

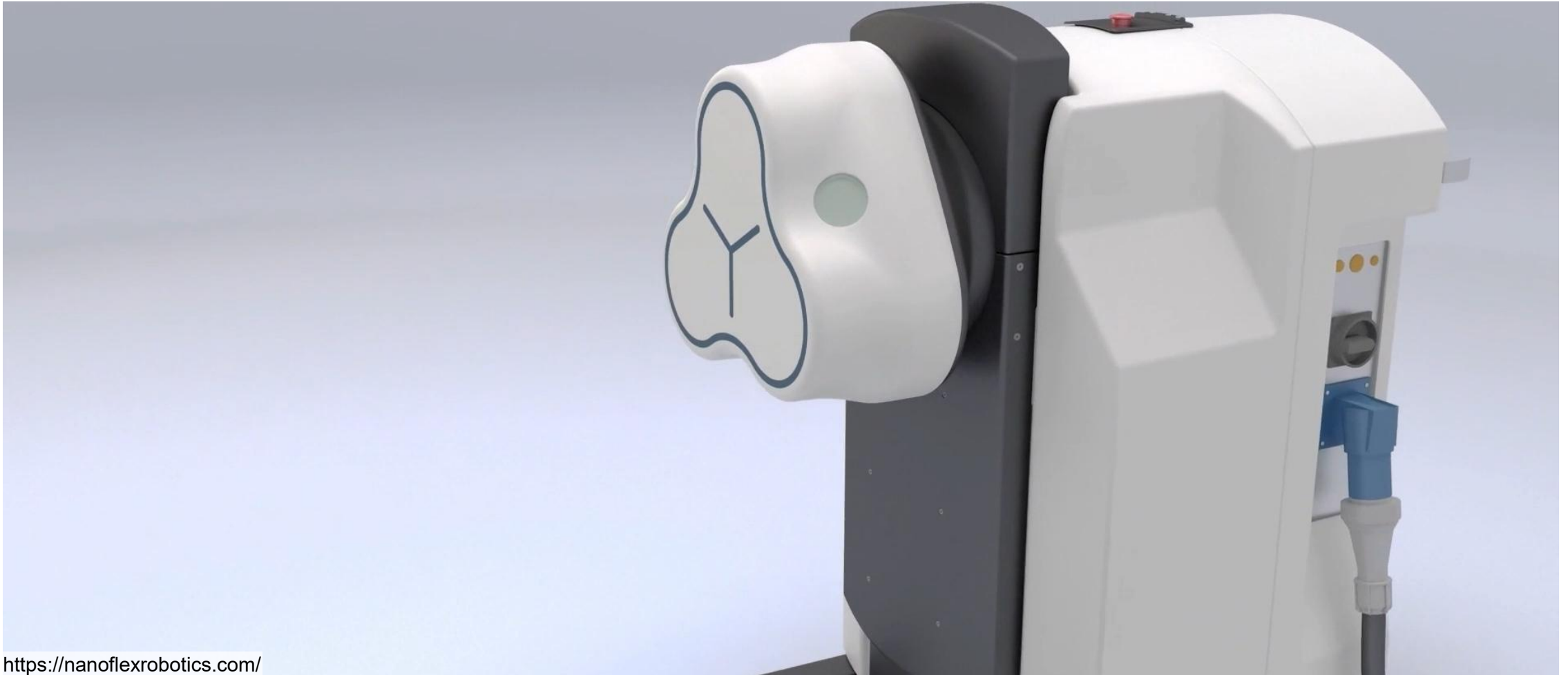
# A Physics-Informed Neural Network for the Calibration of Electromagnetic Navigation Systems

P. Ernst<sup>1</sup>, S. Gervasoni<sup>1,2</sup>, D. Sivakumaran<sup>1,2</sup>, E. Masina<sup>1</sup>, D. Sargent<sup>1,2</sup>, B. J. Nelson<sup>2</sup>, Q. Boehler<sup>2</sup>

<sup>1</sup>MagnebotiX AG, Zurich Switzerland

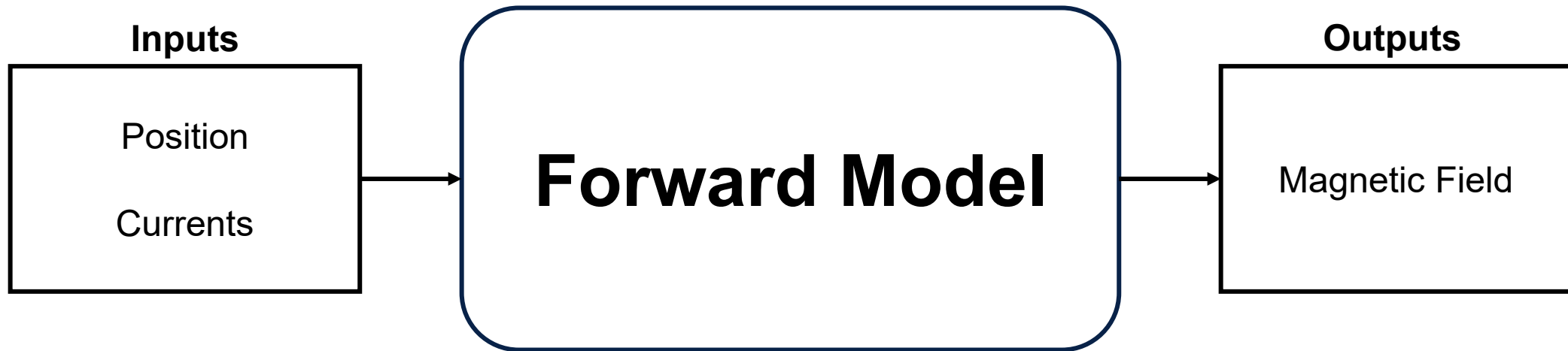
<sup>2</sup>ETH Zurich, Multi-Scale Robotics Lab, Zurich Switzerland

# Electromagnetic Navigation Systems

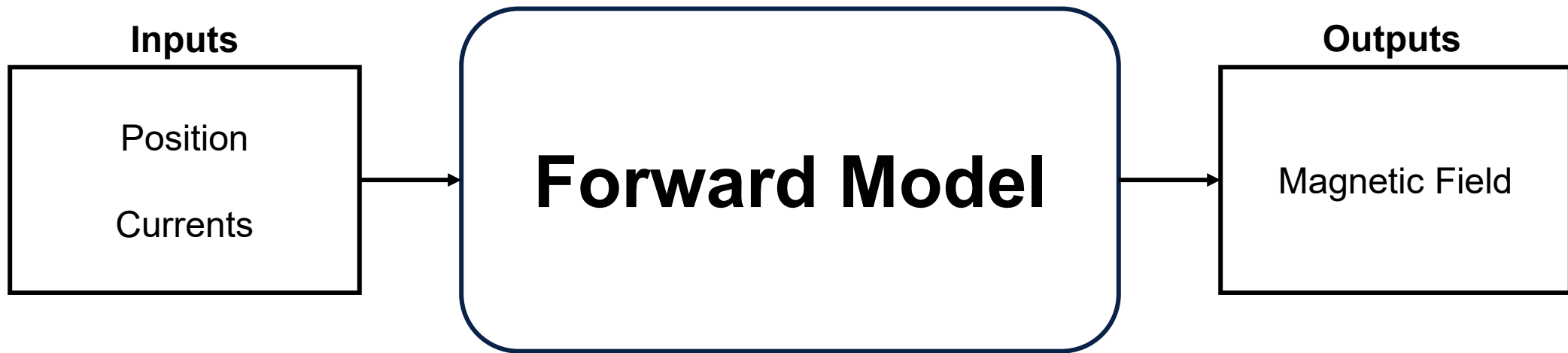


- Used to navigate Microrobots & Surgical Tools
- Precise Torque & Force Control requires Field and Gradient models

# Calibration

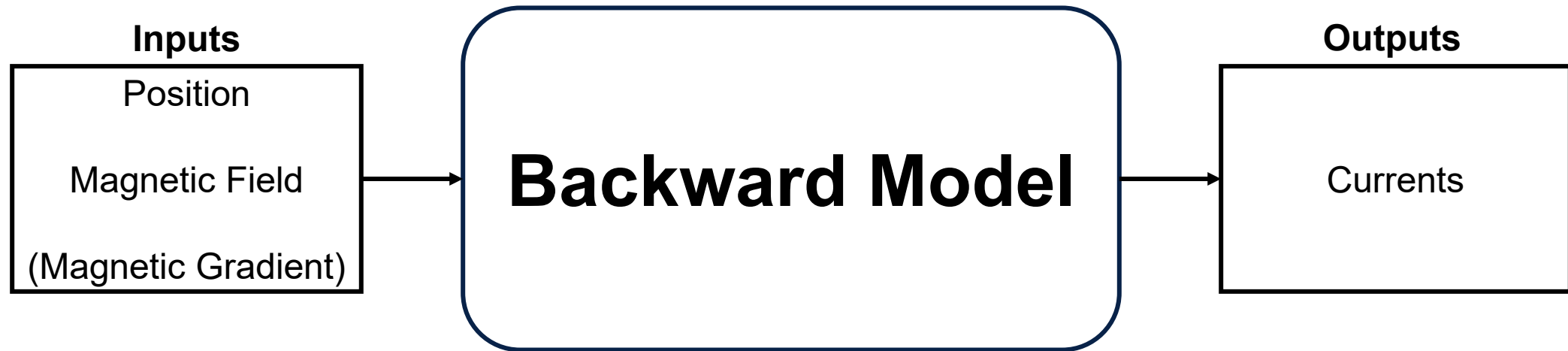


# Calibration

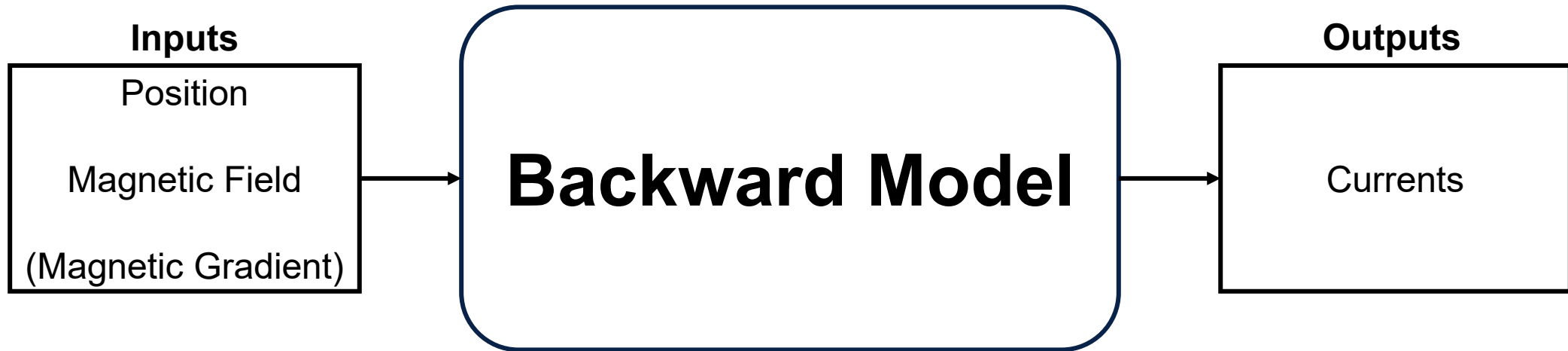


- **Additional Output:**  
Analytical derivation of magnetic gradient
- **Dataset:**  
Forward Model is fitted to a system with dataset

# Calibration



# Calibration



- **Physics Consistency:**  
Inverse of the fitted Forward Model
- **Control:**  
Can be used for control tasks

# Existing Methods

## Classical Methods

Multipole Electromagnet Model (MPEM) <sup>1</sup>

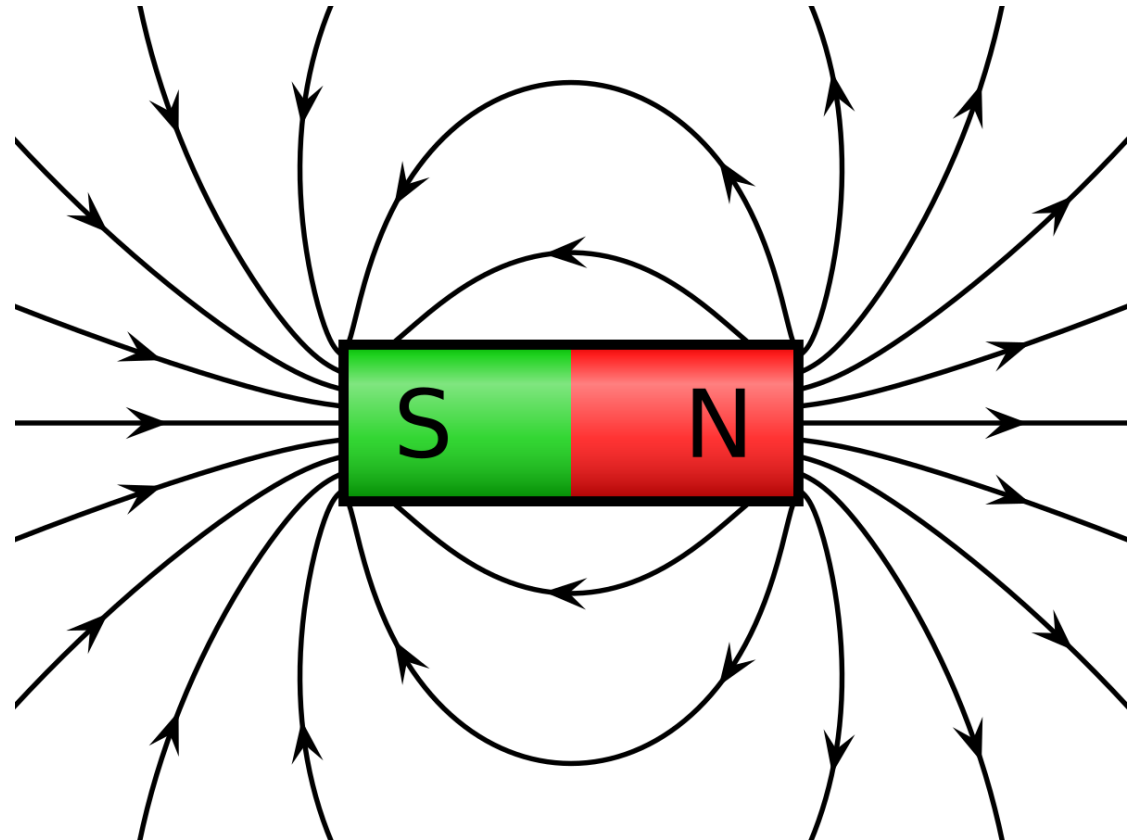


Fails under Magnetic Saturation



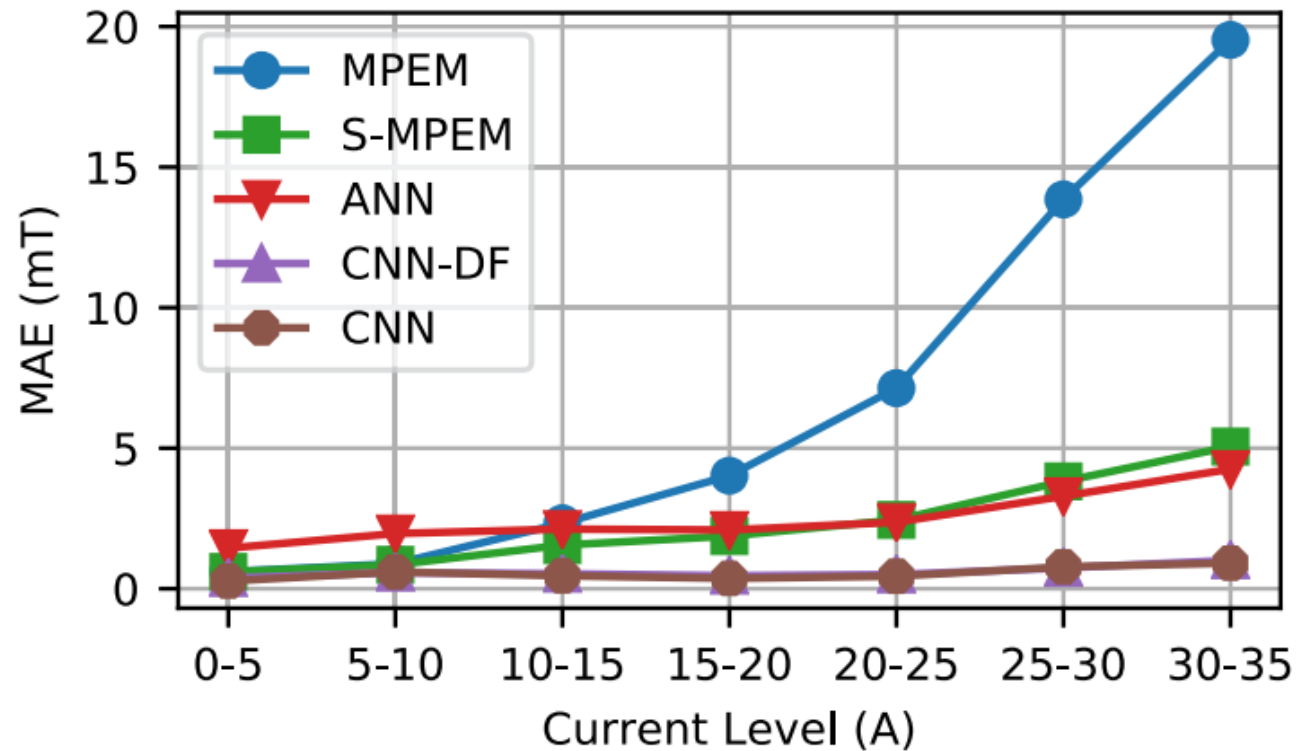
Guaranteed Maxwell consistency

$$\nabla \cdot \mathbf{B} = 0 \text{ and } \nabla \times \mathbf{B} = 0$$



<sup>1</sup> Petruska, Andrew J., et al. "Model-based calibration for magnetic manipulation." IEEE Transactions on Magnetics 53.7 (2017): 1-6.

# Existing Methods



## Machine Learning Methods

Artificial Neural Network (ANN)<sup>2</sup>

Convolutional Neural Network (CNN)<sup>2</sup>



Models Nonlinearity



Violates Maxwell Equations

<sup>2</sup>Charreyron, Samuel L., et al. "Modeling electromagnetic navigation systems." IEEE Transactions on Robotics 37.4 (2021): 1009-1021.



# Existing Methods

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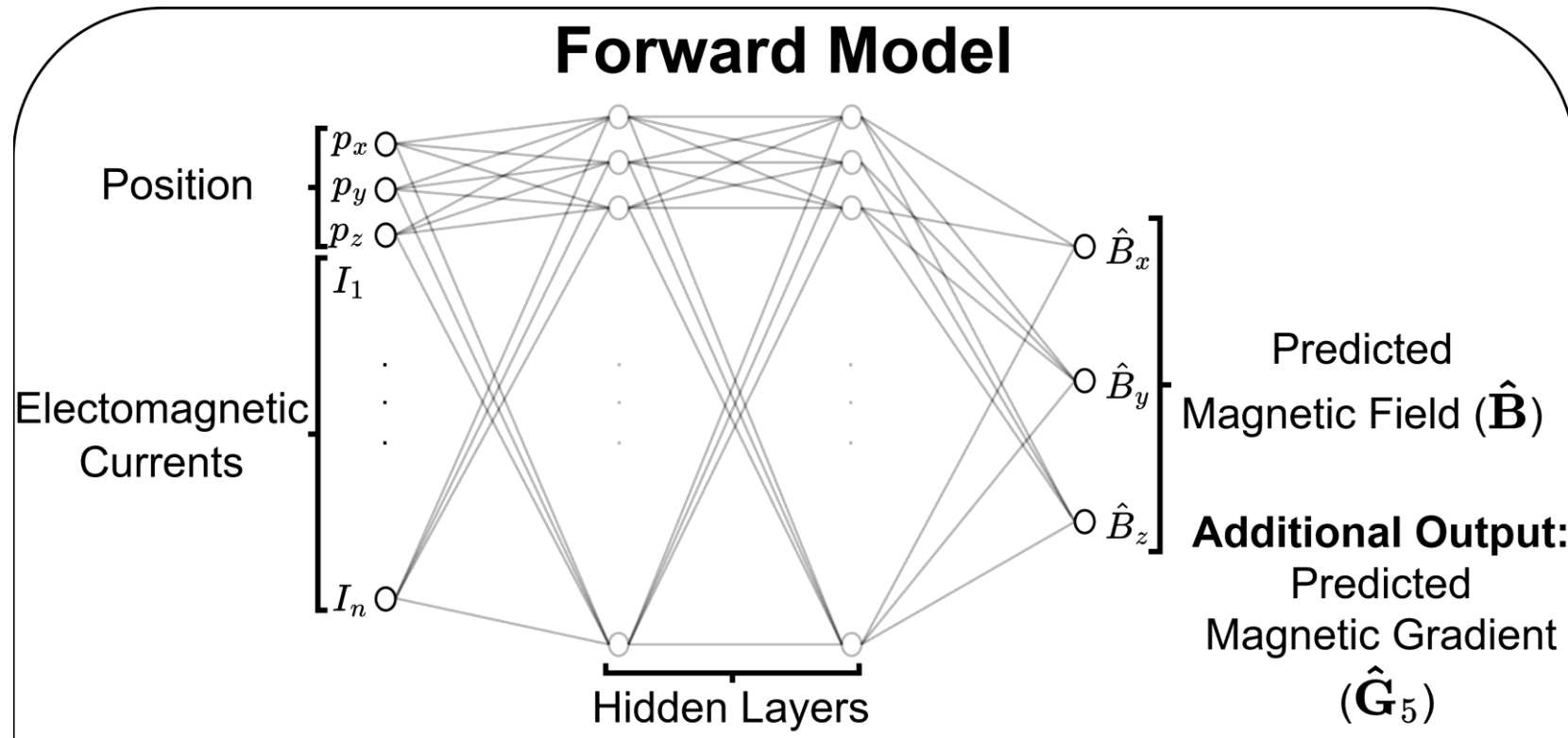


Violates Maxwell Equations

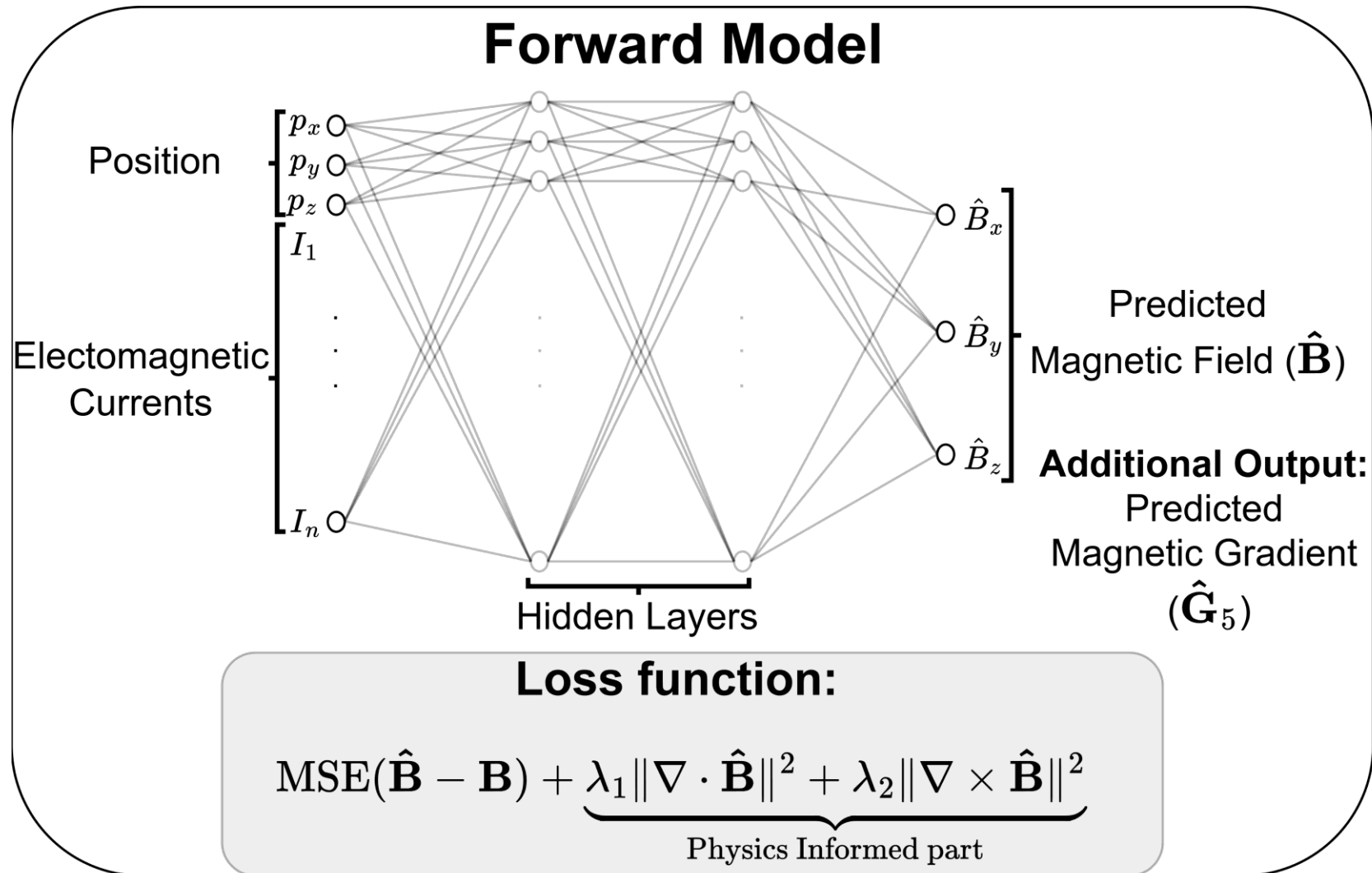
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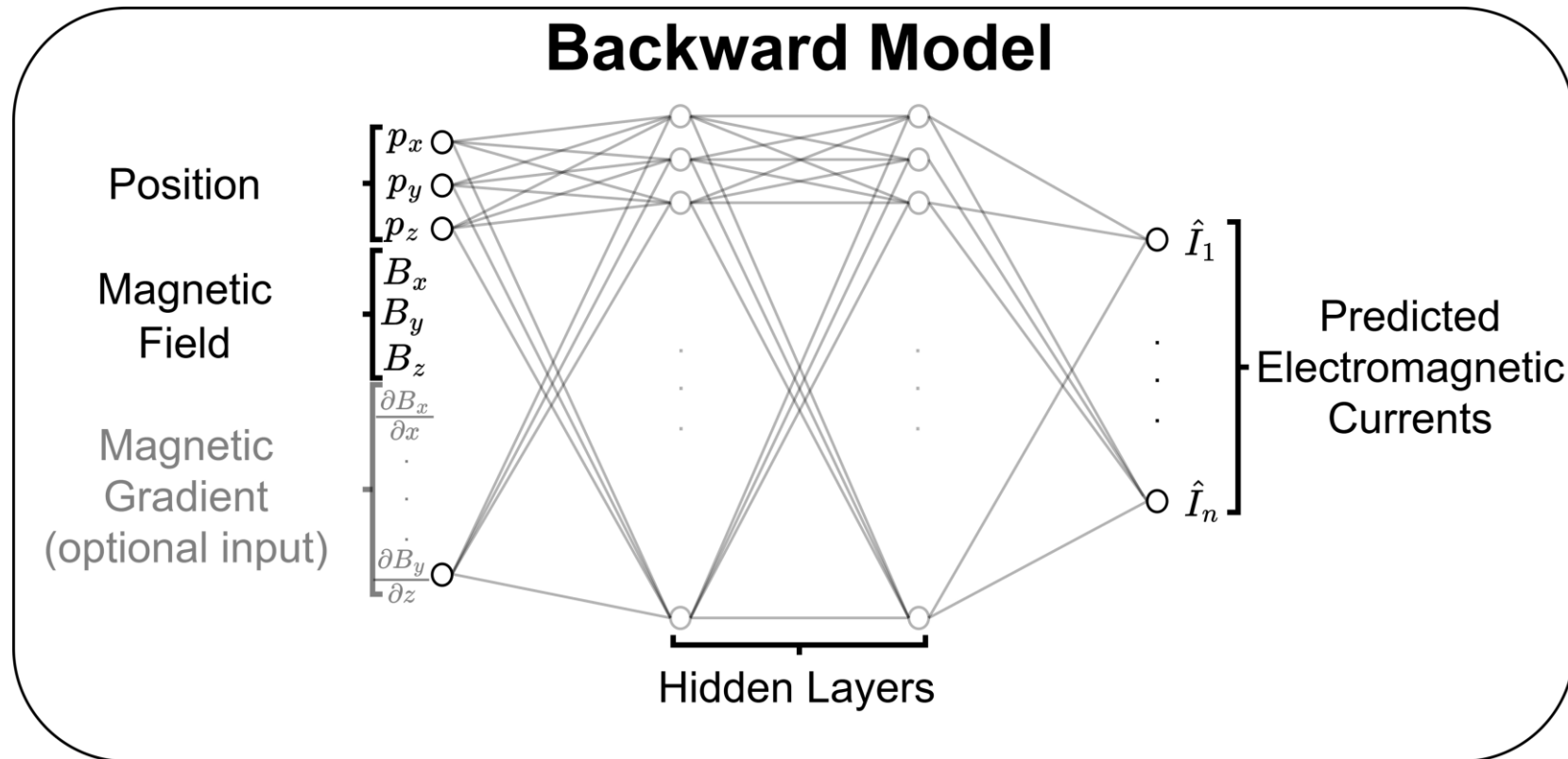
# Approach – Forward Model



# Approach – Forward Model



# Approach – Backward Model



**Without** Magnetic Gradient:

**With** Magnetic Gradient:

**Unsupervised Learning**

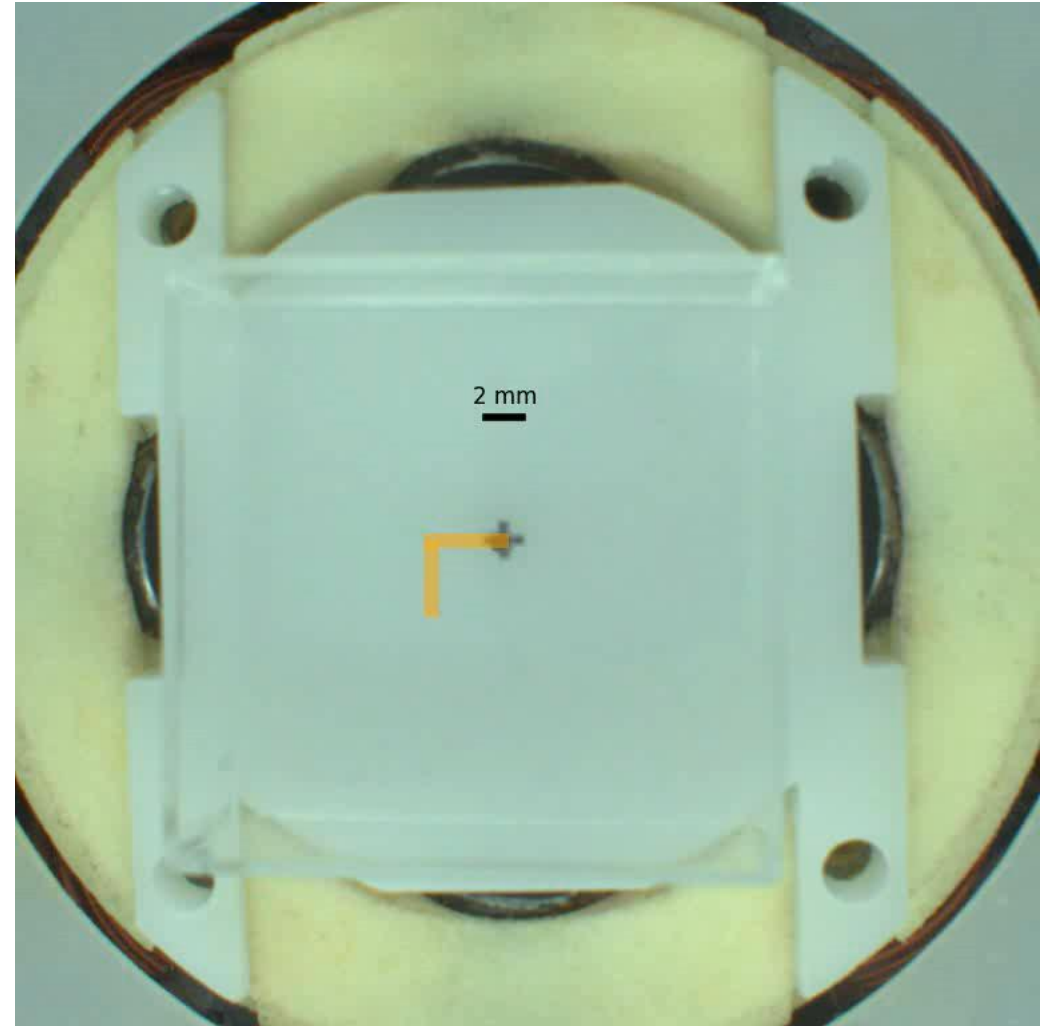
**Supervised Learning**

# Results – Open-loop Control

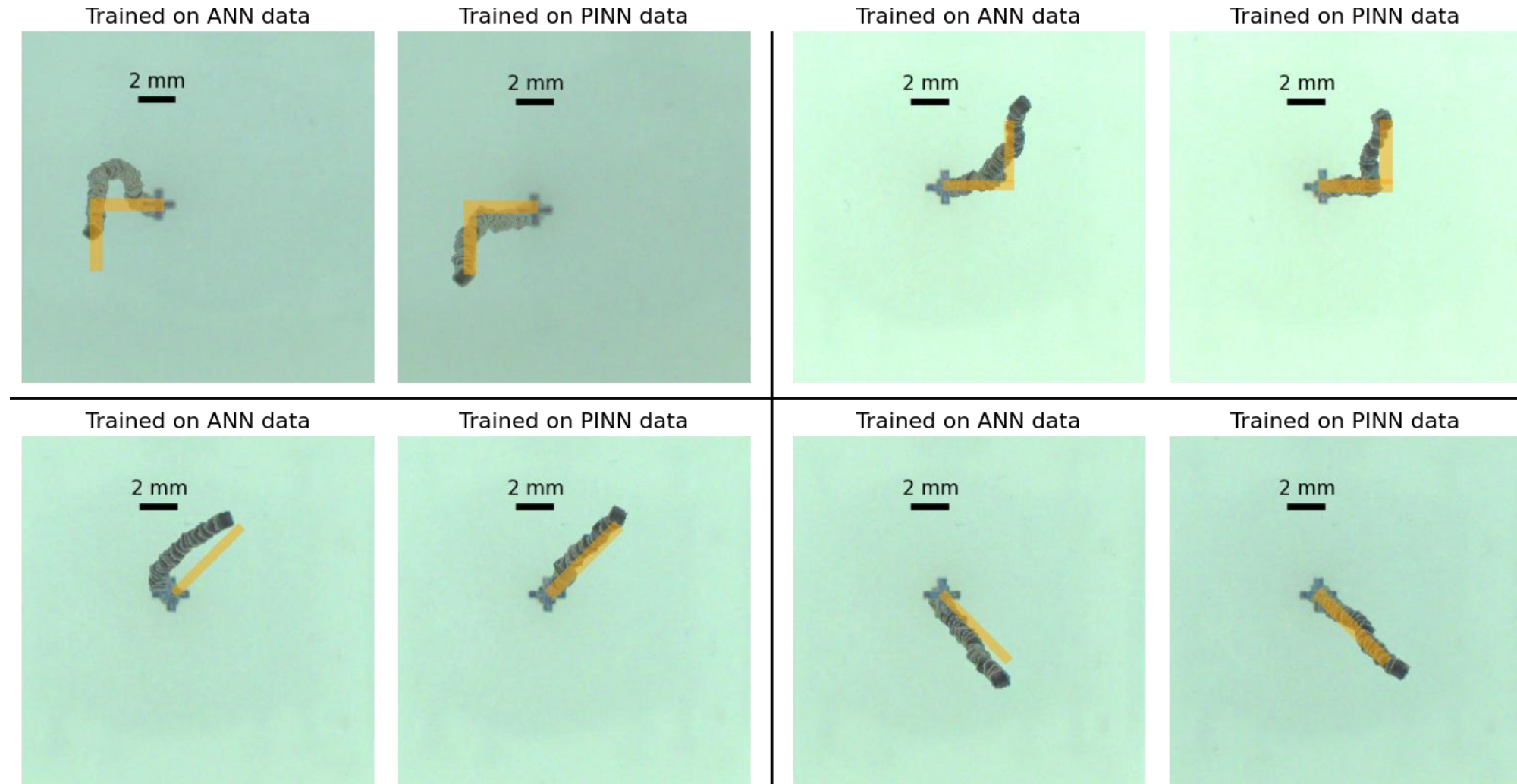
Trained on ANN Data



Trained on PINN Data



# Results – Open-loop Control



# Implications

## Balance:

- PINN balances accuracy & physics consistency

## Inverse Solution:

- PINN leads to better inverse solution
- Inverse solution improves open-loop control

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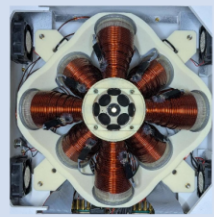
### Introduction

**Electromagnetic Navigation Systems** enable precise control of microrobots and magnetic tools in biomedicine.

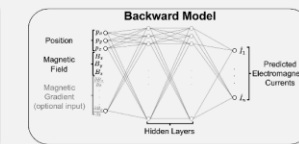
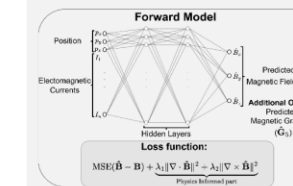
- Accurate field and gradient models** are critical for force and torque control.
- Conventional linear models** (e.g. Multipole Electromagnet Model) respect physics but do not capture saturation.
- Data-driven models** (e.g. ANN, CNN) capture nonlinearities but violate Maxwell's equations, impeding accurate estimation of magnetic gradients.

**We introduce** a Physics-Informed Neural Network (PINN) that

- Embeds Maxwell's constraints,
- Predicts fields & gradients consistently,
- Enables reliable inverse models,
- Improves open-loop control performance.



### Methods



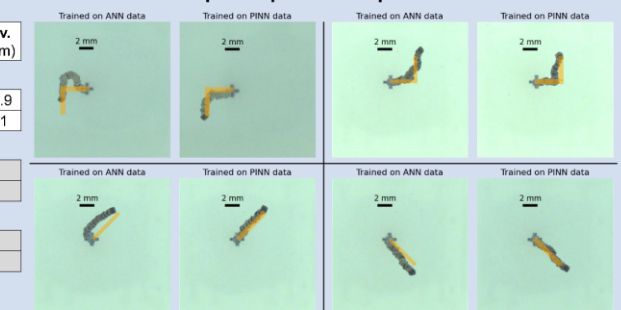
- Forward Model (PINN):** promotes  $\nabla \cdot \mathbf{B} = 0$  and  $\nabla \times \mathbf{B} = 0$ .
- Backward Models:** w/o  $\nabla \mathbf{B}$ : efficient current sets (low norm), w/  $\nabla \mathbf{B}$ : precise force control.
- Consistency:** backward models use the trained PINN, ensuring physics compliance.

### Results

#### Prediction Accuracies

Model	RMSE	R <sup>2</sup>	Curl (T/m)	Div. (T/m)
<b>Forward Model</b>				
ANN	1.88	0.993	20.9	33.9
PINN	3.24	0.981	12.5	6.1
<b>Backward Model w/o <math>\nabla \mathbf{B}</math></b>				
ANN	0.7	0.999		
PINN	0.6	0.999		
<b>Backward Model w/ <math>\nabla \mathbf{B}</math></b>				
ANN	0.785	0.884		
PINN	0.567	0.936		

#### Open-loop Control Experiment



### Conclusion

- PINN balances accuracy and physics consistency.
- PINN-trained backward model lead to better inverse solution.
- Introduced model leads to improved open-loop control.