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

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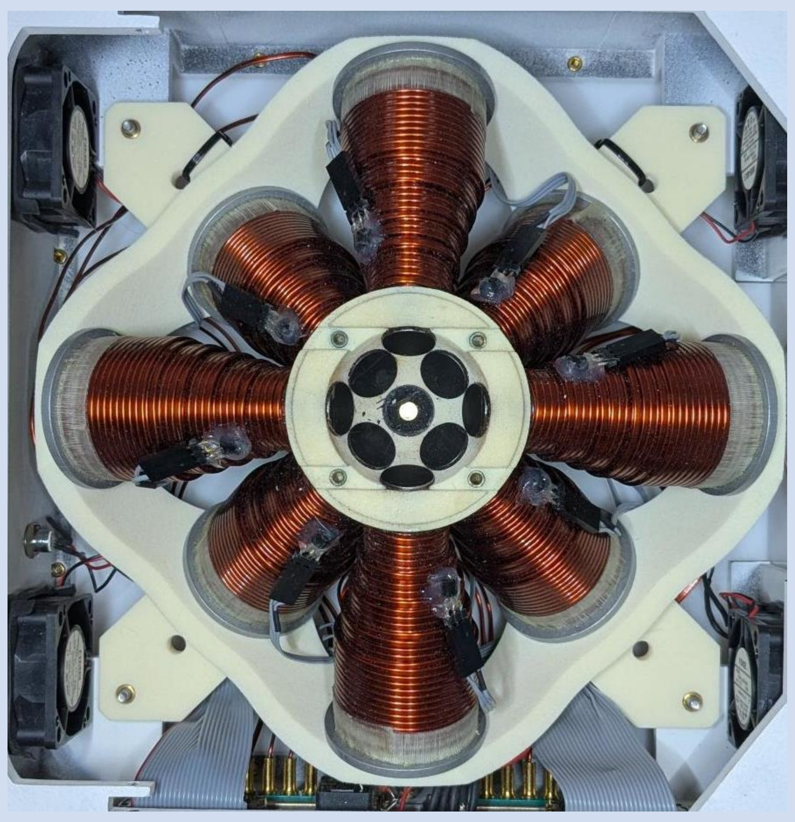
Introduction

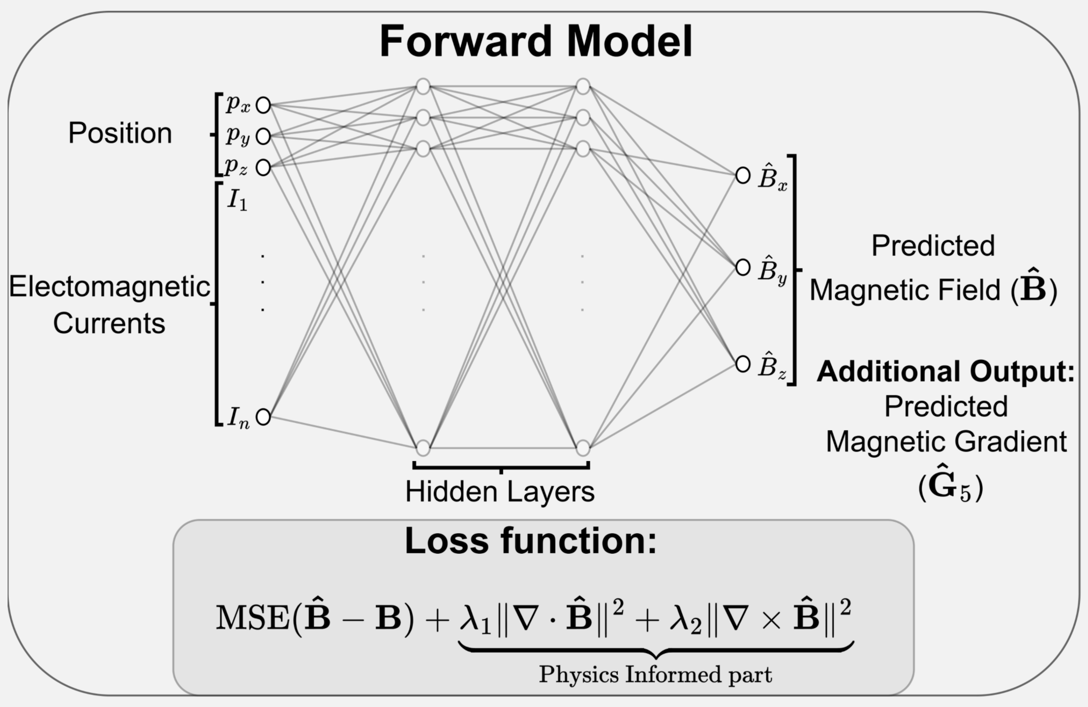
Electromagnetic Navigation Systems enable precise control of microrobots and magnetic tools in biomedicine.

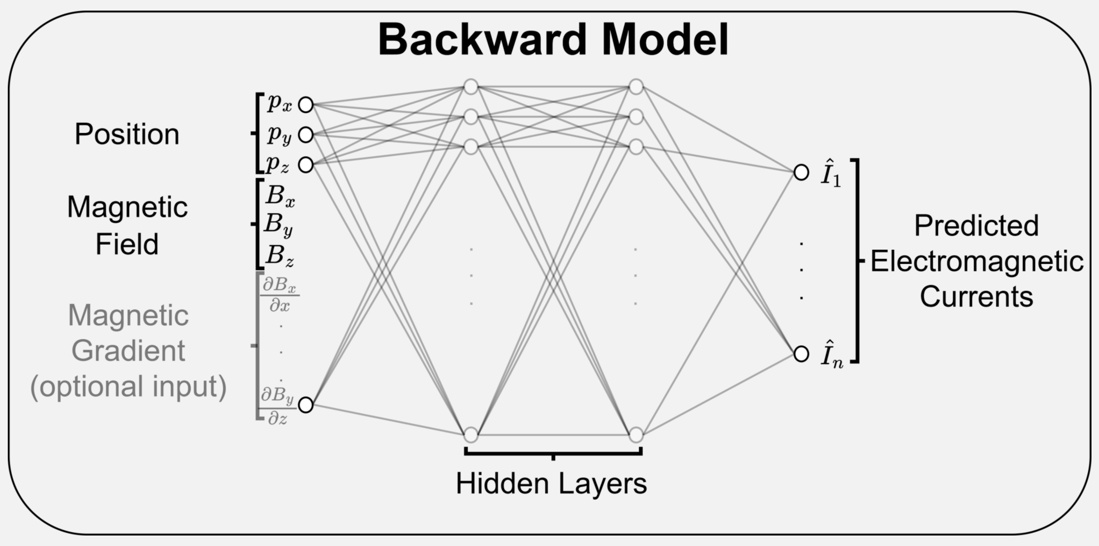
- **Accurate field and gradient models** are critical for force and torque control.
- **Conventional linear models** (e.g. Multipole Electromagnet Model) respect physics but do not capture saturation.
- **Data-driven models** (e.g. ANN, CNN) capture nonlinearities but violate Maxwell's equations, impeding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





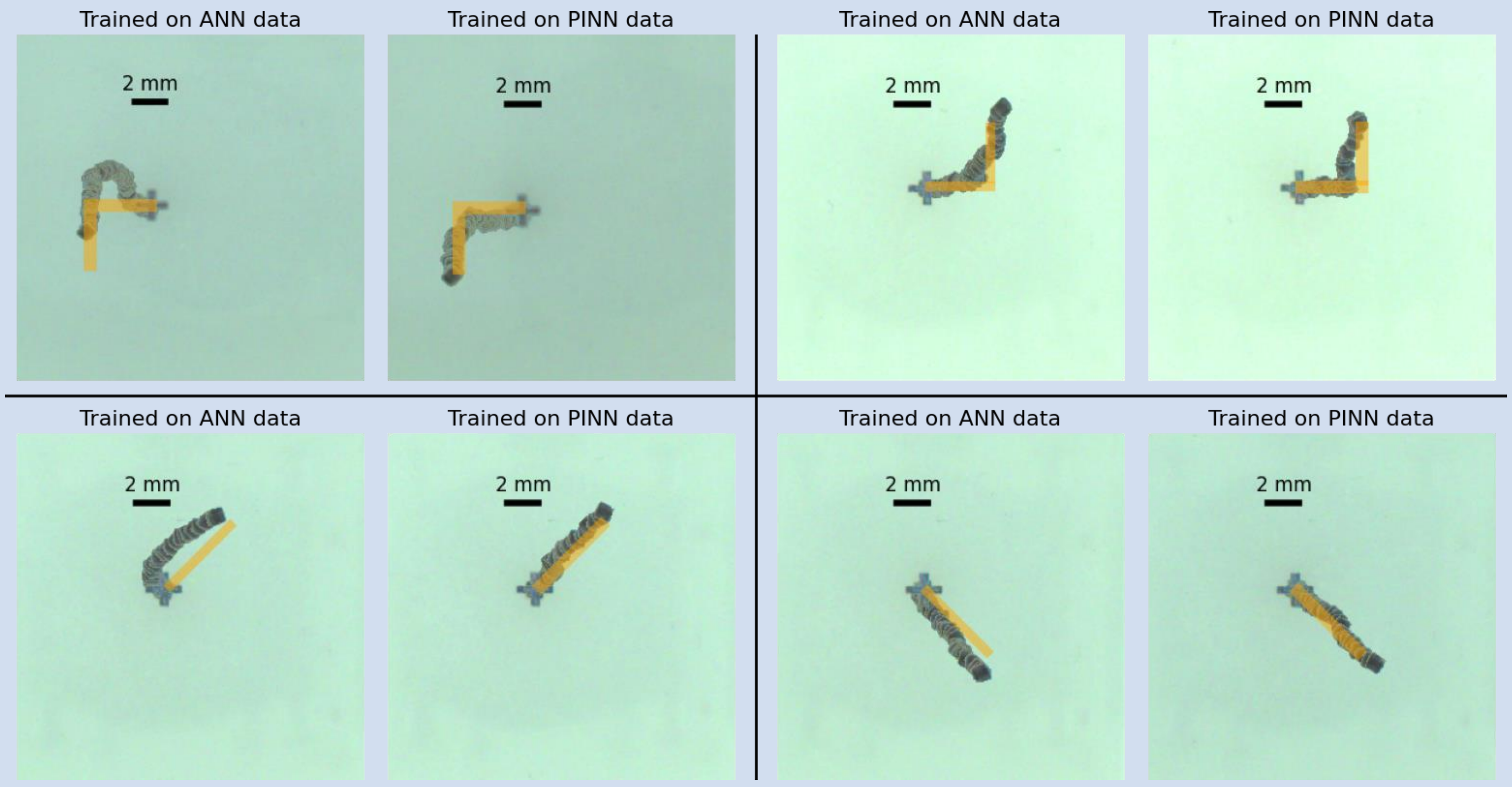
- **Forward Model (PINN):** promotes $\nabla \cdot \mathbf{B} = 0$ and $\nabla \times \mathbf{B} = \mathbf{0}$.
- **Backward Models:** w/o $\nabla\mathbf{B}$; efficient current sets (low norm), w/ $\nabla\mathbf{B}$; precise force control.
- **Consistency:** backward models use the trained PINN, ensuring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

Results

Prediction Accuracies

Model	RMSE	R^2	Curl (T/m)	Div. (T/m)
Forward Model				
ANN	1.88	0.993	20.9	33.9
PINN	3.24	0.981	12.5	6.1
Backward Model w/o $\nabla\mathbf{B}$				
ANN	0.7	0.999		
PINN	0.6	0.999		
Backward Model w/ $\nabla\mathbf{B}$				
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**.