Machine Learning for Skyrmion Dynamics: Automating Micromagnetic Simulation

Junjian Chi[1], Santhosh Sivasubramani[1], Joydeep Ghosh[1], Vihar Georgiev[2], Rishad Shafik[3] and Themis Prodromakis[1]

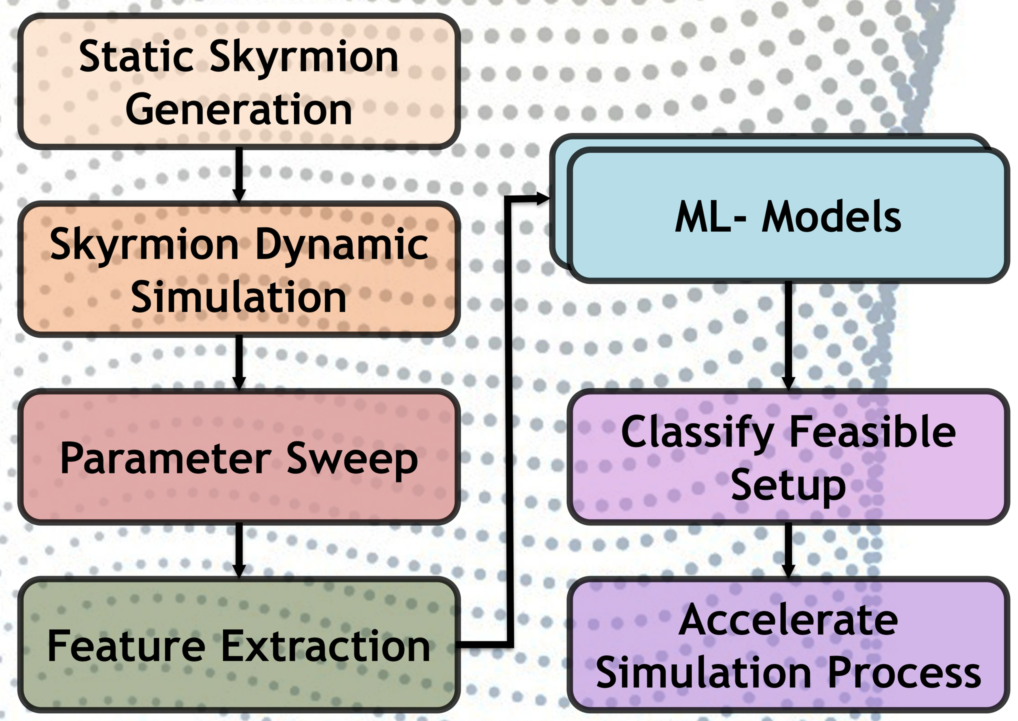
[1]Centre for Electronics Frontiers, School of Engineering, University of Edinburgh, Edinburgh EH9 3BF, U.K.
[2]School of Engineering, University of Glasgow, Glasgow G12 8LT, U.K.
[3]School of Engineering, Newcastle University, Newcastle upon Tyne, NE1 7RU, U.K.

Email: s2900607@ed.ac.uk, ssivasub@ed.ac.uk

Introduction

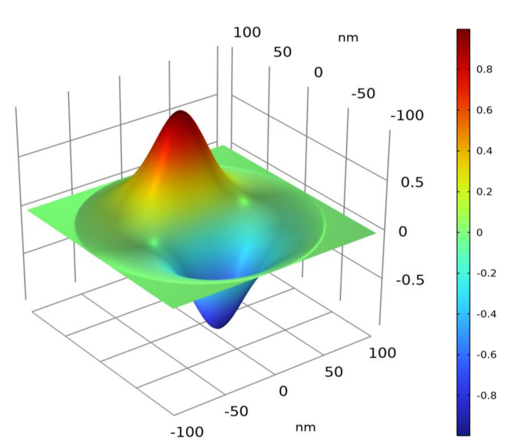
Since the middle of the 20th century, silicon-based semiconductor is used widely for the information storage. Though the number of transistors used in CMOS technologies is increasing exponentially every year according to the Moore's law for obtaining higher gain and signal-to-noise ratio (SNR), the power budgets have started to limit its increment. Beyond-CMOS technology has been developed due to its potential of achieving lower energy consumption [2].

Magnetic skyrmion is a type of the topology protected magnetic textures, which exhibits high endurance and rapid information carriers. Skyrmions can be driven by various external field without causing damage to itself, such as spin waves and electric currents [3]. It is significant to simulate skyrmion dynamics under different setup to understand its behavior and build a wide range of beyond-CMOS electronic devices. Landau-Lifshitz-Gilbert (LLG) Equation are typically solved using the finite difference method (FDM). While this approach introduces large computational complexity, we aim to implement machine leaning methods to accelerate the simulation process, specifically for the design of shift register device.



Method - Datasets Generation

Stable Skyrmion



LLG Equation

$$\frac{dm}{dt} = -\gamma_0\, m \times H_{eff} + \alpha\left(m \times \frac{dm}{dt}\right) + \tau_{STT}$$

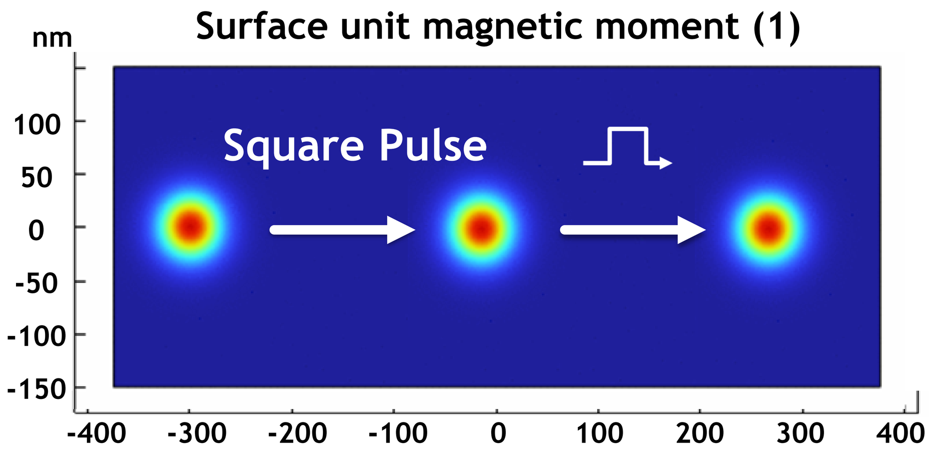
$$\text{where, } \tau_{STT} = \left(\frac{\mu_B P}{e M_s} j \cdot \nabla\right) m - \beta\, m \times \left(\frac{\mu_B P}{e M_s} j \cdot \nabla\right) m$$

α : Gilbert damping
γ_0 : Gyromagnetic ratio
H : External field
P : Spin polarization
j : Charge current density
β : Non-adiabatic coefficient

Spin-Transfer Torque (STT) -- Driving Force

- Spin-polarized current passes through a ferromagnetic into another magnetic layer
- Transfers angular momentum directly from conduction electrons to local magnetization

Surface unit magnetic moment (1)



Parameter Sweeping - Preparing Training Datasets

Dynamic Parameters (STT) @ 1000 samples

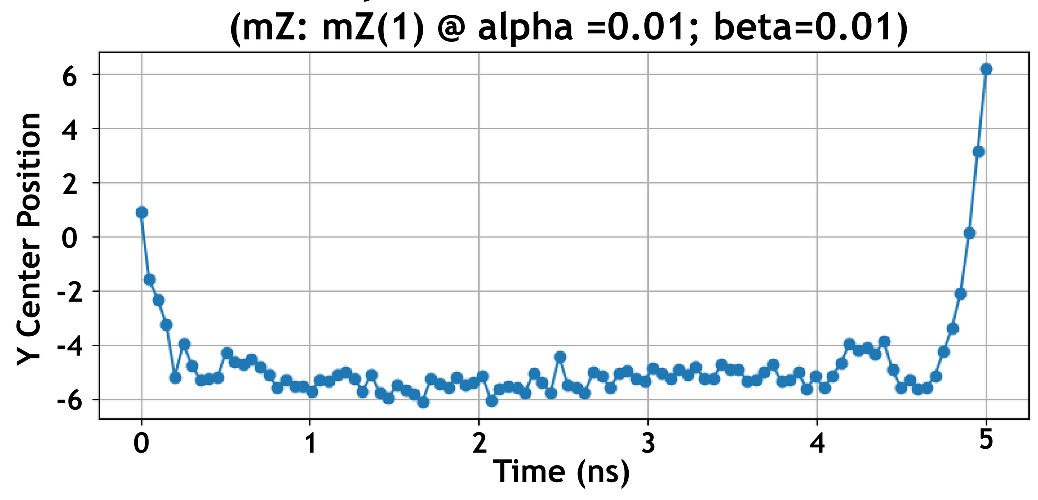
- **Non-adiabatic Coefficient** ∈ {0, 0.01, 0.02, 0.04, 0.08, 0.12, 0.18, 0.2, 0.25, 0.3}
- **Gilbert Damping** ∈ {0.005, 0.01, 0.02, 0.04, 0.08, 0.12, 0.16, 0.2, 0.25}
- **Current Density** ∈ {3e10, 5e10, 7e10, 9e10, 1e11, 3e11, 5e11, 7e11, 9e11, 1e12, 3e12 } A/m^2

Analysis - Feature Engineering

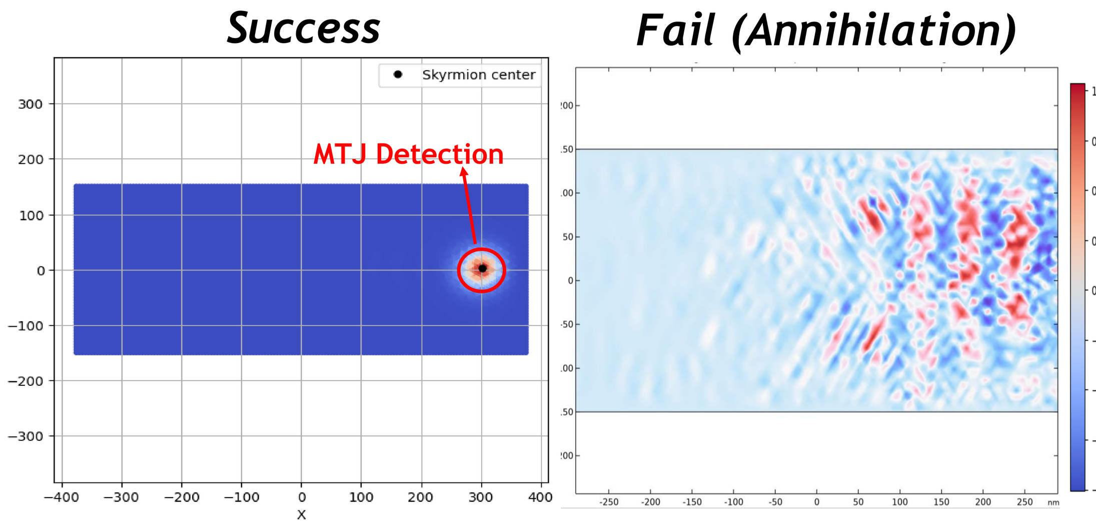
Table. 1. Raw Magnetic Moments Output (.csv)

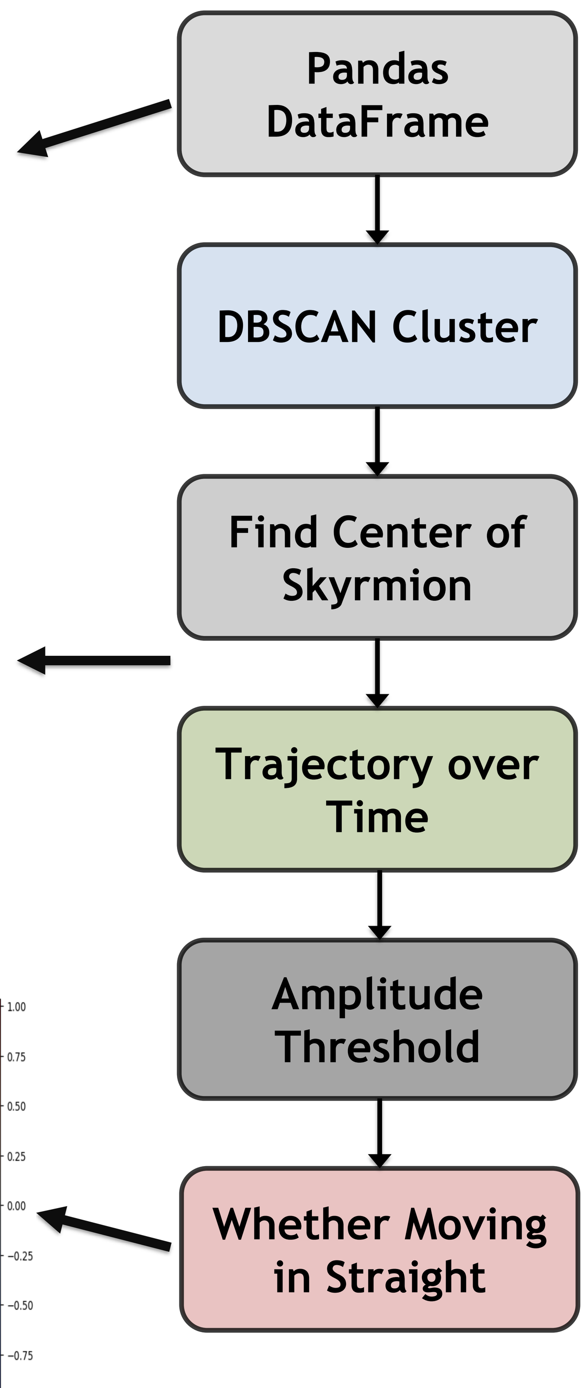
X axis (nm)	Y axis (nm)	t (ns)	mX (1)	mY (1)	mZ (1)
85.23706	45.57035	0	0.007319	-0.01558	-0.99985
89.10066	45.39904	5.45E-2	0	0	-1
87.24963	48.86208	1.09E-1	0	0	-1
83.37908	48.87785	1.64E-1	0.007933	-0.01529	-0.99985

Skyrmion Y Position vs Time
(mZ: mZ(1) @ alpha =0.01; beta=0.01)



Success *Fail (Annihilation)*





Analysis - Machine Learning

Table. 2. Pre-processed Data Sample

jx	alpha	beta	result
1E+11	0.005	0	success
1E+11	0.005	0.01	success
1E+11	0.005	0.02	success
1E+11	0.005	0.04	fail
1E+11	0.005	0.08	fail
1E+11	0.005	0.12	fail
1E+11	0.005	0.2	fail
1E+11	0.01	0	success

Best Skyrmion Movement Classifier -- Gradient Boosting

$$F_0(x) = \arg\min_{\rho} \sum_{i=1}^{N} L(y_i, \rho)$$

For m = 1 to M do:

$$\tilde{y}_i = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F=F_{m-1}(x)} \quad \text{for } i = 1, \ldots, N$$

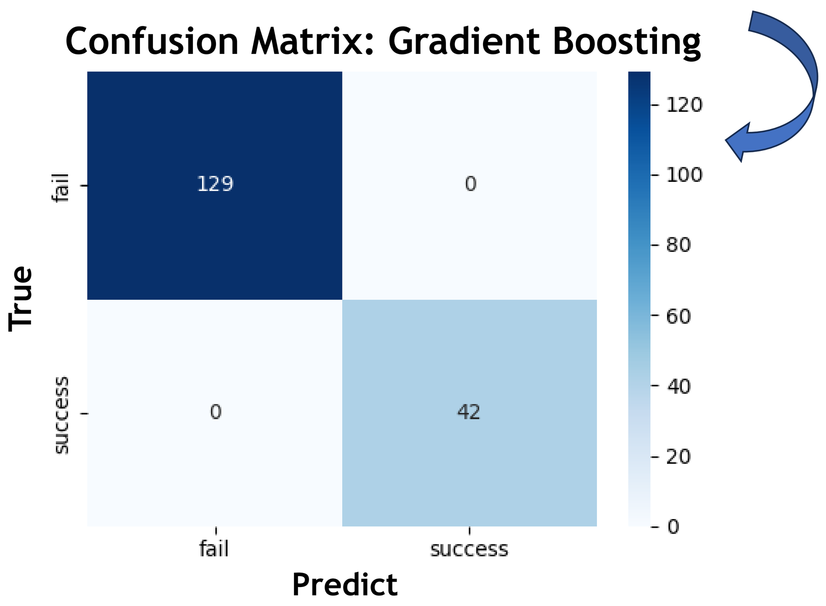
$$a_m = \arg\min_{a,\beta} \sum_{i=1}^{N} \left(\tilde{y}_i - \beta h(x_i; a)\right)^2$$

$$\rho_m = \arg\min_{\rho} \sum_{i=1}^{N} L\left(y_i, F_{m-1}(x_i) + \rho h(x_i; a_m)\right)$$

$$F_m(x) = F_{m-1}(x) + \rho_m h(x; a_m)$$

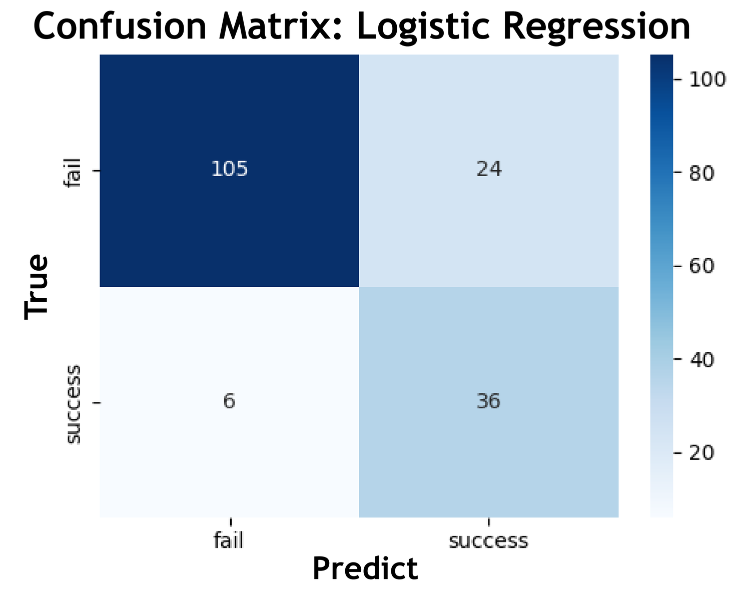
end For
end Algorithm

Confusion Matrix: Gradient Boosting

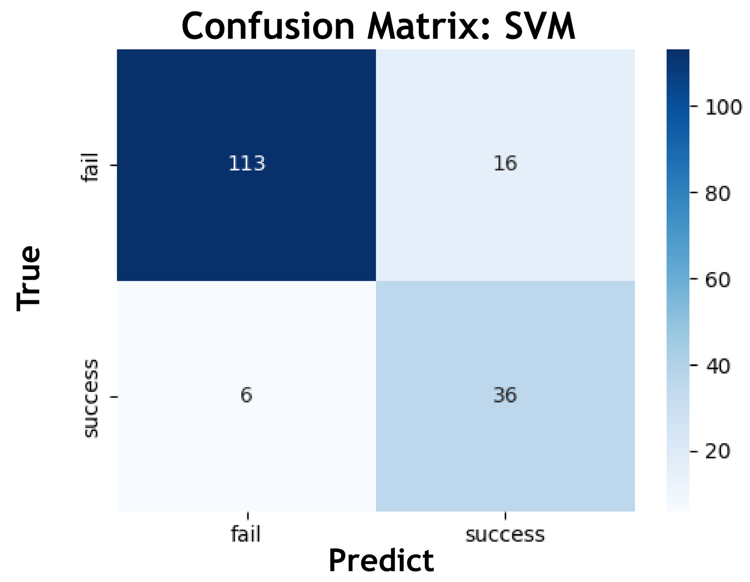


Confusion Matrices Comparison of Other Models

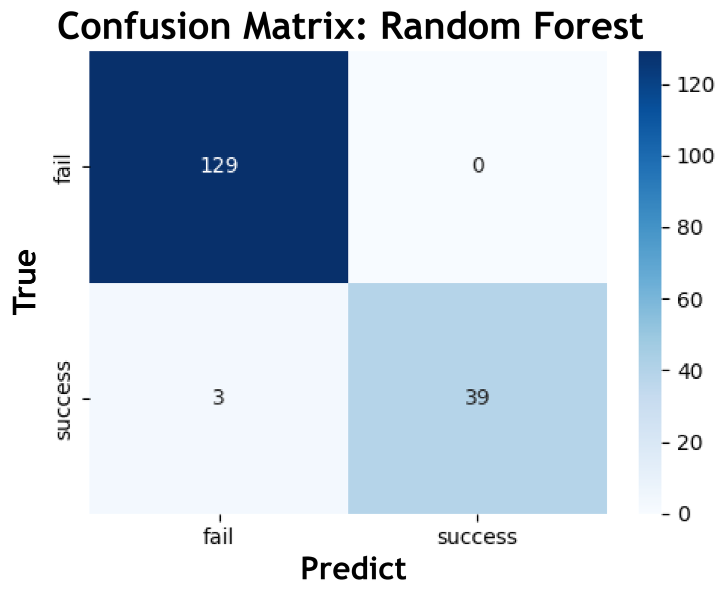
Confusion Matrix: Logistic Regression



Confusion Matrix: SVM



Confusion Matrix: Random Forest



Conclusions

- A machine learning-based approach was successfully developed to classify skyrmion dynamics without relying on time-consuming traditional simulations.
- The use of COMSOL-generated datasets combined with feature engineering enables efficient training of classifiers.
- Among the tested models, the Gradient Boosting classifier achieved 100% testing accuracy, demonstrating excellent predictive capability using only three LLG parameters.
- This method provides a fast and reliable tool for predicting skyrmion behavior (annihilation or targeted motion).

We acknowledge support of the UKRI AI programme, and the Engineering and Physical Sciences Research Council, for APRIL- EPSRC AI Hub for Productive Research and Innovation in electronics [grant number EP/Y029763/1]. The 2025 Research placements were supported by Google DeepMind, the Hg Foundation and the Royal Academy of Engineering under the Google DeepMind Research Ready scheme [grant number GDMRR-2425-1-156].

[1] L. Zhao, C. Hua, C. Song, W. Yu, and W. Jiang, 'Realization of skyrmion shift register', Science Bulletin, vol. 69, no. 15, pp. 2370–2378, Aug. 2024, doi: 10.1016/j.scib.2024.05.035.
[2] Y. Cai, J. Li, and D. Wang, 'Fast and generalizable micromagnetic simulation with deep neural nets', *Nat Mach Intell*, vol. 6, no. 11, pp. 1330–1343, Nov. 2024, doi: 10.1038/s42256-024-00914-7.
[3] CHAPPERT C, FERT A, DAU F N V. The emergence of spin electronics in data storage [J]. Nature Materials, 2007, 6(11): 813.

APRIL AI Hub Linktree

UK AI Research Symposium, Newcastle, 8-9 September 2025

APRIL | AI Hub for Productive Research & Innovation in Electronics

UKRI Engineering and Physical Sciences Research Council