Abstract

Understanding the behavior of magnetic skyrmions is fundamental to the next generation of data storage devices. Skyrmion lattices can be studied using *in situ* Lorentz Transmission Electron Microscopy (LTEM), but the images are difficult to interpret. In this work, we have developed a machine learning technique to perform instance segmentation on LTEM images of skyrmion lattices and thus extract quantitative information. We used micromagnetics software to simulate 10,000 skyrmion lattices, from which we created ground truths of skyrmion sizes and positions and further simulated corresponding LTEM images. We then trained a convolutional neural network (CNN) on these simulated LTEM images and ground truths using supervised learning. Our results demonstrate that the CNN can accurately identify skyrmion locations and extent in both simulated and experimental data, providing a technique for quantitative analysis of skyrmion lattices going forward.

SIMULATION-TRAINED MACHINE LEARNING FOR SEGMENTING NÉEL-TYPE SKYRMIONS

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Motivation

- Magnetic skyrmions are topologically protected vortex-like spins observed in ferromagnetic thin films. [1]

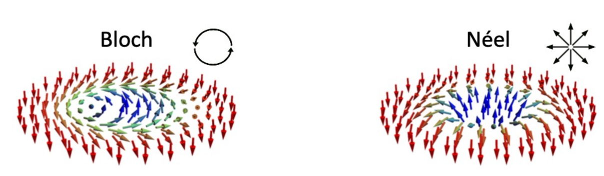


Fig. 1 Bloch and Néel skyrmion lattices. Néel Skyrmions show the strongest potential for future device applications.

- The solitonic nature of skyrmions give them high stability against perturbations and allows efficient transport under electrical current. [2]
- Understanding the behavior of skyrmions and skyrmion lattices is fundamental to the next generation of data storage devices.
- Skyrmion lattices can be studied *in situ* Lorentz Transmission Electron Microscopes (LTEM); however, the images are not visually intuitive.

We are developing a machine learning technique to perform instant segmentation on LTEM images of skyrmion lattices and thus extract quantitative information through *in situ* experiments.

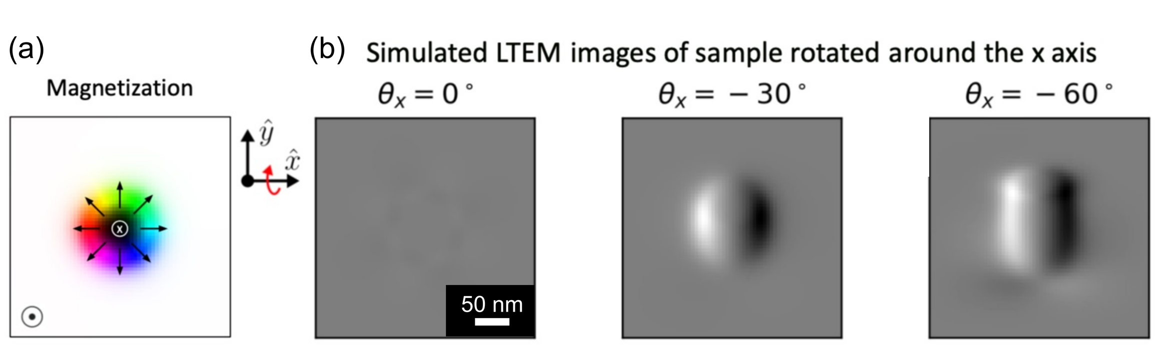
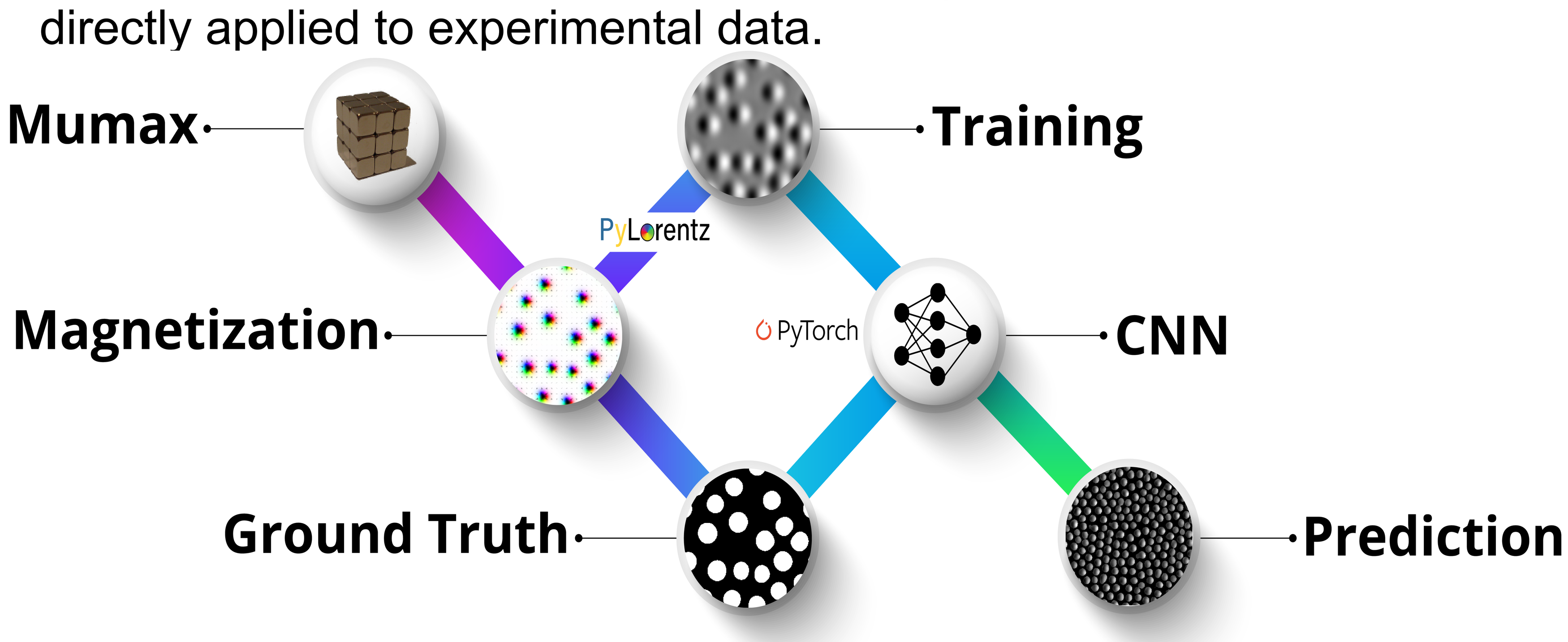


Fig. 2 LTEM Images of a Néel Skyrmion with (a) magnetization (b) and simulated LTEM image at -25 µm defocus and varying tilts.

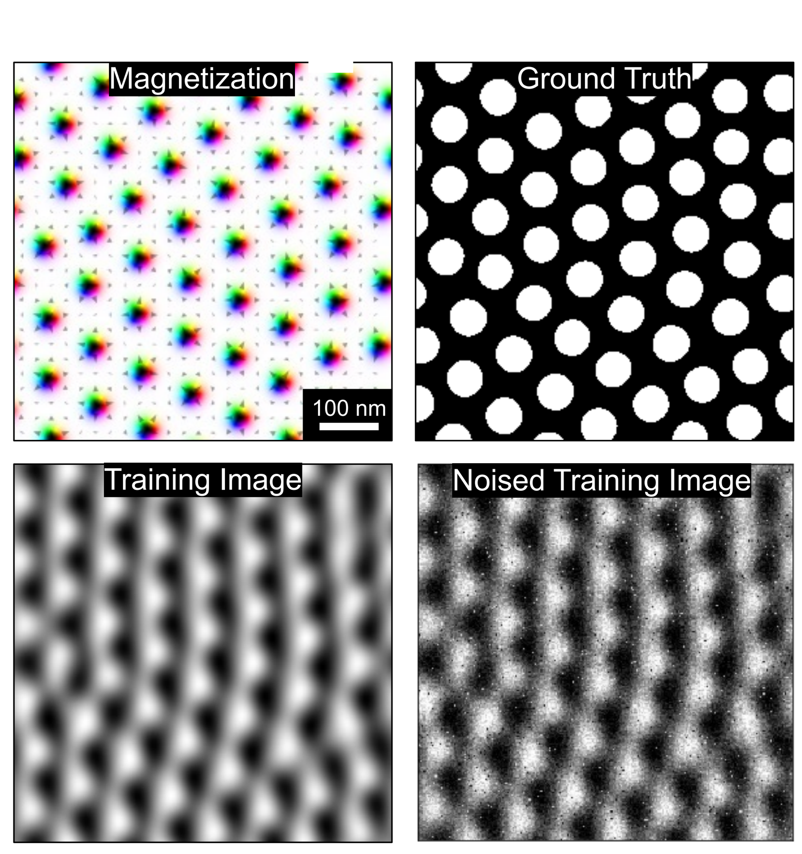
Overview

- We performed supervised learning and trained a convolutional neural network (CNN) with simulated LTEM images and corresponding ground truths containing skyrmion sizes and locations.
- Magnetizations are simulated in Mumax via micromagnetics. [3]
- Magnetization outputs are used to create training images using the PyLorentz package and ground truths/labels.
- A CNN is trained on 10,000 simulated images and labels and can be directly applied to experimental data.



Input Simulated Images

- Imaging skyrmions through LTEM requires defocusing and tilting the sample for an image to appear.
- The skyrmions within the image appear as brighter or darker regions relative to background.
- The training images mimic this scenario and noise is applied before they are inputted into the CNN.



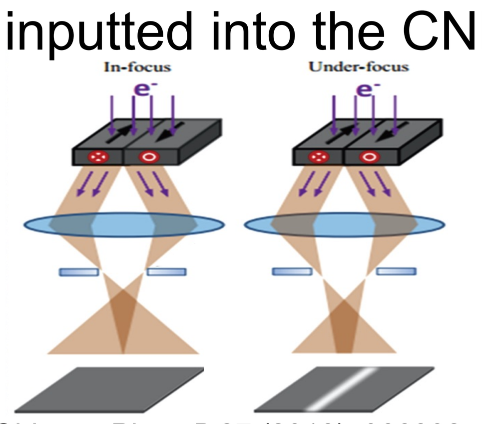


Fig 3. Diagram of LTEM

Chinese Phys. B 27 (2018): 066802

Convolutional Neural Network

- A neural network (NN) is a computing system based on biological brains comprised of connected nodes that mimic neurons.
- We use supervised learning where the program is given training data and the corresponding ground truth/label.
- NN training consists of inputting training data, comparing the prediction with the label and receiving a loss, and improvement occurs by backpropagating through the layers and optimizing connections.
- The specific NN network used is a fully convolutional neural network based on a four-layer U-Net architecture. [4]

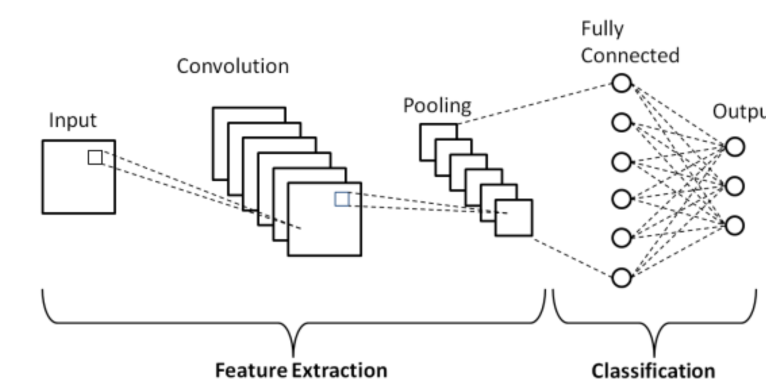


Fig. 4 Diagram of a CNN
Applied Sciences 9 (2019): 10.3390/app9214500

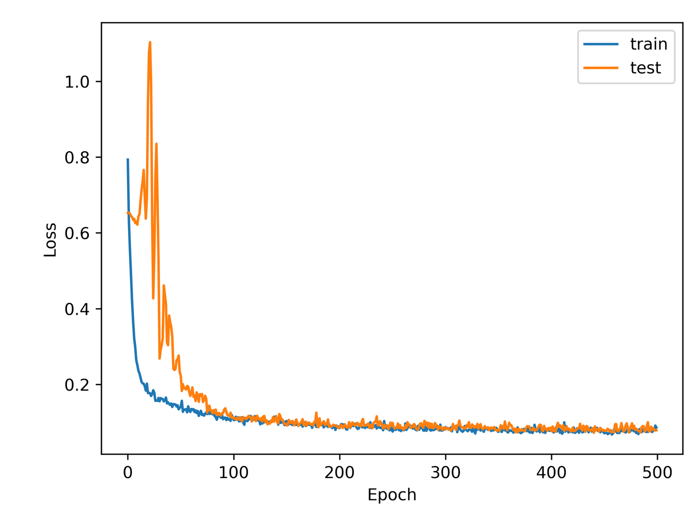
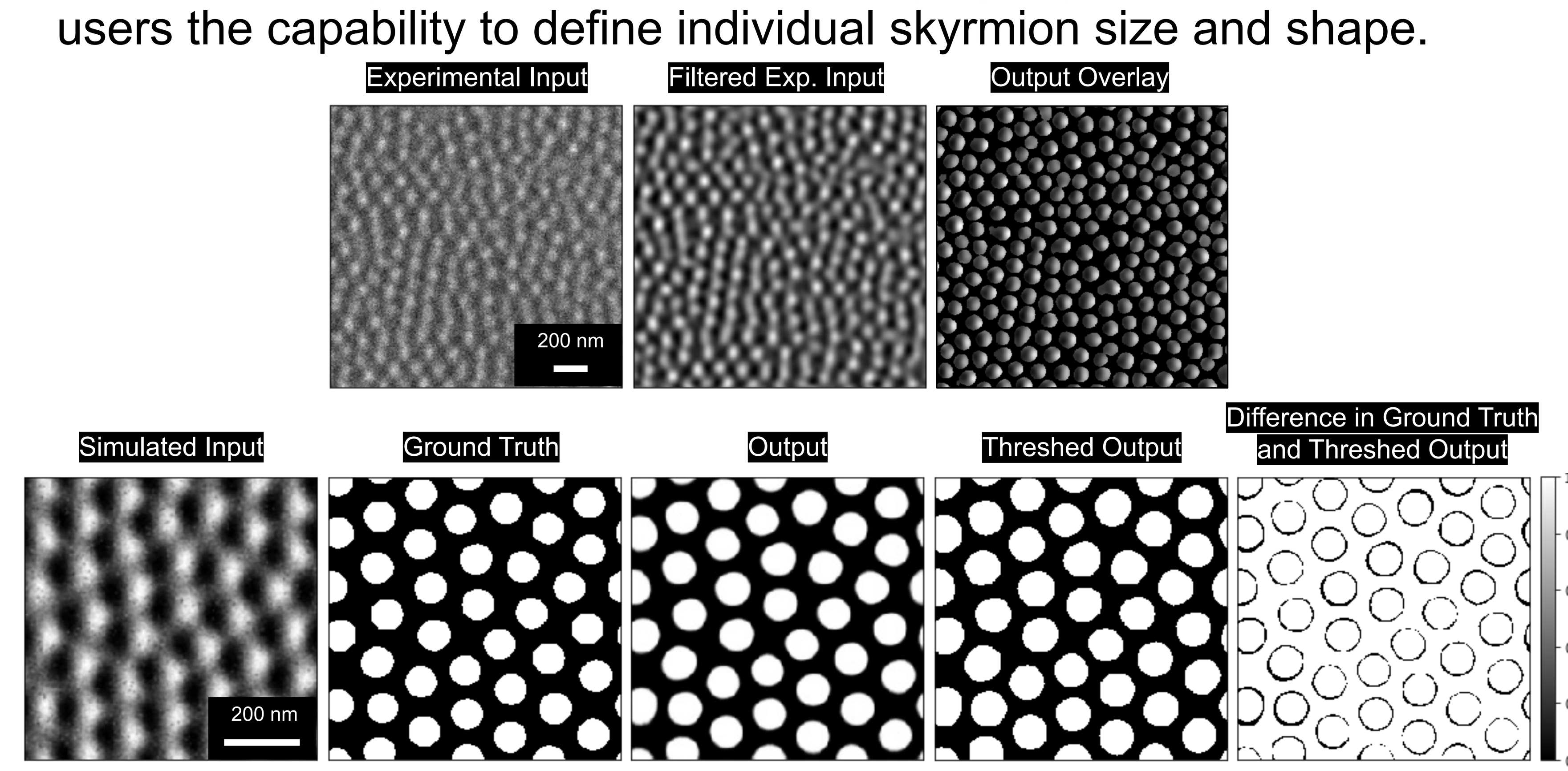


Fig. 5 CNN Loss for 500 epochs

Results

- The CNN is capable of accurately identifying skyrmions and allows users the capability to define individual skyrmion size and shape.



Conclusions and Next Steps

- Skyrmions are posed to be an advancement for future memory devices, and we have demonstrated a new method to analyze them.
- We will continue to optimize the CNN to become more accurate and adapt to more general imagining conditions.
- The CNN will enable immediate feedback during *in situ* experiments making them more quantitative and able to discover new scientific phenomenon.
- Next steps:
  - Applying the CNN to skyrmion discernment (Fig. 6)
  - Looking at skyrmion deformation events (Fig. 7)

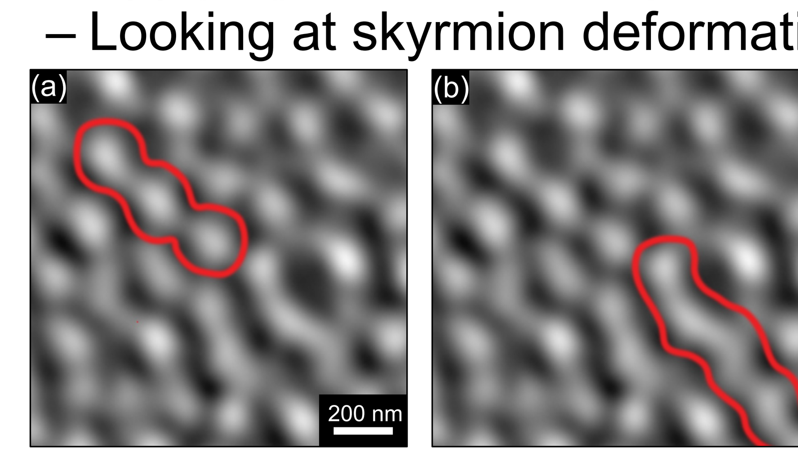


Fig. 6 It is difficult to identity whether a skyrmion is either a strip/maze domain or several small skyrmions in alignment. The CNN could help distinguish between these scenarios especially close to the Curie temperature.

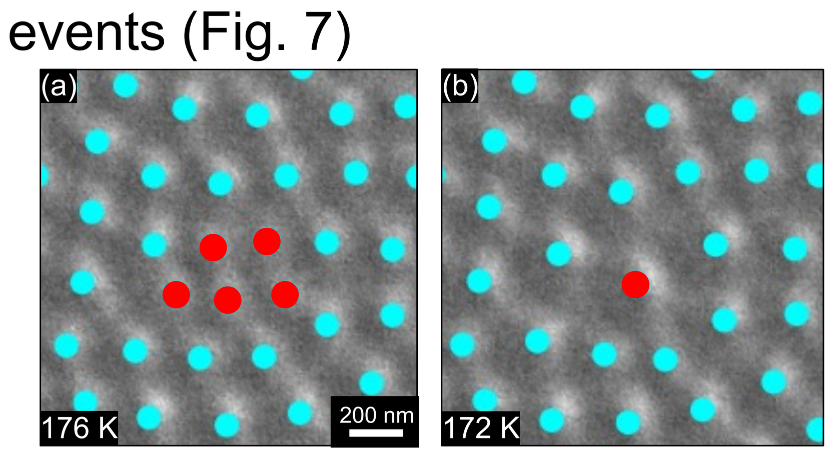


Fig. 7 During cooling, skyrmion disappearance events occur wherein two or more skyrmions are replaced with one or more larger skyrmions. By studying the size, shape deformation before and after these events we hope to understand how and why these events take place.

Acknowledgements

- This work is supported by the U.S. Department of Energy, Office of Science, Office of Basic Energy Sciences, Materials Sciences and Engineering Division. Use of the Center for Nanoscale Materials, an Office of Science user facility, is supported by the U.S. Department of Energy, Office of Science, Office of Basic Energy Sciences, under Contract No. DE-AC02-06CH11357.

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