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NeurVLA: Unleashing Failure-Handling Capability of Vision-Language-Action Models via Neural-Symbolic Reasoning

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Motivation and Introduction

Two closely interconnected issues in existing VLA models:

- Coarse-grained failure correction
- Unreliable failure prevention

Key observation underlying these limitations:

- Fine grained failure correction requires ***precise analysis*** of object states from observations
- Reliable failure prevention demands ***explicit modeling and verification*** of action induced state transitions

Contribution:

- We propose **NeurVLA**, a reasoning framework that jointly addresses failure correction and prevention for VLA models by integrating ***Observation-Grounded Failure Correction*** with ***Trajectory-Modeling Failure Prevention***.
- **NeurVLA** further proposes ***Reasoning-Guided Action Learning*** to internalize the failure-handling capability derived from the above reasoning processes in VLA models.
- Extensive experiments demonstrate that **NeurVLA** consistently achieves strong performance and robust generalization across diverse embodied tasks.

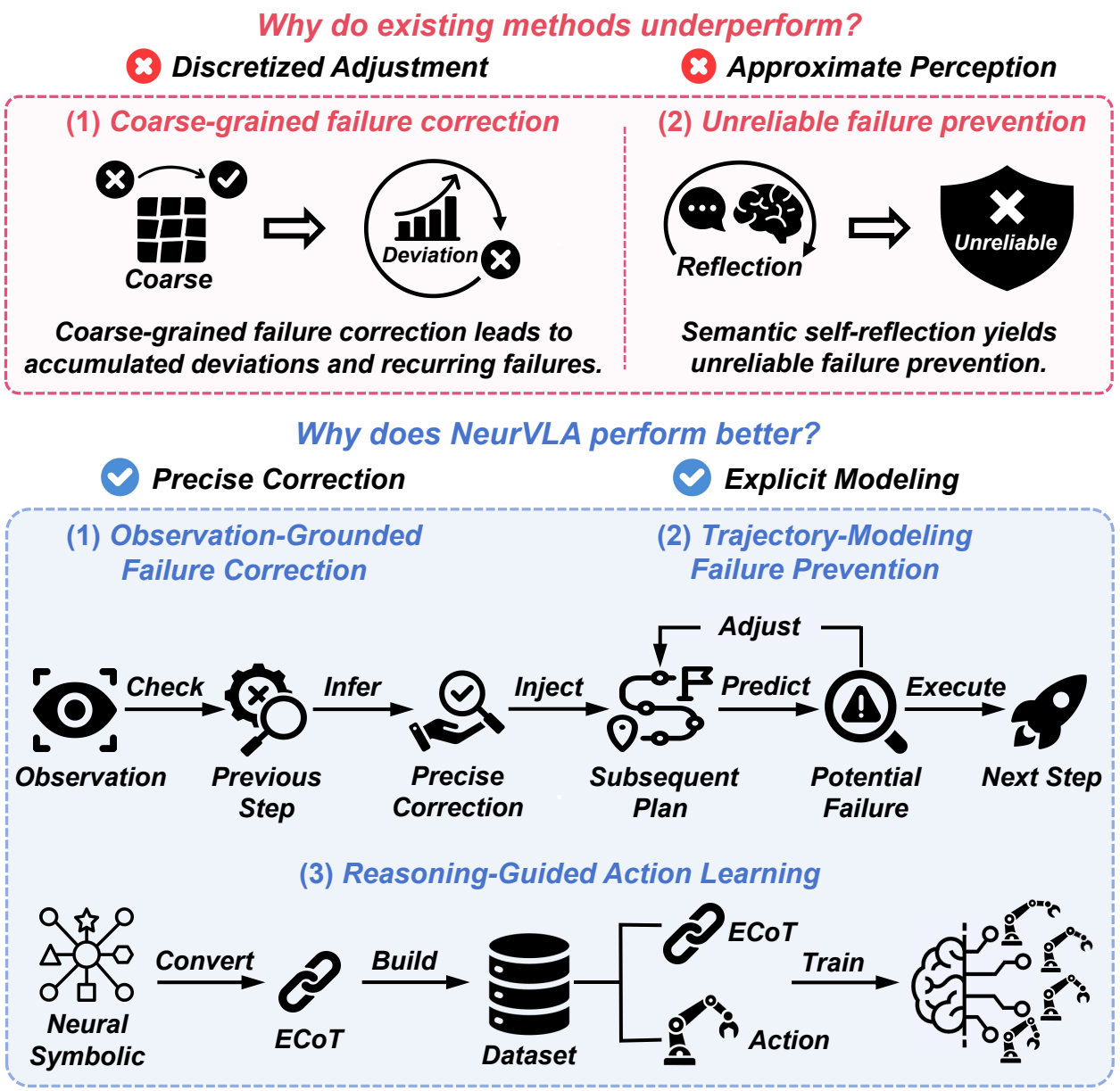

Figure 1. **NeurVLA** is a framework that overcomes core limitations of existing VLA methods, namely coarse-grained failure correction and unreliable failure prevention, and further internalizes failure-handling capability into VLA model.

Method

NeurVLA divides VLA task completion into several ***iterations***, where each ***iteration*** consists of ***generating a reasoning process*** and ***executing a semantically meaningful action***. In each ***iteration***, given the current observation *o* and the task instruction *inst*, **NeurVLA**:
(i) assesses whether the previous action has been successfully completed based on the observation, and injects fine-grained corrective steps when necessary;
(ii) analyzes the updated plan by explicitly modeling motion trajectories and potential collisions, iteratively refining the plan until safety is verified;

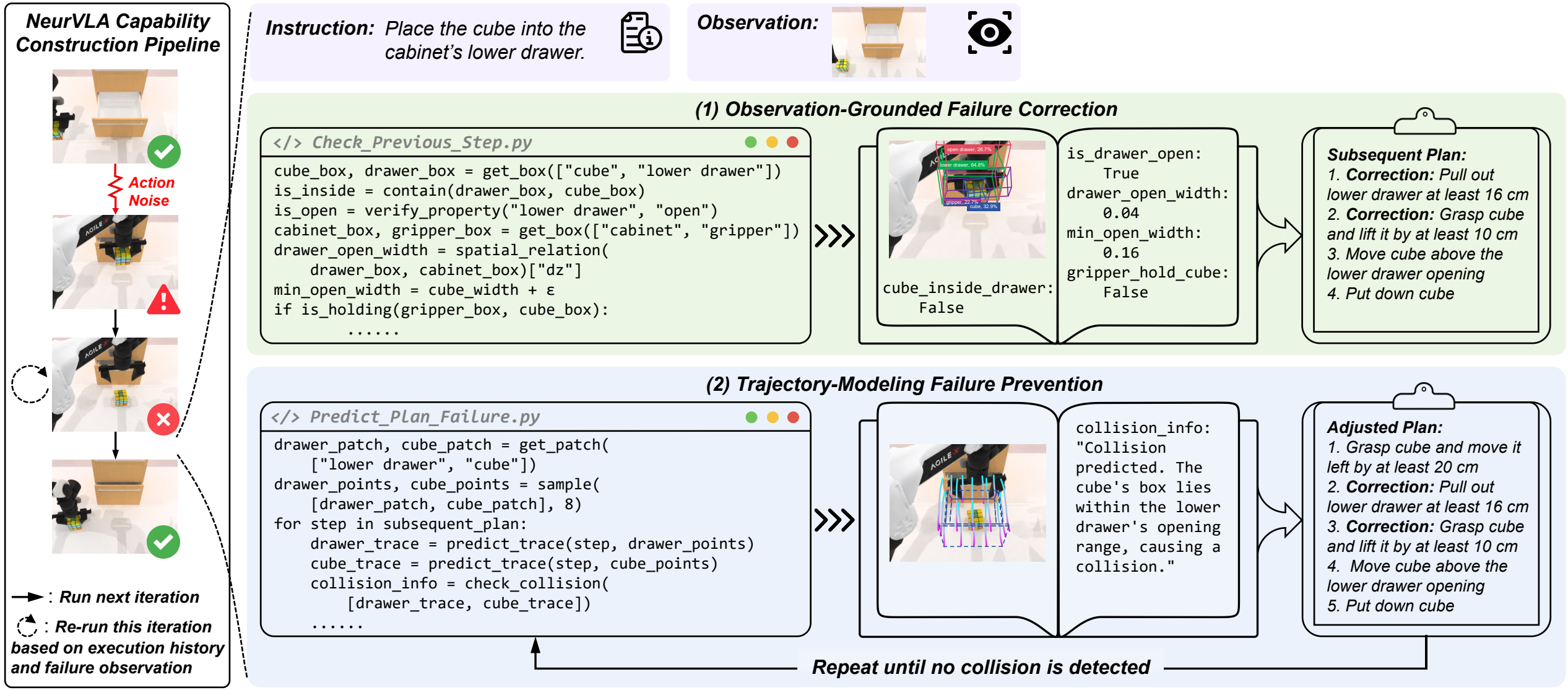

Figure 2. Overview of **NeurVLA**. **NeurVLA** jointly constructs and internalizes robust failure-handling capabilities for VLA models. It (1) programmatically checks completion of the previously executed actions from observations to enable fine-grained failure correction, (2) predicts potential failures in the subsequent plan via executable trajectory simulation for reliable failure prevention, and, after using policy code to obtain the corresponding actions, it (3) internalizes failure-handling capability by first converting the above reasoning processes into introspective ECoTs, and then performing SFT and contrastive learning on ECoT-actions.

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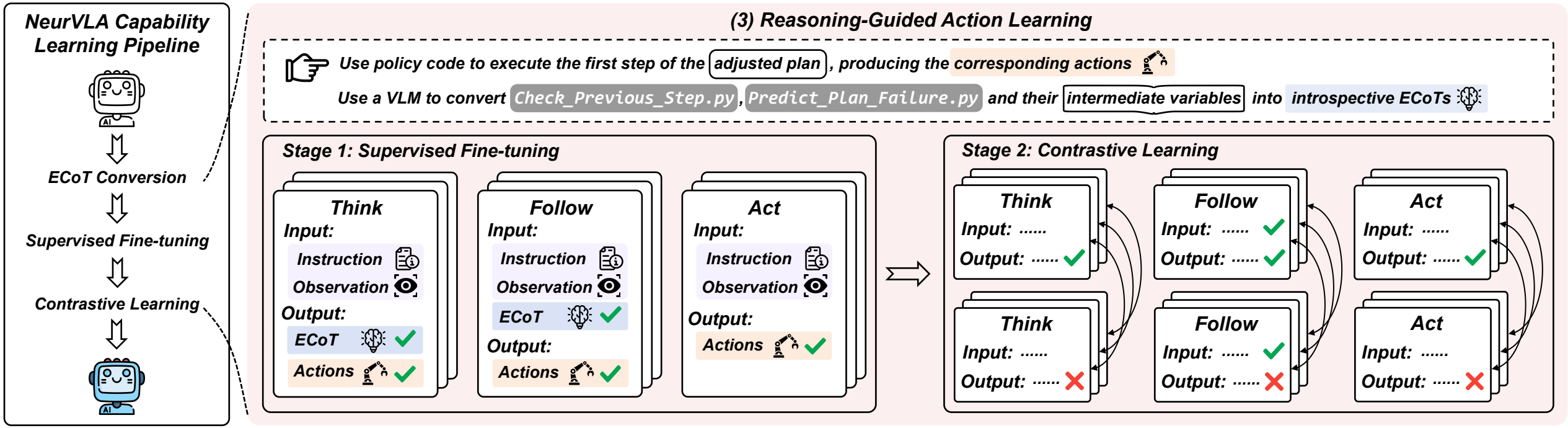
NeurVLA divides VLA task completion into several ***iterations***, where each ***iteration*** consists of ***generating a reasoning process*** and ***executing a semantically meaningful action***. In each ***iteration***, given the current observation *o* and the task instruction *inst*, **NeurVLA**: **(iii)** After translating the plan into policy code blocks to interact with the environment, it converts the above reasoning processes into ECoTs, and performs ***Reasoning-Guided Action Learning***.



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Simulation Experiments

Table 1. **Comparison of VLA models on LIBERO.**

Method	Spatial	Object	Goal	Long	Avg
Regression or classification-based VLA					
OpenVLA	84.7	88.4	79.2	53.7	76.5
SpatialVLA	88.2	89.9	78.6	55.5	78.1
UniVLA	96.5	96.8	95.6	92.0	95.2
NORA	92.2	95.4	89.4	74.6	87.9
- *CollabVLA*	93.4	96.2	92.2	81.3	90.8
- *FailSafe*	94.2	96.5	93.5	85.8	92.5
- **NeurVLA**	**97.1**	**98.3**	**96.7**	**92.2**	**96.1**
Flow-matching or diffusion-based VLA					
π_0	96.8	98.8	95.8	85.2	94.2
ThinkAct	88.3	91.4	87.1	70.9	84.4
FPC-VLA	87.0	92.0	86.2	82.2	86.9
InstructVLA	92.4	95.6	92.0	76.6	89.2
- *CollabVLA*	93.6	96.4	93.2	80.7	91.0
- *FailSafe*	93.9	96.5	93.6	81.1	91.3
- **NeurVLA**	**97.5**	**99.2**	**97.3**	**92.4**	**96.6**

Table 2. **Performance comparison on SimplerEnv.**

Method	Google Robot								WidowX Robot					Avg
	Pick Coke Can		Move Near		Open/Close Drawer		Avg		Put Spoon	Put Carrot	Stack Blocks	Put Eggplant	Avg	
	VM	VA	VM	VA	VM	VA	VM	VA	Success					
Regression or classification-based VLA														
OpenVLA	16.3	54.5	46.2	47.7	35.6	17.7	32.7	40.0	0.0	0.0	0.0	4.1	1.0	24.6
CoT-VLA	60.3	71.8	61.5	57.2	48.0	35.2	56.6	54.7	17.9	18.2	15.1	42.6	23.5	44.9
SpatialVLA	81.0	89.5	69.6	71.7	59.3	36.2	70.0	65.8	20.8	20.8	25.0	70.8	34.4	56.7
NORA	81.6	56.2	69.0	77.9	30.1	24.5	60.2	52.9	71.3	40.9	35.7	83.8	57.9	57.0
- *CollabVLA*	85.8	69.1	77.8	**86.1**	42.8	32.4	68.8	62.5	76.5	49.2	46.1	85.9	64.4	65.2
- **NeurVLA**	**90.6**	**89.8**	**82.1**	84.5	**63.4**	**41.7**	**78.7**	**72.0**	**82.7**	**56.3**	**52.8**	**89.9**	**70.4**	**73.7**
Flow-matching or diffusion-based VLA														
π_0	72.7	75.2	65.3	63.7	38.3	25.6	58.8	54.8	29.1	0.0	16.7	62.5	27.1	46.9
ThinkAct	92.0	84.0	72.4	63.8	50.0	47.6	71.5	65.1	58.3	37.5	8.7	70.8	43.8	60.1
FPC-VLA	95.3	91.3	93.8	86.7	**76.4**	30.7	88.5	69.6	79.2	58.3	45.8	75.0	64.6	74.2
InstructVLA	79.6	92.3	68.3	71.9	52.3	61.7	66.7	75.3	47.1	40.4	20.6	71.5	44.9	62.3
- *CollabVLA*	86.1	93.6	80.4	82.7	63.2	65.3	76.6	80.5	62.2	49.7	31.9	76.3	55.0	70.7
- **NeurVLA**	**96.5**	**98.2**	**94.8**	**95.1**	74.9	**76.6**	**88.7**	**90.0**	**83.8**	**63.5**	**52.8**	**91.2**	**72.8**	**83.8**

Table 3. **Evaluation on the CALVIN ABC→D benchmark.**

Method	Tasks completed in a row (%) ↑					Avg Len.
	1	2	3	4	5	
Regression or classification-based VLA						
OpenVLA	91.3	77.8	62.0	52.1	43.5	3.27
UniVLA	95.5	85.8	75.4	66.9	56.5	3.80
NORA	93.9	82.7	70.2	61.4	51.4	3.60
- *FailSafe*	95.6	87.1	78.3	72.5	64.4	3.98
- **NeurVLA**	**96.4**	**89.0**	**82.1**	**74.8**	**66.3**	**4.09**
Flow-matching or diffusion-based VLA						
π_0	93.8	85.0	76.7	68.1	59.9	3.84
UniCoD	97.3	89.5	82.3	75.2	67.0	4.11
InstructVLA	93.1	83.8	72.6	63.6	55.4	3.69
- *FailSafe*	95.4	87.9	77.8	70.9	63.8	3.96
- **NeurVLA**	**97.9**	**90.3**	**83.4**	**75.8**	**69.6**	**4.17**

☞ **NeurVLA** consistently improves task success rates across multiple robotic manipulation benchmarks, demonstrating strong generalization across diverse tasks, environments, and VLA architectures.

Real-world Experiments

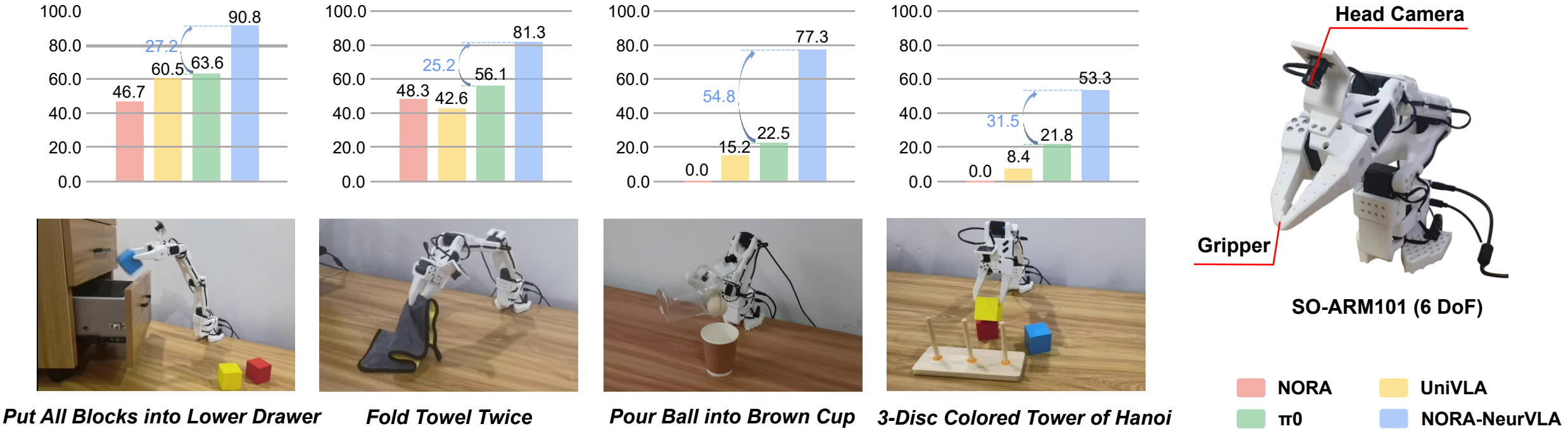
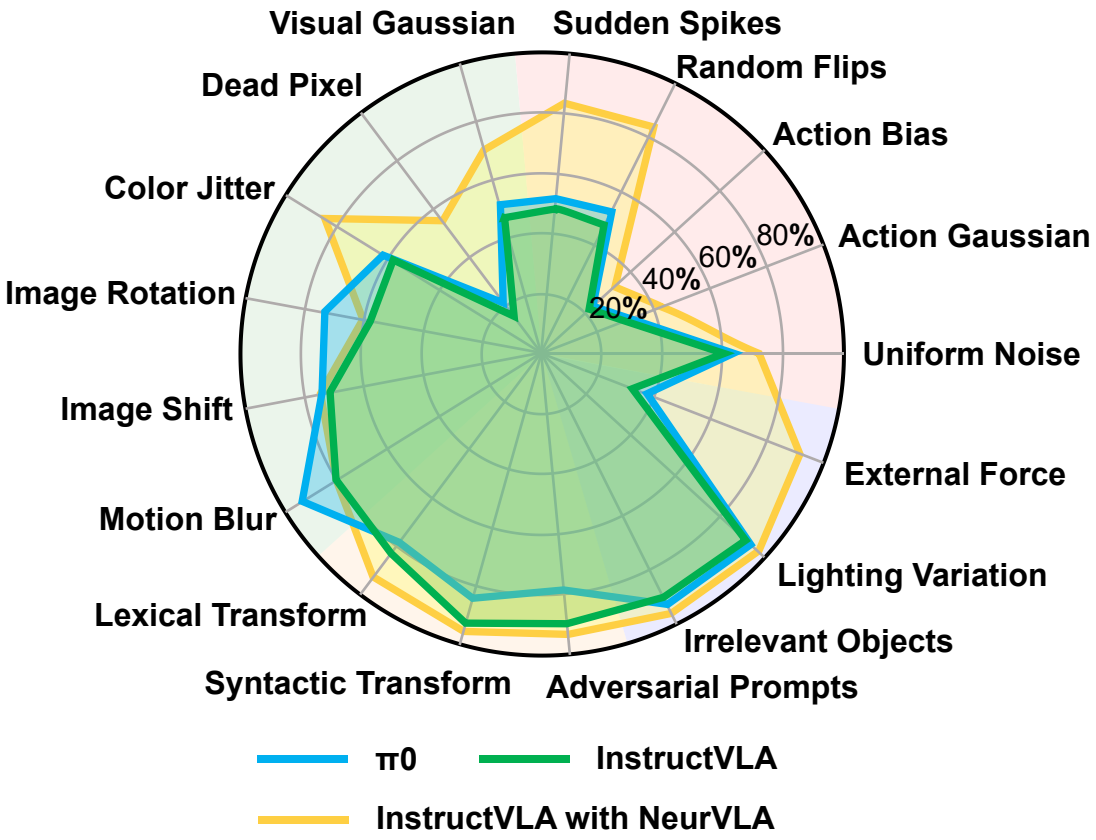


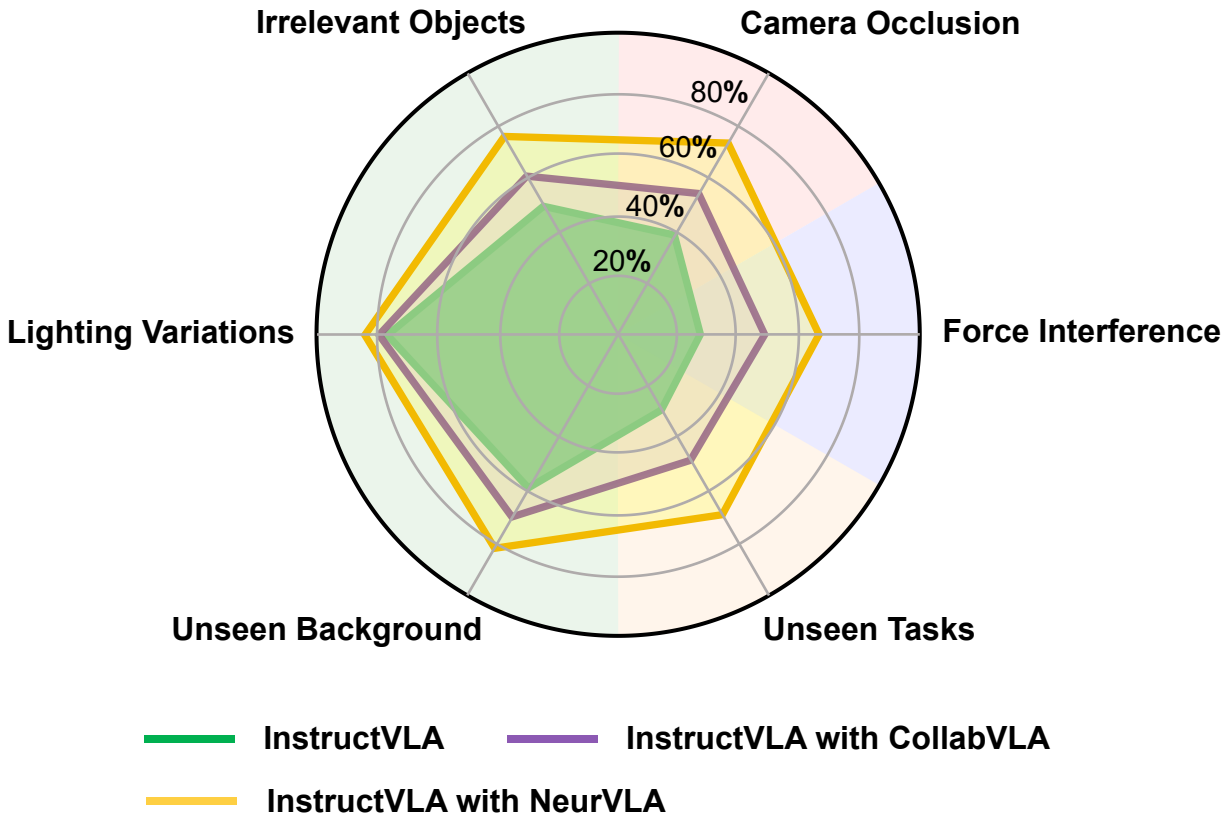
Figure 3. Comparison of NORA, UniVLA, π0, and NORA with **NeurVLA** on four real-world tasks.

NeurVLA can effectively handle complex daily manipulation tasks that inherently require long-horizon reasoning, fine-grained control, and failure-handling capabilities.

Robustness Experiments



(a) Performance under various simulated perturbations.



(b) Performance under various real-world perturbations.

Figure 4. Robustness of **NeurVLA** across different perturbations in both simulated and real-world environments.

NeurVLA maintains high success rates under action disturbances, environmental changes, visual noise, and external interference, indicating more reliable deployment stability.

Thanks!