

Introduction & Background

Jet in crossflow (JICF) contains an unstable upstream shear layer that governs vortex rollup and mixing.

This canonical configuration appears in gas-turbine dilution, film cooling, fuel injection, and thrust-vector-control systems.

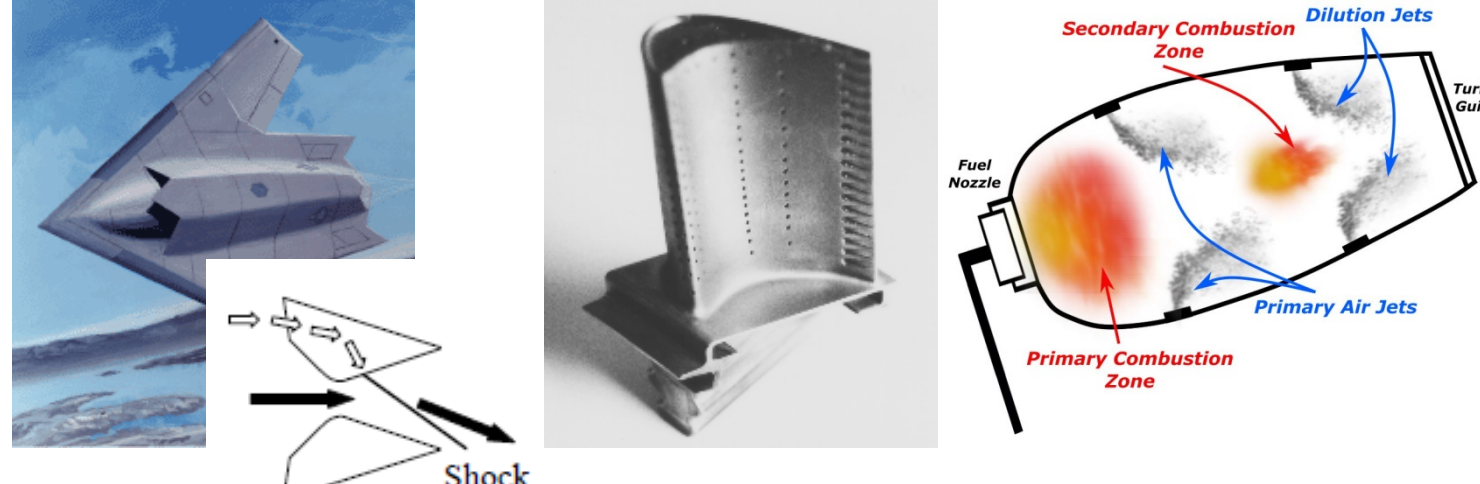


Figure 1: Some applications of JICF, Fluidic Thrust Vectoring (left), Film Cooling (middle), and Dilution air jet in gas turbine engine (right).

Upstream shear layer (USL) strongly influences jet penetration, mixing, and instability behavior. However, its dynamics occur at >1 kHz, whereas the available particle image velocimetry (PIV) measurements are acquired at 5 Hz.

Momentum Flux Ratio (J) is one of the deciding factors in determining USL instability behavior.

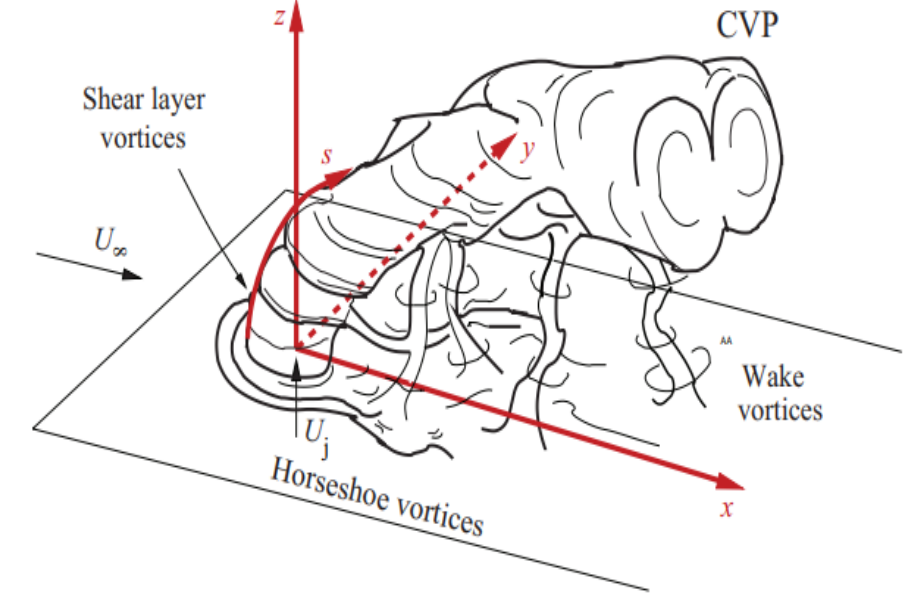


Figure 2: Schematic of flush-injected round jet in crossflow. Adapted from Fric and Roshko (1994).

This research therefore has two components: improve experimental repeatability, and reconstruct USL dynamics from sparse PIV using Machine Learning (ML).

Methods

Experimental Hardware

Problem: Existing hot-wire and laser-sheet adjustments coupled multiple degrees of freedom, making alignment slow and difficult to reproduce.

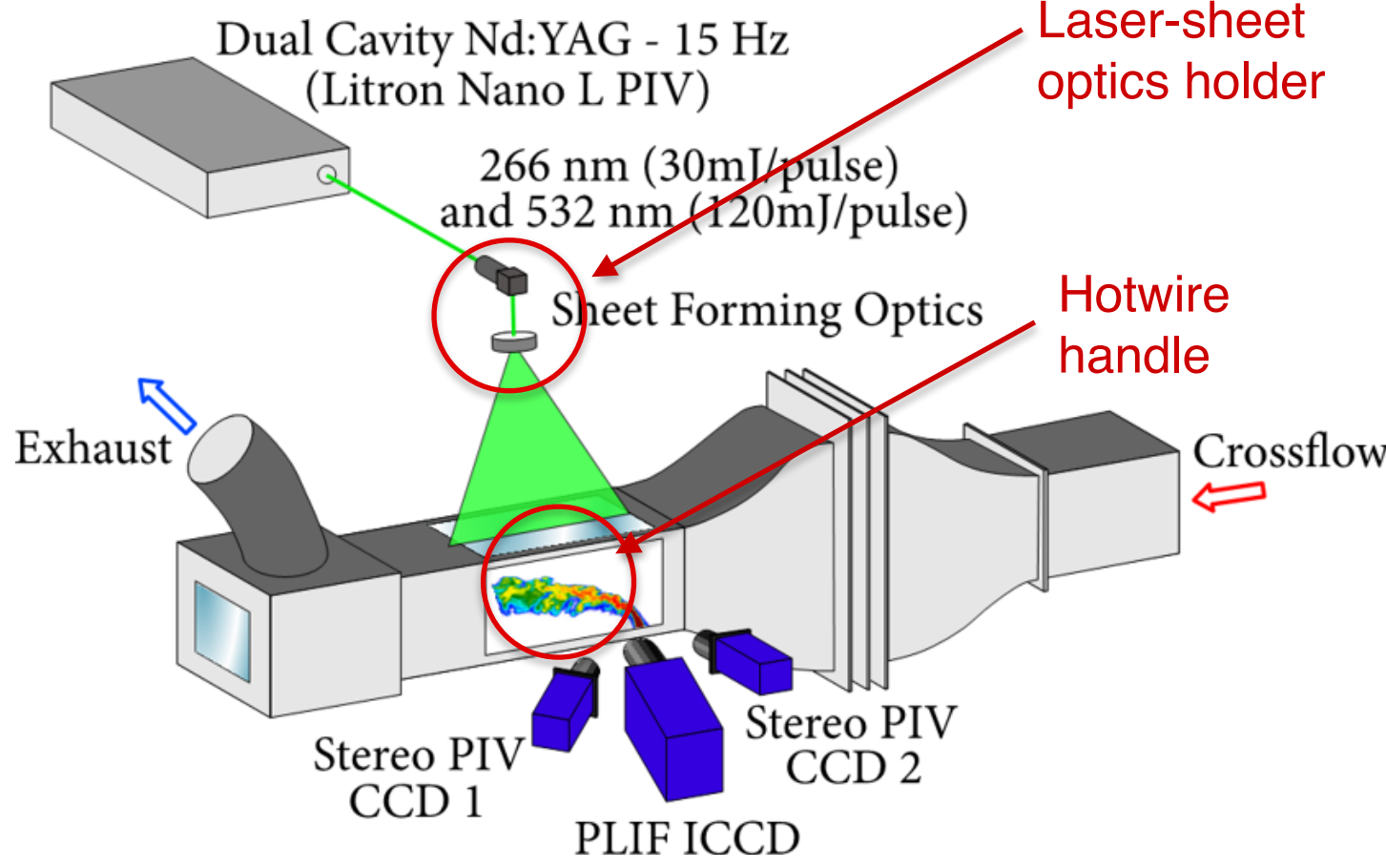


Figure 3: 3D schematic of the JICF wind tunnel and optical diagnostic configuration.

Approach: CAD prototyping and 3D printing were used to redesign both mechanisms for simpler, more repeatable calibration.

Dimensional calibration prints were first used to determine suitable clearances for moving and mating features before fabrication of the final assemblies.

Table 1. Measured design clearances (in.) for HeyGear Reflect RS printer

Shape	Transition Fit	Tight Fit
Cylinder	0.003	0.000
SpurGear	0.006	0.002
Square	0.002	0.001

Machine-Learning Flow Analysis

Step1: A single snapshot is preprocessed to reject noise; Well-shaped blobs are then labelled as training data for neural network classifier;

After training, the classifier assigned each candidate vortex a confidence weight, $0 \leq w_i \leq 1$.

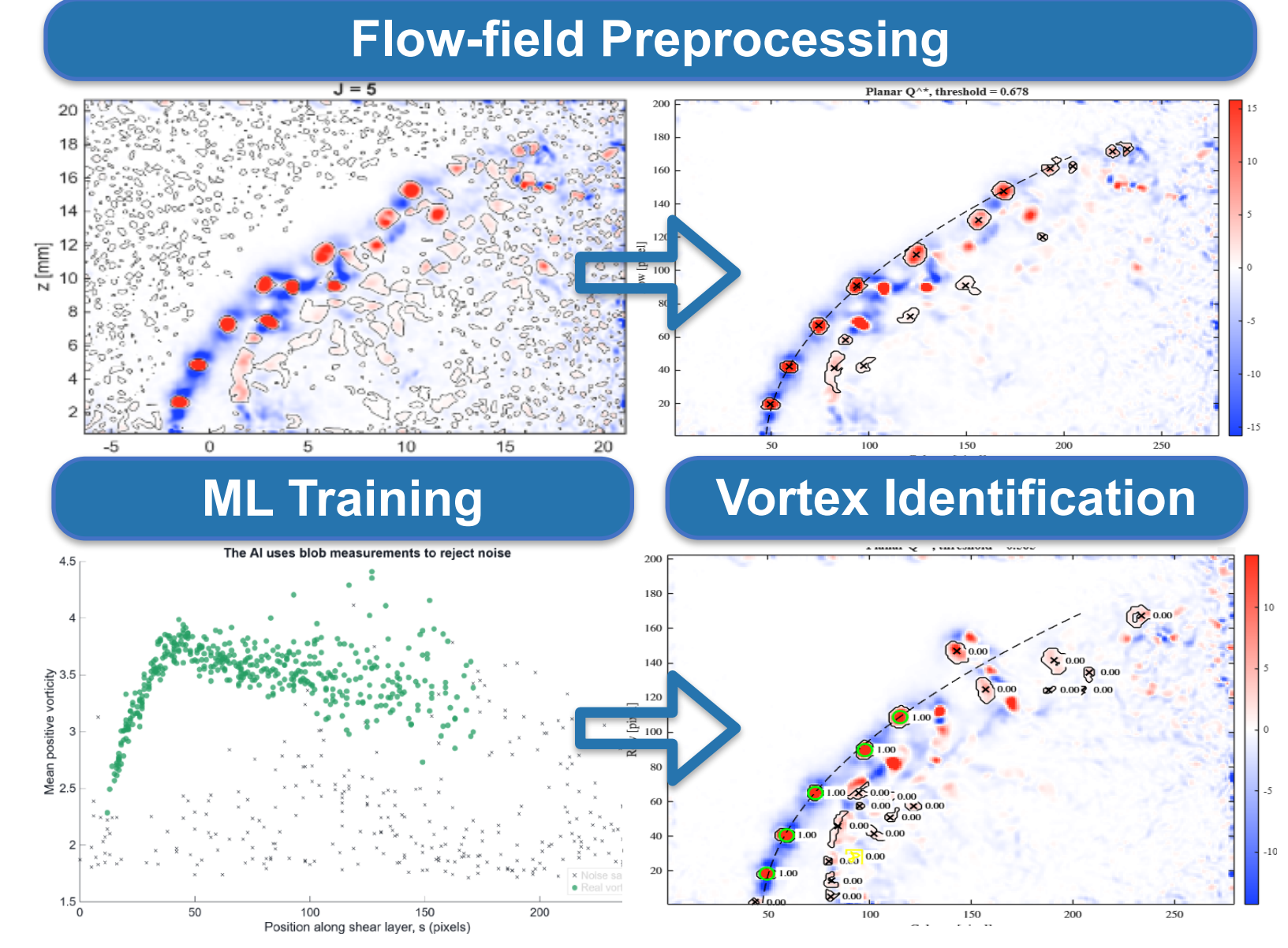


Figure 4: A flowchart of step1.

Step2: The avg. phase of each snapshot was estimated from all detected vortices along USL:

$$z_f = \frac{\sum_i w_i \exp(i2\pi s_i / \lambda)}{\sum_i w_i}, \quad \Phi_{ML} = \arg(z_f)$$

s_i : Path progress along USL;
 λ : characteristic vortex spacing

All snapshots are then sorted based on their phase to reconstruct the flow dynamics.

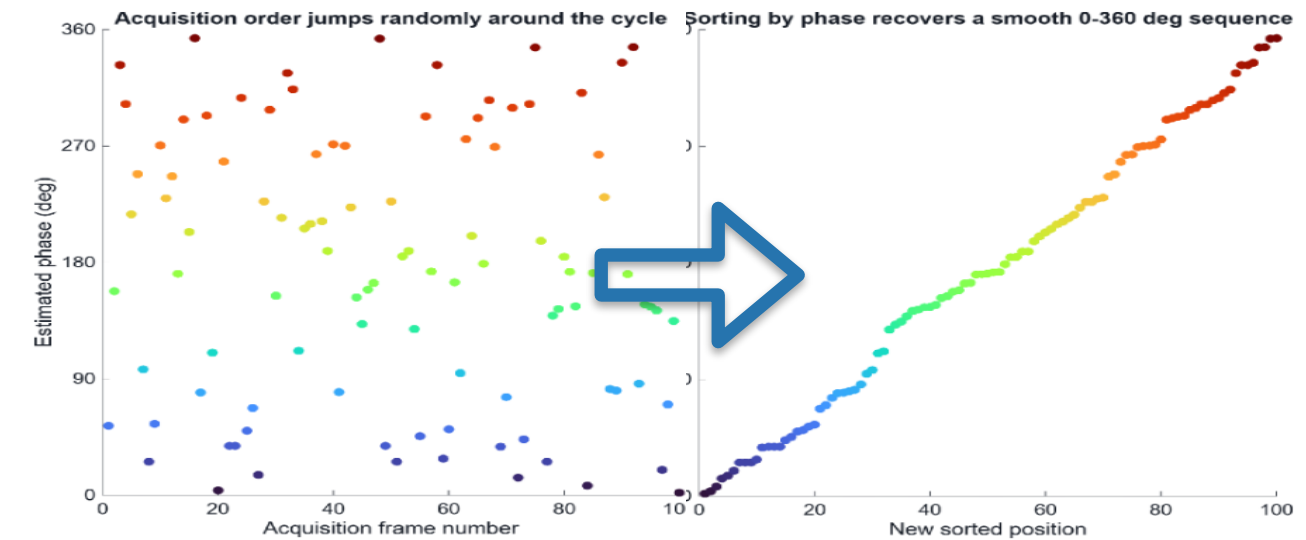


Figure 5: The sparse PIV image is sorted based on their ML phases.

Results

Experimental Hardware

Hot-wire handle: separates translation from rotation and provides 5:1 geared angular control.

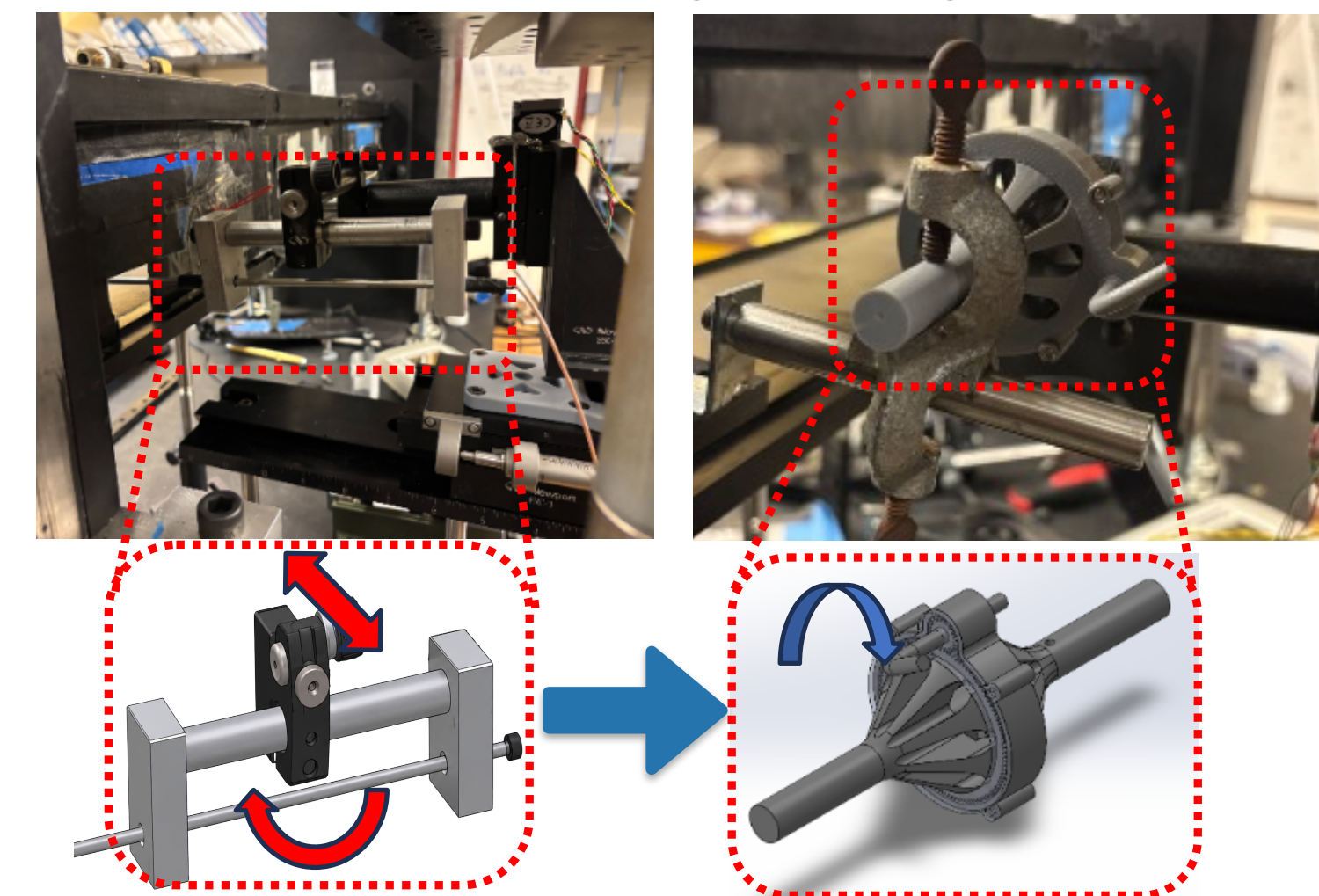


Figure 6: The old design with x-axis position and yz-plane rotation operated simultaneously (left); The new design separates translation and rotation, with 1:5 gearbox facilitates small rotation.

Laser-sheet holder: replaces the three-screw mount with single-axis geared rotation

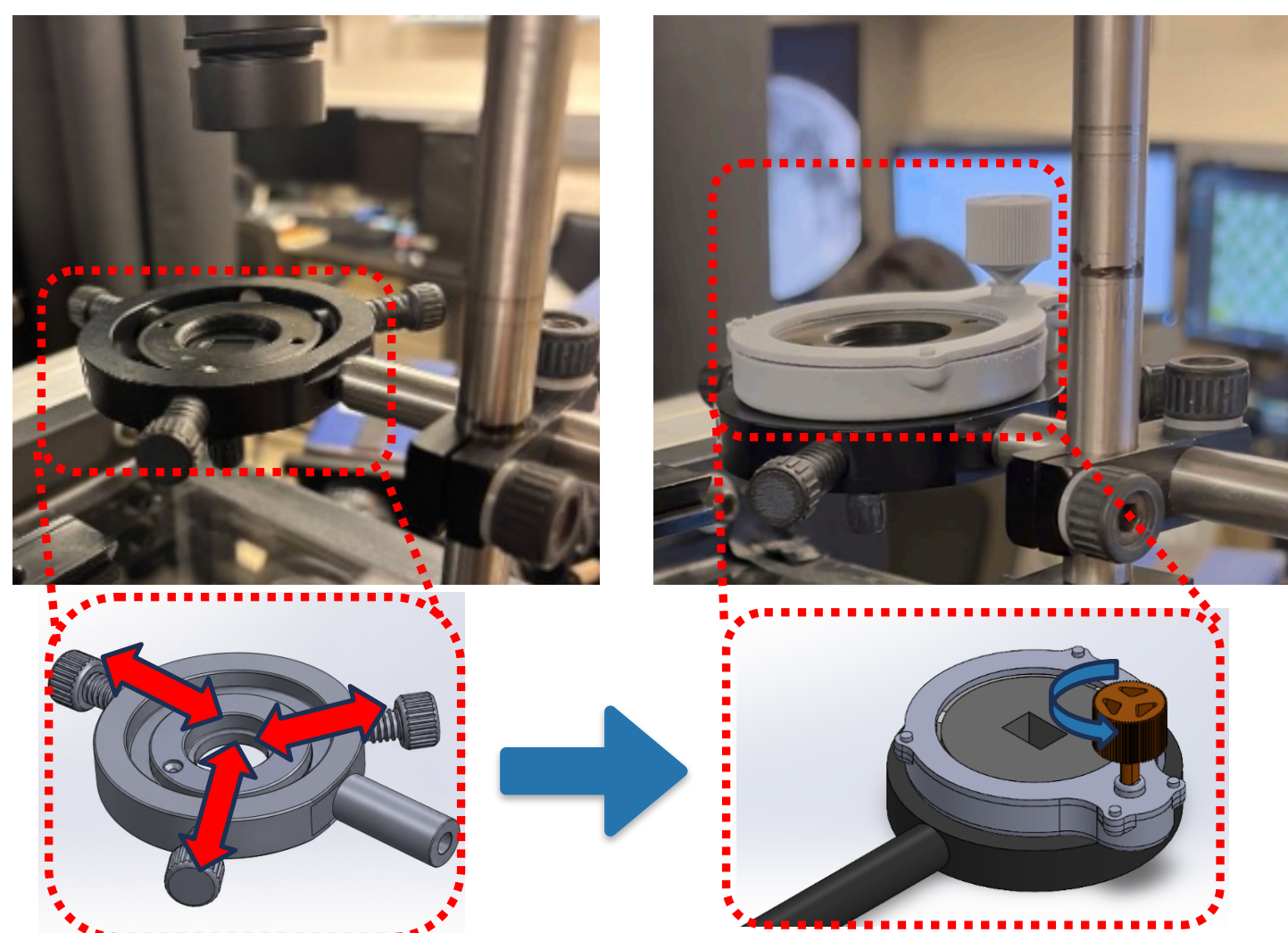


Figure 7: The old design with two degrees of freedom (left); The new design has only one degree of freedom, with 1:4 gearbox facilitates small rotation.

Machine-Learning Flow Analysis

Classifier Performance

The classifier reached 98.3% accuracy across all experimental J from 1 to 30; It was trained using labelled vortex data from J = 1,2,5,8,11,16,20,30; Accuracy represents correct classification of labeled vortex and noise candidates in held-out validation data.

Validation Confusion Matrix for Model 5

	Noise	Real
Noise	4594	49
Real	59	1646

Figure 8: The confusion matrix of the trained model that reaches 98.3% accuracy.

ML Phase Estimation Validation Across J

ML-derived phase was validated against POD-derived phase for each snapshot. Agreement is highest at intermediate J and decreases toward the limits of the tested range.

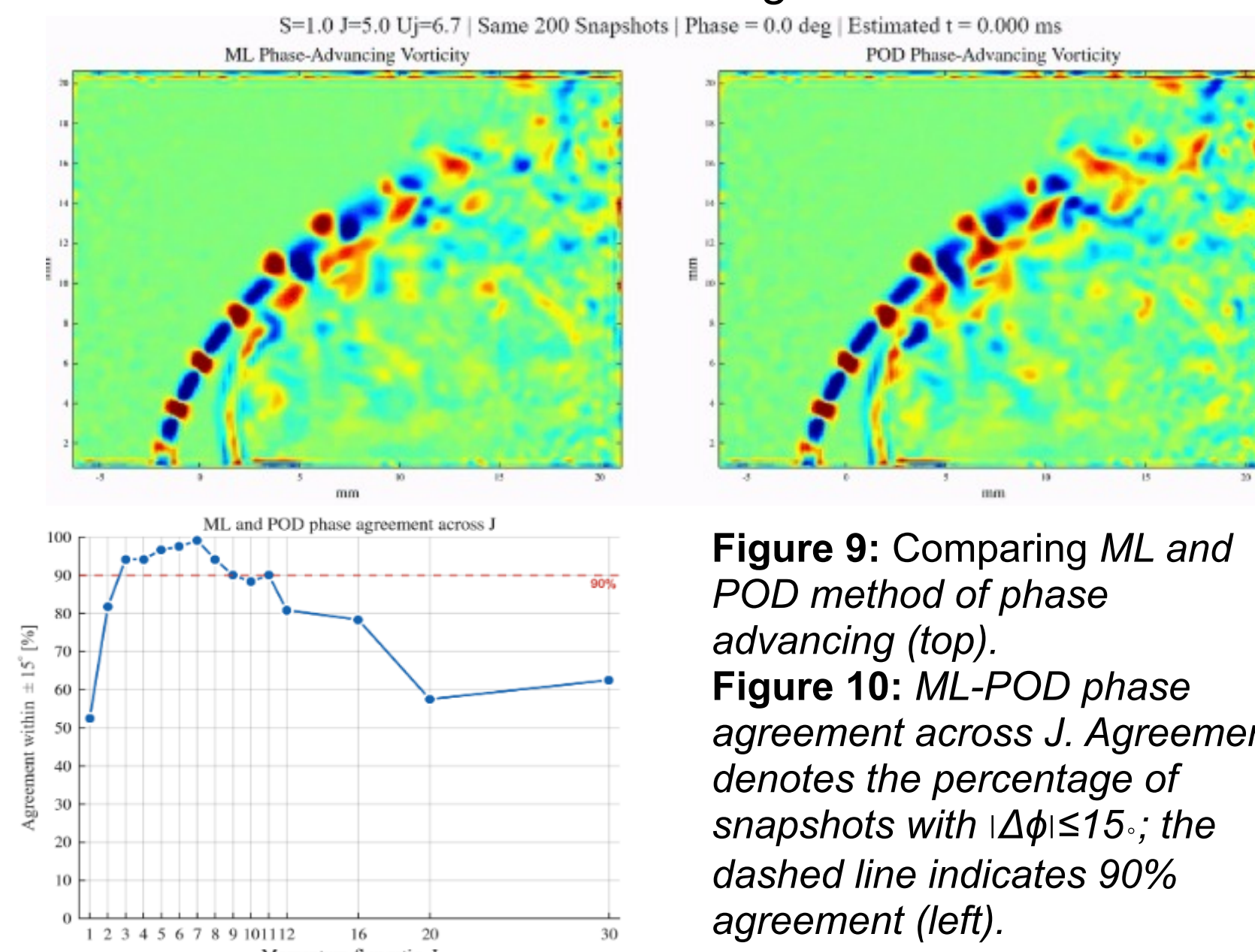


Figure 9: Comparing ML and POD method of phase advancing (top).
Figure 10: ML-POD phase agreement across J. Agreement denotes the percentage of snapshots with $|\Delta\phi| \leq 15^\circ$; the dashed line indicates 90% agreement (left).

Conclusion & Future Direction

The redesigned experimental hardware provides simpler and more repeatable control of diagnostic alignment.

The ML workflow identifies coherent USL vortices and uses their spatial distribution to estimate the phase of sparsely sampled PIV snapshots.

Across multiple J, ML-derived phases show $>90\%$ agreement with POD over convective instability J regions.

Performance decreases at very low and high J, where too few well-defined vortex blobs are present to reliably determine phase, defining the current operating range of the method.

The future direction of this research would be serving as another method to cross-validate POD method, to help the development of reduced order JICF model.

Reference & Acknowledgements

- [1] Megerian et al., JFM, 2007
- [2] Getsinger et al., JFM, 2014
- [3] Gevorgyan et al., JFM, 2016
- [4] Shoji et al., JFM, 2020
- [5] Liu, Y. H., Ph.D. prospectus, 2026

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