

We present a real-world case where a state-of-the-art deep model collapses under slight input drift, uncovering a deployment pitfall. Modern deep nets often boast near-perfect performance Smith2024, Lee2023, but bridging from lab to production is non-trivial. Numerous studies discuss domain shift Ganin2016, Tsai2022, robust training Madry2018, and transfer learning Kolesnikov2020. We train a vision transformer on CIFAR-10 with standard augmentations Krizhevsky2009. In deployment, we observe a sharp drop in accuracy when the input distribution shifts slightly. We evaluate three adaptation strategies: (a) naive fine-tuning on a small unlabeled batch via pseudo-labels; (b) batch-normalization recalibration; (c) contrastive pretraining on unlabeled data.

Method	In-domain Acc	Deployment Acc	
None (baseline)	94.1	72.3	
[t] Fine-tune (pseudo)	93.5	82.0	Accuracy under color drift.
BN-recalib	94.0	83.4	
Contrastive pretrain	93.8	86.1	

Discussion We pinpointed two culprits: (i) collapsed feature-covariances in early layers, (ii) overconfident pseudo-labels. Conclusion Minor real-world shifts can still break today’s best models. Our analysis suggests practitioners should monitor model performance in the wild and consider robustness during training.