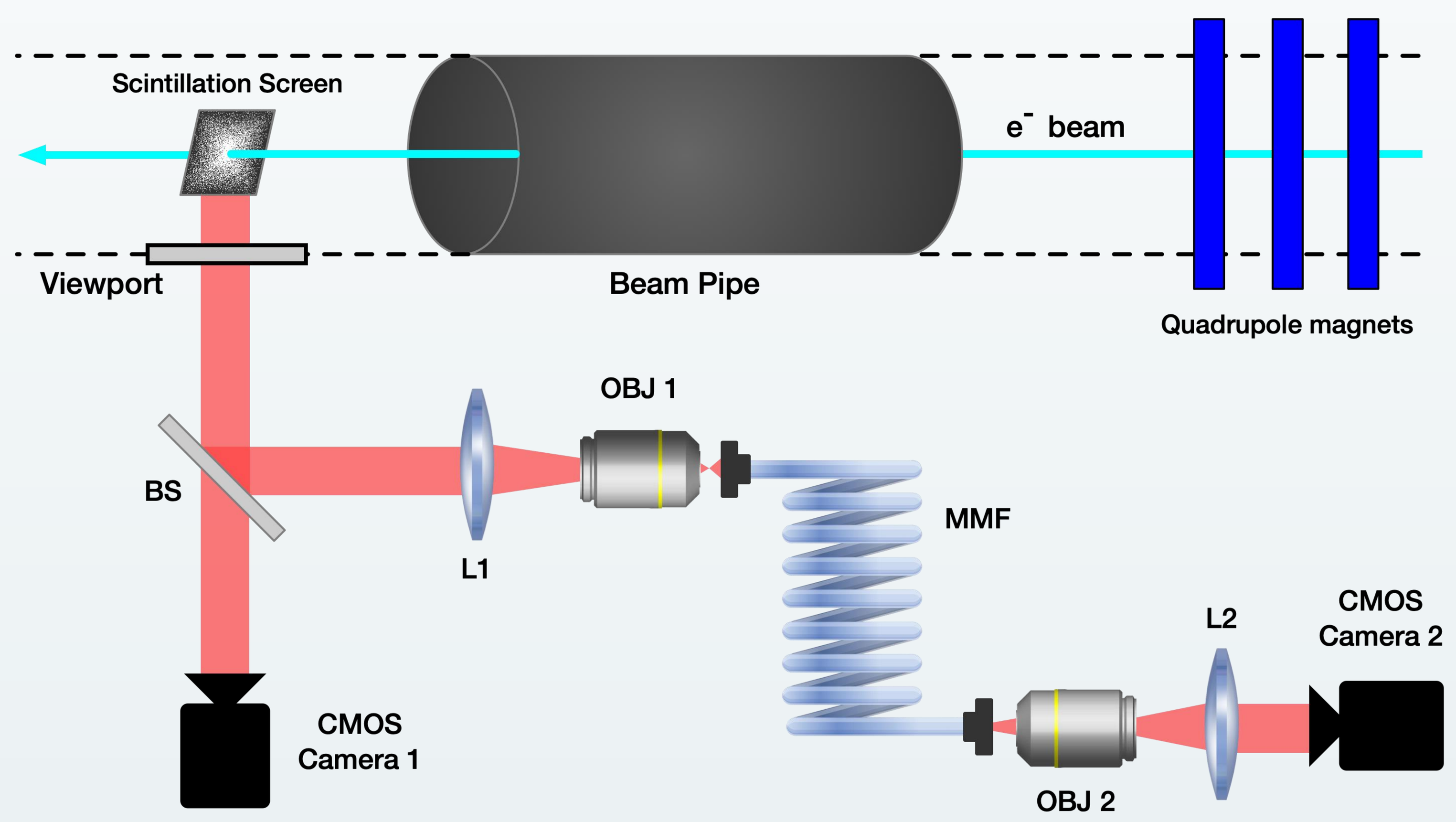


*Figure 1. Schematic diagram of data collection experiment with electron beam.*

**Experiment**: Camera 1 is positioned near the beam pipe characterized by high radiation, recording the beam's transverse distribution on a scintillating screen. A beam splitter divides this initial image into a secondary path, which shrunk via a lens system, and then transmitted through an MMF to lower radiation area. At the distal end of the fiber, Camera 2 captures the output image.

**Dataset**: Data acquisition occurred at the CERN's CLEAR facility, employing the abovementioned apparatus. A quadrupole scan was implemented to modify the 150 MeV electron beam's size and position, resulting in a collection of approximately 6000 paired images for training and evaluation.

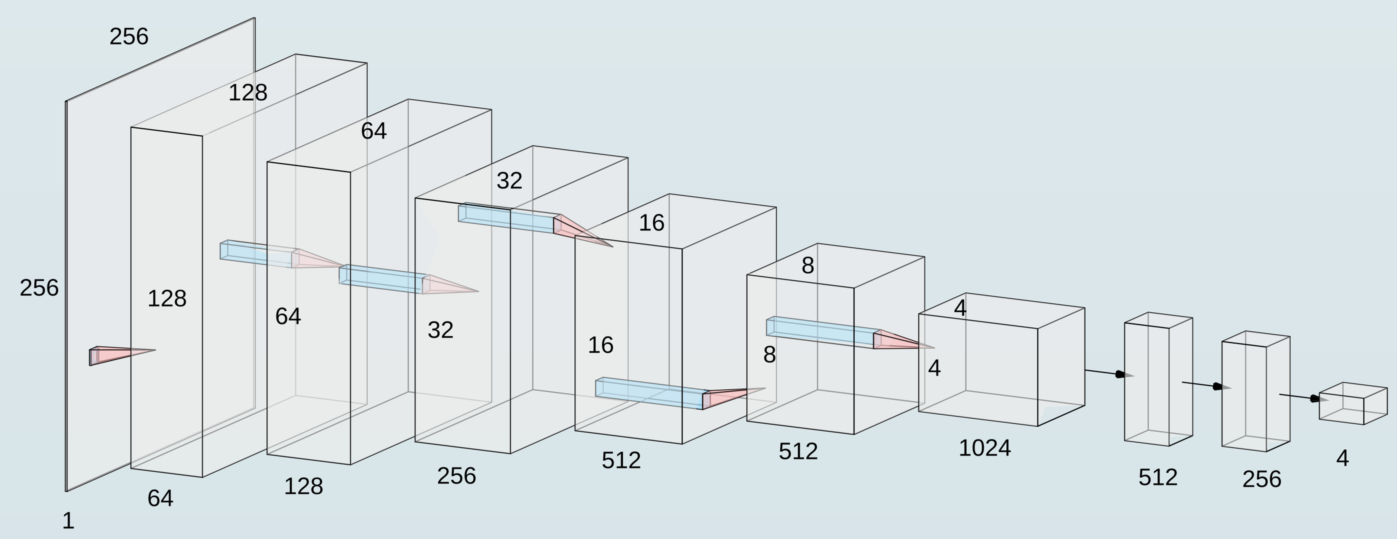


*Figure 2. Convolutional encoder-regressor network.*

**Model**: an image encoder incorporating 6 layers of convolution kernel to compress the fiber output and extract abstract representations from the irregular speckle patterns generated by MMF[2]. This process is followed by a fully connected dense network, which performs regression analysis to derive four beam parameters from the encoder latent space.

## References

[1] Trad, Georges, and Stephane Burger. "Artificial Intelligence-Assisted Beam Distribution Imaging Using a Single Multimode Fiber at CERN." JACoW IPAC 2022 (2022): 339-342.
[2] Isola, Phillip, et al. "Image-to-image translation with conditional adversarial networks." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

## Preliminary Results

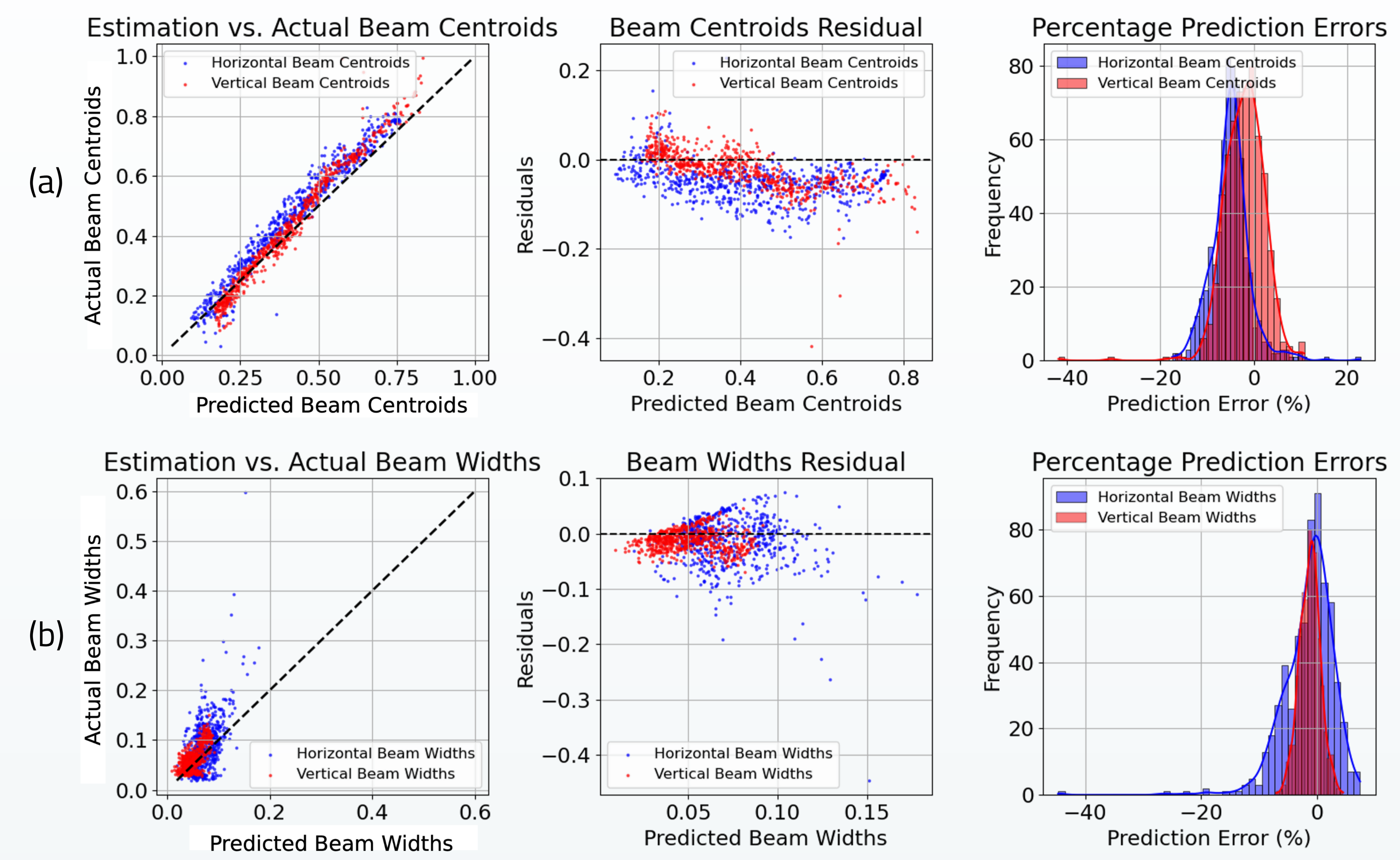


*Figure 3. Test set prediction statistics. (a) beam centroids. (b) beam widths.*

**Fig. 3** displays the estimation results for the beam parameters over 600 samples from the testset. Most predictions cluster around the diagonal, indicating relatively small prediction errors. The error distribution is slightly shifted from the center; this shift is due to an imbalance in the dataset, where more data pertain to certain positions and sizes.

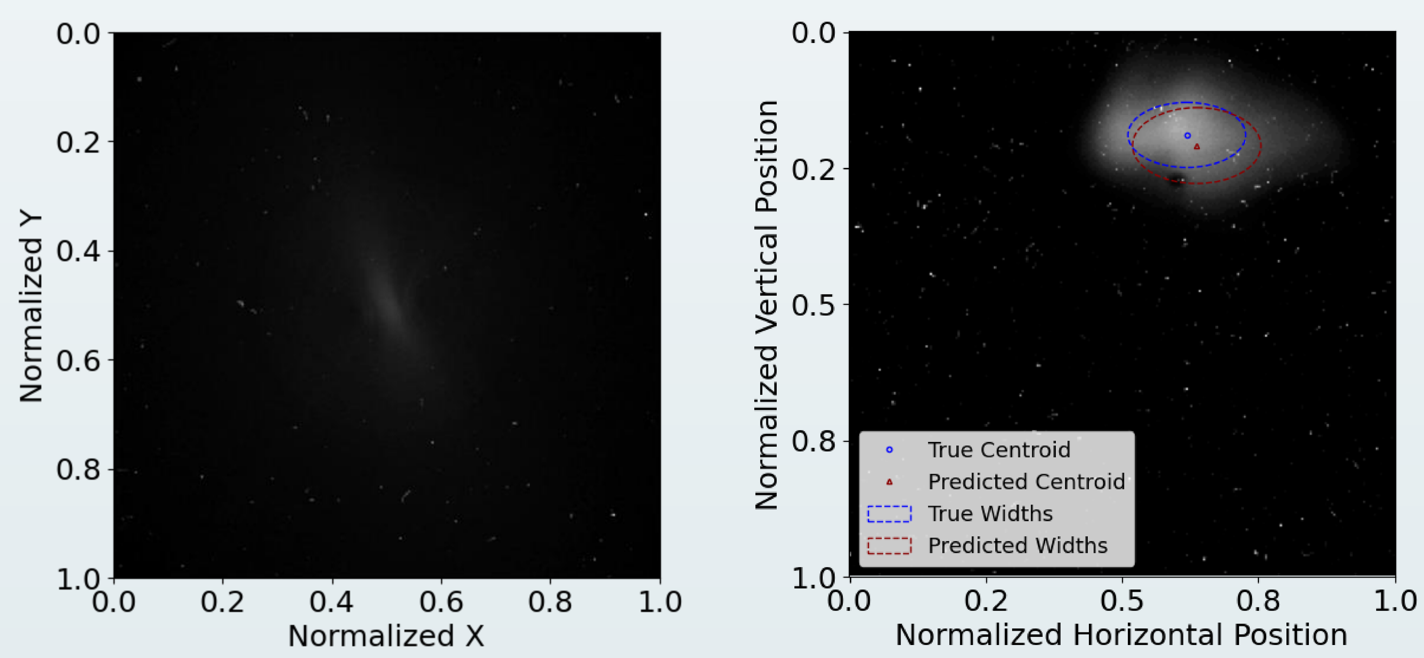


*Figure 4. Transverse beam parameter prediction on a test sample.*

**Fig. 4** illustrates a prediction example using test data. The left image shows the input data to the model from MMF output. The right image compares the real beam parameters with the model's estimation, demonstrated on the corresponding original beam image.

## Conclusion & Future Works

Test set prediction RMSE of maximum 0.069 is achieved. A clear correlation was observable between the real and predicted values. The prediction bias due to the unbalanced training set distribution could be improved by enhancing the variability of the dataset in the future.

**Future works**:

- Utilizing Digital Micromirror Devices (DMD): Employ DMD to generate large, high-variance datasets using computer-simulated patterns.
- Perturbation studies: Investigate the impacts of mechanical vibrations, thermal variations, and radiation accumulation's effects on fiber's transmission property.
- Machine learning models: Explore cutting-edge models, such as the Swin-Transformer, as the encoder.

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