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Deep learning camera calibration in fringe projection profilometry

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Motivation: Camera calibration of Fringe Projection Profilometry (FPP) is essential for accurate 3D reconstruction of the measured object. Current calibration methods, such as OpenCV, struggle in certain environments where high environmental and process-related noise exist - leading to poor calibration.

Methodology: Deep learning has emerged as a reliable approach to solve complex problems. In this work, a deep learning model, YOLOv11, is introduced to assist feature detection in calibration board.

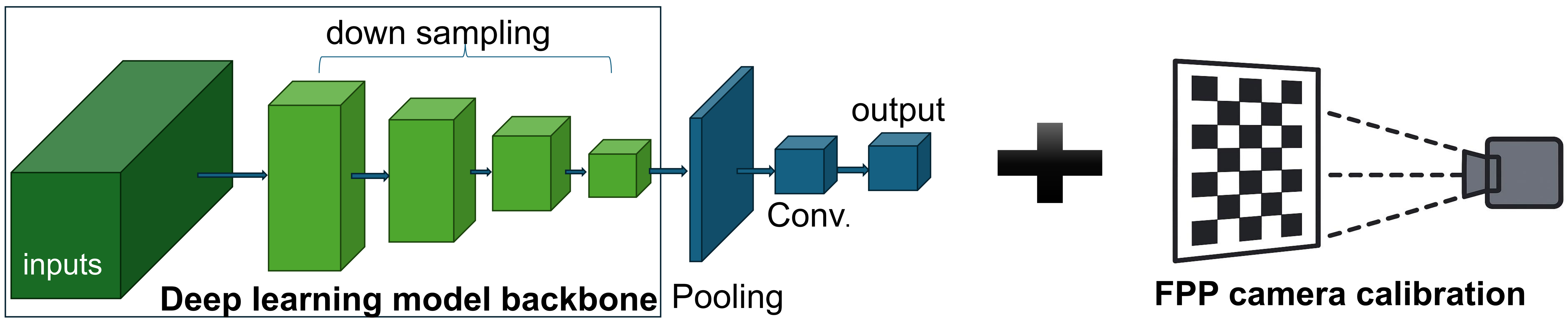
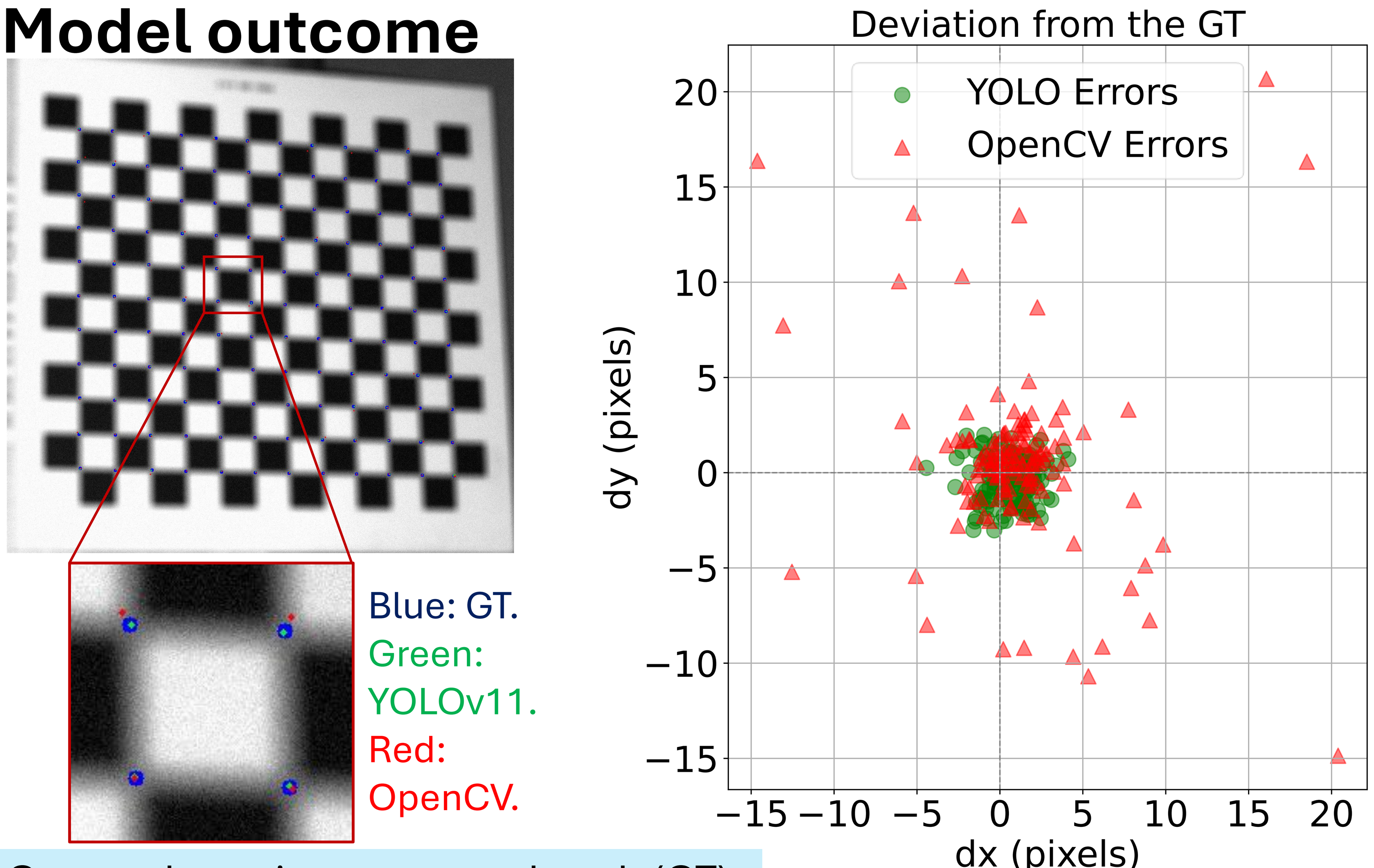


Figure 1: Illustration of the use of the deep learning model in our work.

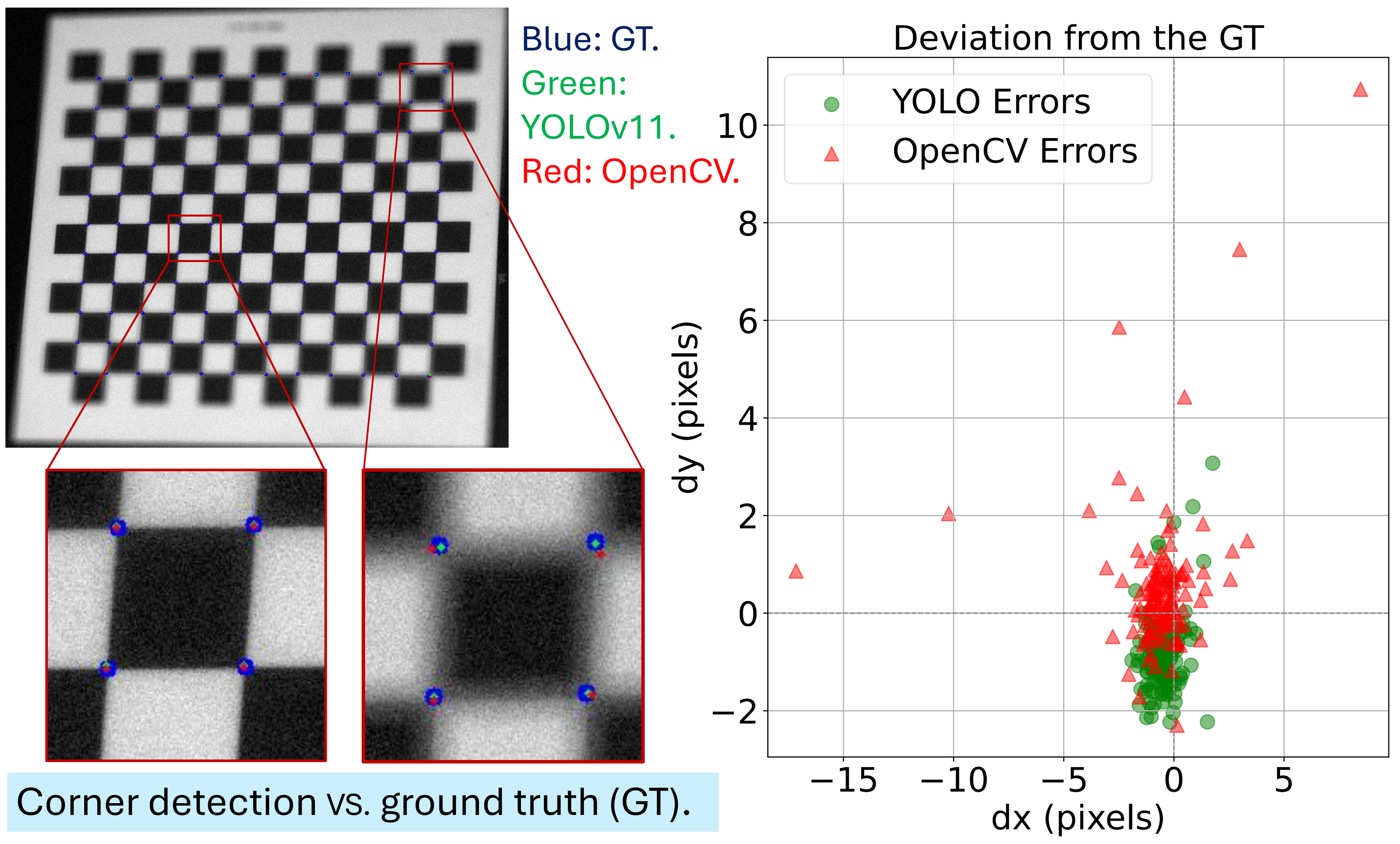
The model is trained and validated with 3.8K checkerboard images. The rest of the camera calibration is done with OpenCV algorithm. The results are compared with full calibration done using OpenCV. Verification of the method is completed in accordance with VDI/VDE 2634-2 standard.

Model outcome



Corner detection vs. ground truth (GT).

Figure 2: Fully defocused image.



Corner detection vs. ground truth (GT).

Figure 3: Partially defocused image.

Our model has a reprojection error of **0.025** pixels, as tested using a set of noisy images and another separate set of a mix of clear and noisy images. The OpenCV model gives a reprojection error of **0.32** and **0.12** pixels for the same two sets, respectively.

VDI/VDE 2634-2 standard: Verification of our model is done with a calibrated dumbbell sphere for Spacing Distance (SD) and Form (sphere radius). An average of 5 FPP measurements is taken after calibration with the two image sets.

Table 1: Measurements results after calibration with two images datasets: noisy (set A) and mix of clear and noisy (set B).

Method		GT (mm)	YOLO (mm)	OpenCV (mm)
SD	Set A	49.945	50.114	51.660
	Set B		50.067	50.421
SD (stdv) * 10^{-3}	Set A	-	8	28
	Set B		8	174
Sphere1 radius	Set A	4.997	4.972	5.338
	Set B		4.997	5.137
Sphere1 radius (stdv) * 10^{-3}	Set A	-	20	60
	Set B		12	47
Sphere2 radius	Set A	4.996	4.986	5.424
	Set B		5.000	5.146
Sphere2 radius (stdv) * 10^{-3}	Set A	-	13	37
	Set B		11	56

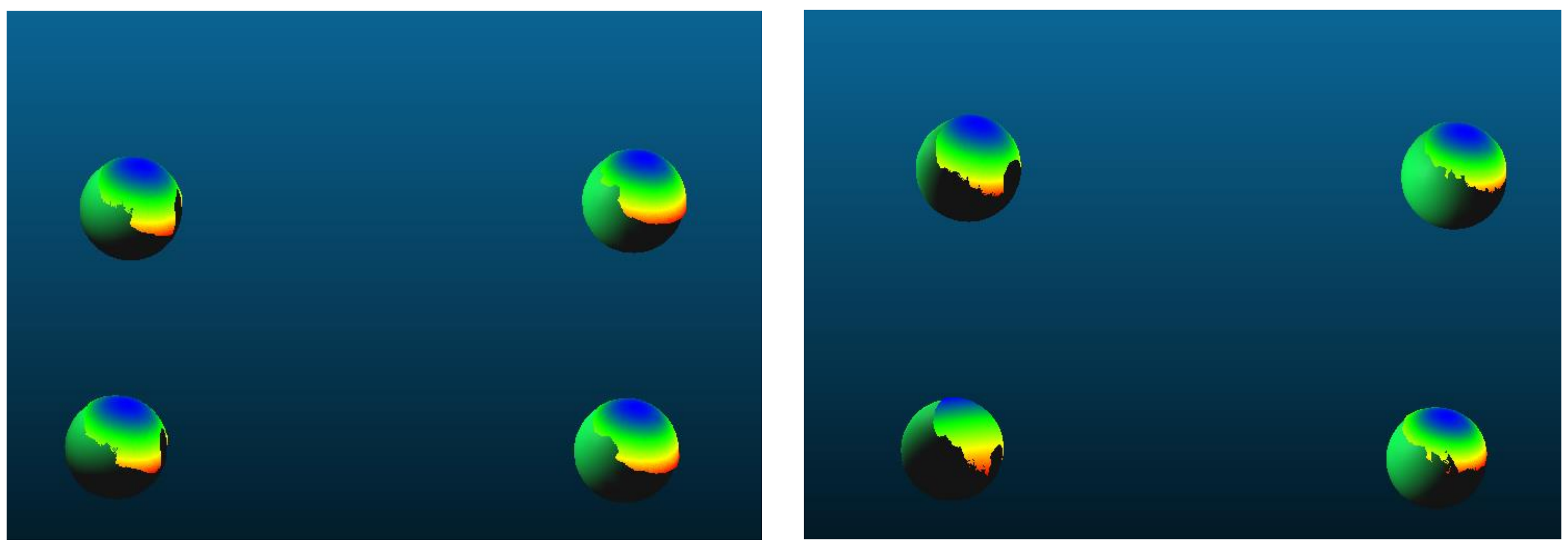


Figure 4: Dumbbell sphere fits for (a) YOLO calibration data and (b) OpenCV calibration data. Top fits represent Set A, while bottom fits represent Set B.

Conclusion:

- YOLOv11 is **faster** and more convenient than OpenCV, with no parameter tuning required.
- **Accurate detection** on calibration board images even under various noisy conditions.
- **YOLOv11** resulted in **0.025 pixels** of reprojection error, **~ 5 times** OpenCV reprojection error when calibrating a mix of noisy and clear images.

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