RUTGERS

WINLAB | Wireless Information Network Laboratory

AI For Behavioral Discovery

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Overview

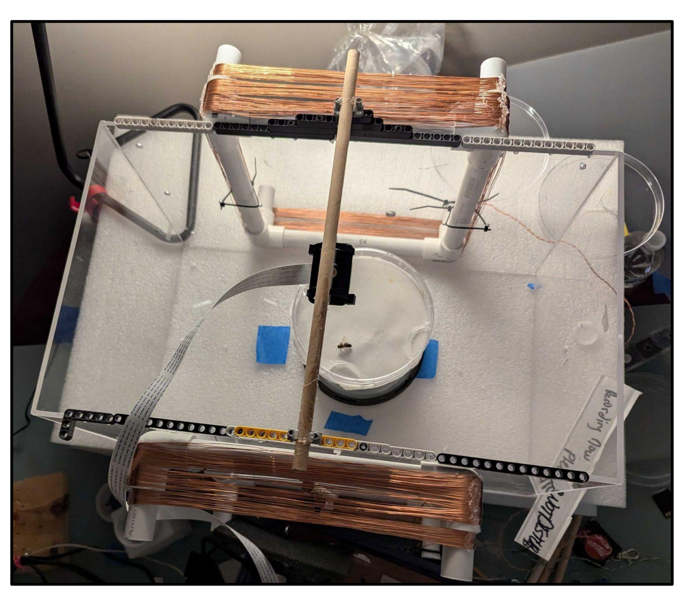
Artificial intelligence (AI) can revolutionize the study of insect behavior by analyzing their positioning and movements. For bees, AI can investigate their repsonses to human-generated electromagnetic fields, aiming to detect any biological impacts. Previous iterations of this project relied on classical condition; this study explores whether AI can identify patterns in behavior. However, our findings indicate that models are highly susceptible to shortcut learning and significantly influenced by covariates.

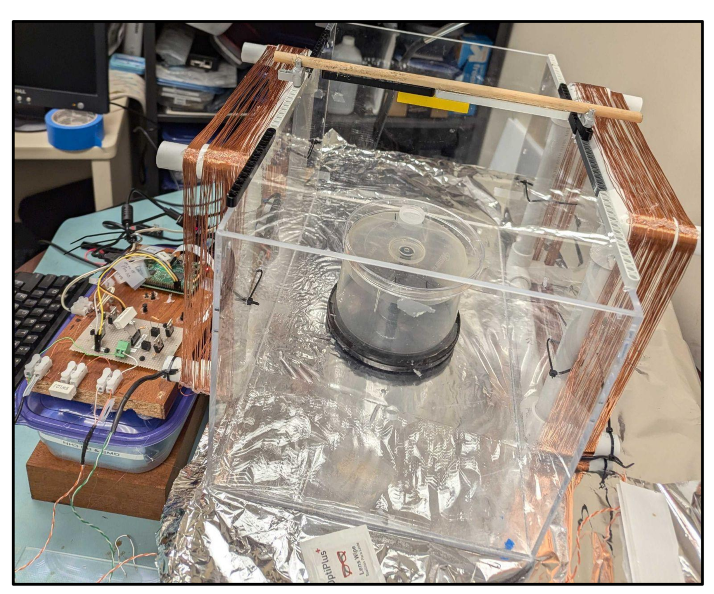
Goals:

- Observe ants and bees in the presence of an electromagnetic field switching between on/off to detect behavioral changes potentially responsible by the radiation.
- Train a deep neural network to detect changes in behavior from the electromagnetic field.

Experiment Setup

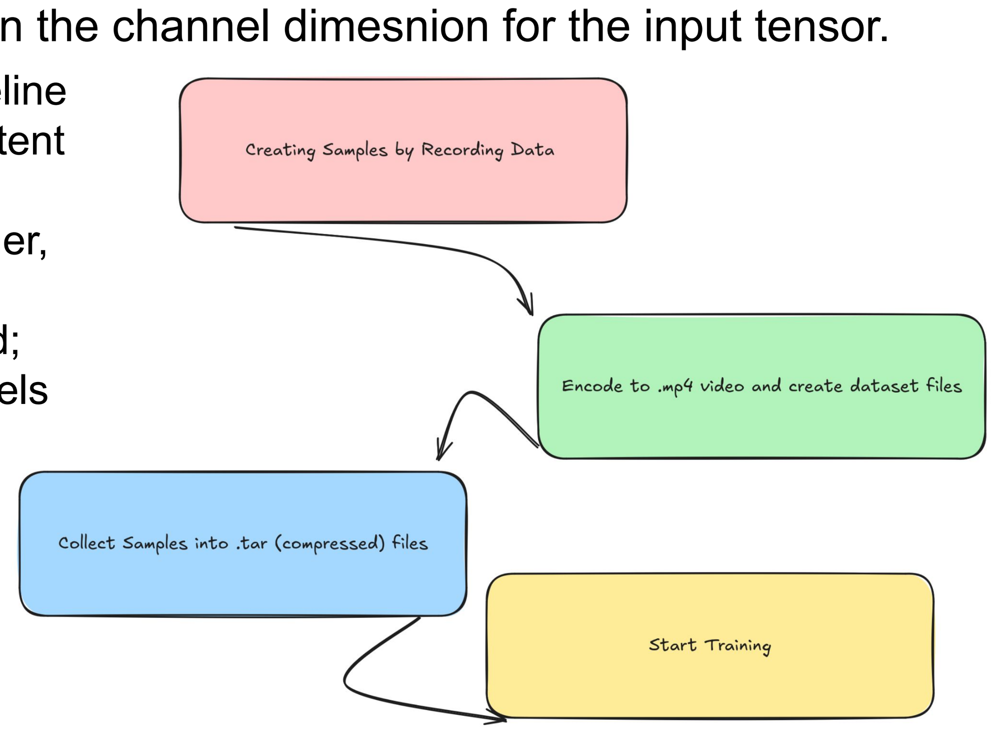
- Resistors allow for highly steady voltage and current over time.
- Raspberry Pi for capturing videos.
- Setup designed to minimize noise while also normalizing to not affect training.
- Copper wire coils are utilized to induce an electromagnetic field.
- Camera fully adjustable so data can be recorded at various angles.
- Camera encoding .h264, with later processing to .mp4.

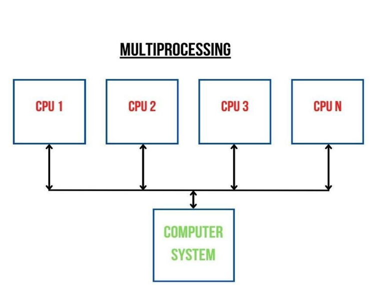


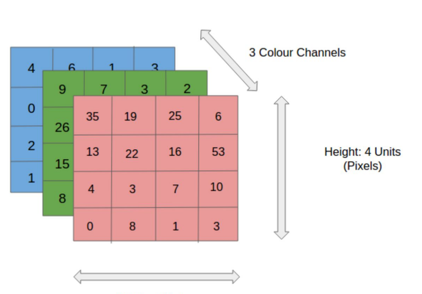


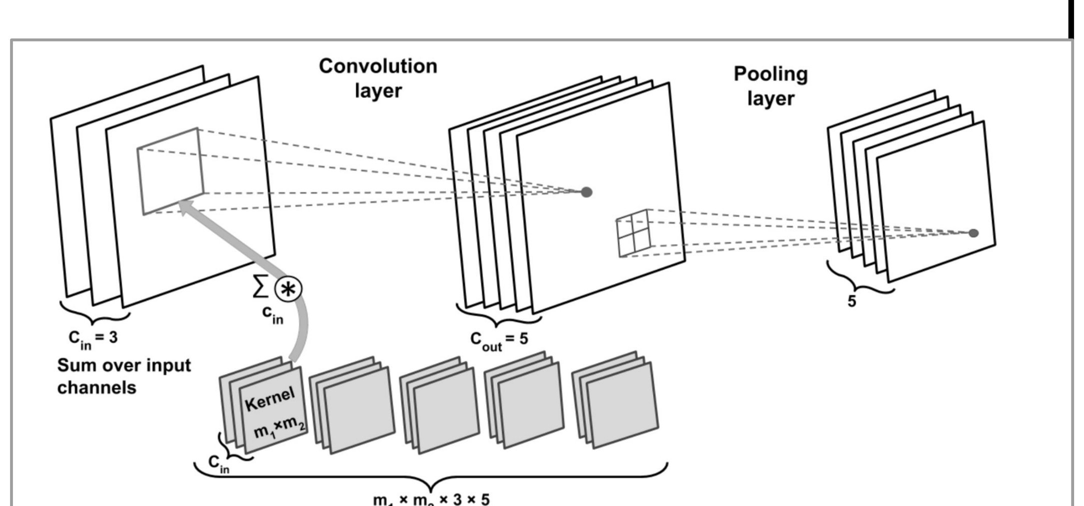
Software Pipeline / Model Architecture

- The Model Architecture, is a Deep Learning Convulutional Neural Network (CNN) Model for Image Recognition/Classification.
- To model movement, we send multiple contiguous frames by frame stacking the images in the channel dimesnion for the input tensor.
- Updated Software Pipeline faster and more consistent than original.
- Created a unified Runner, allows for faster testing
- Multiple frames allowed; showed through channels



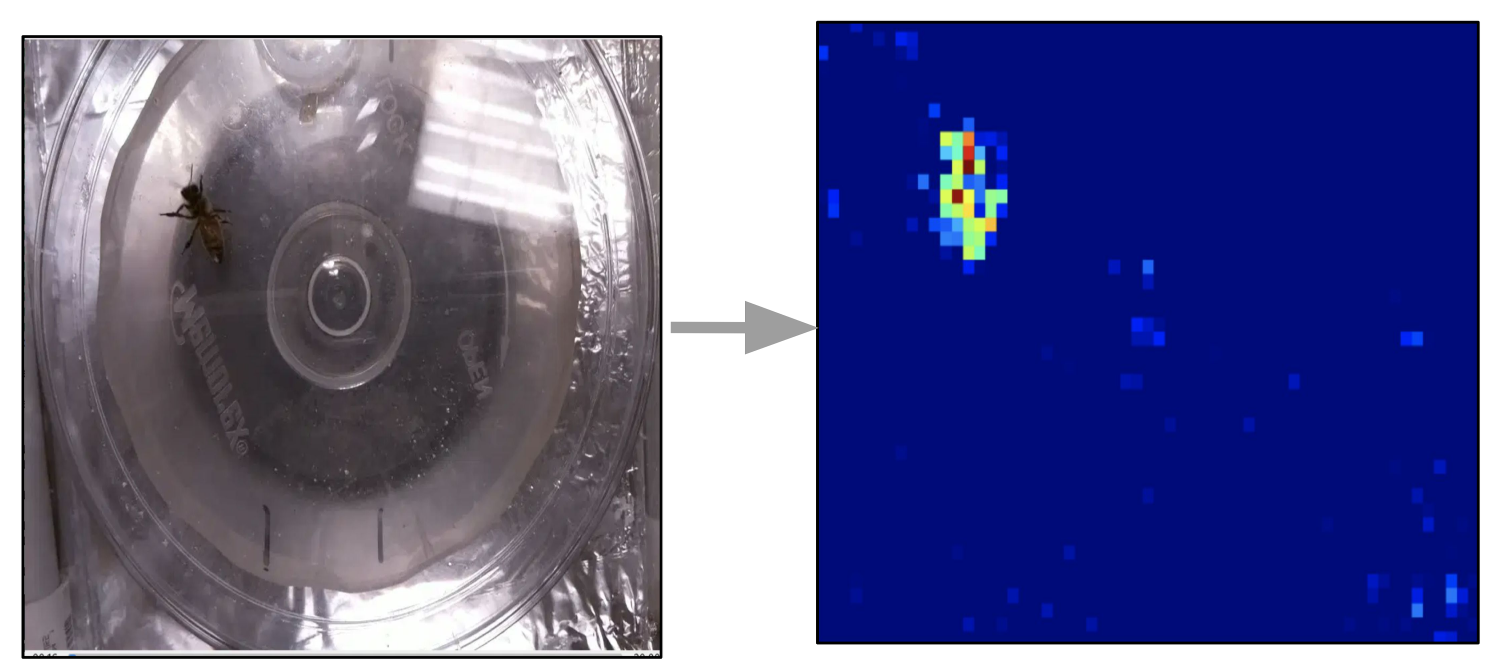




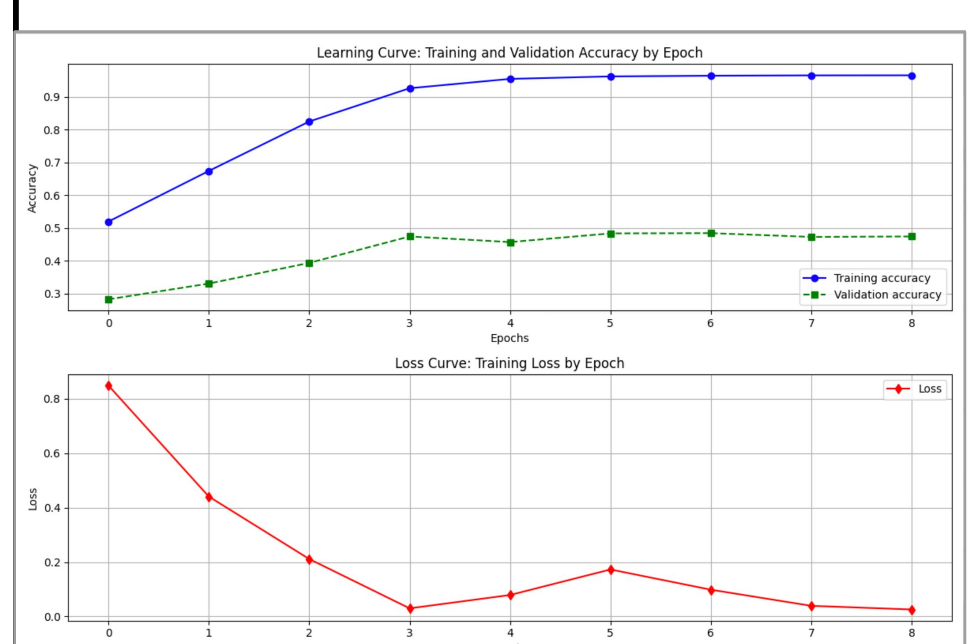


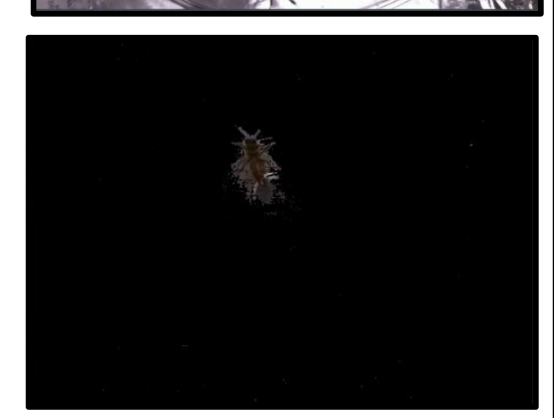
Real Data

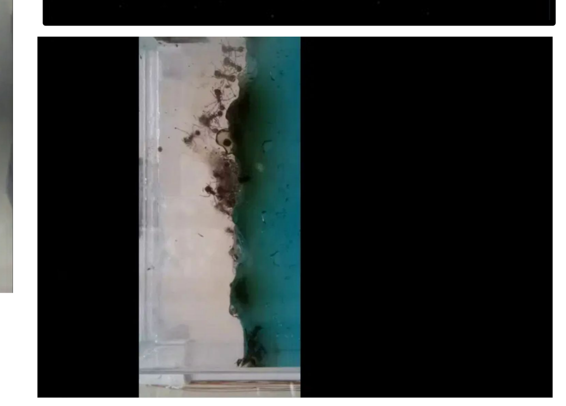
- Recorded data from bees and ants to test our model's understanding and accuracy.
- Testing on bee data confirms that the model focuses on bees, as demonstrated by the Grad-CAM image (Below Right)



- Training with real bee data resulted in model overfitting, with training accuracy at ~99% and testing accuracy at ~52%.





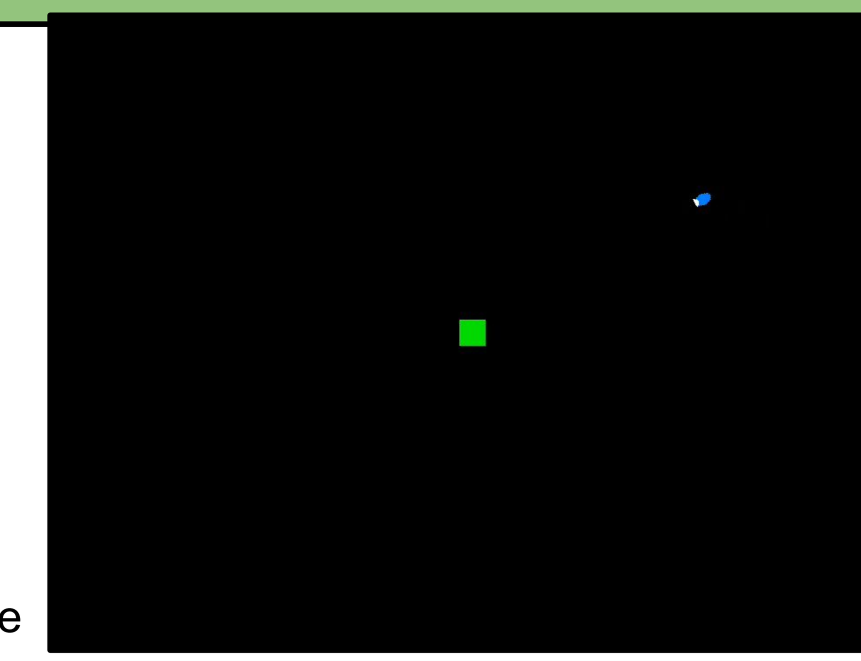


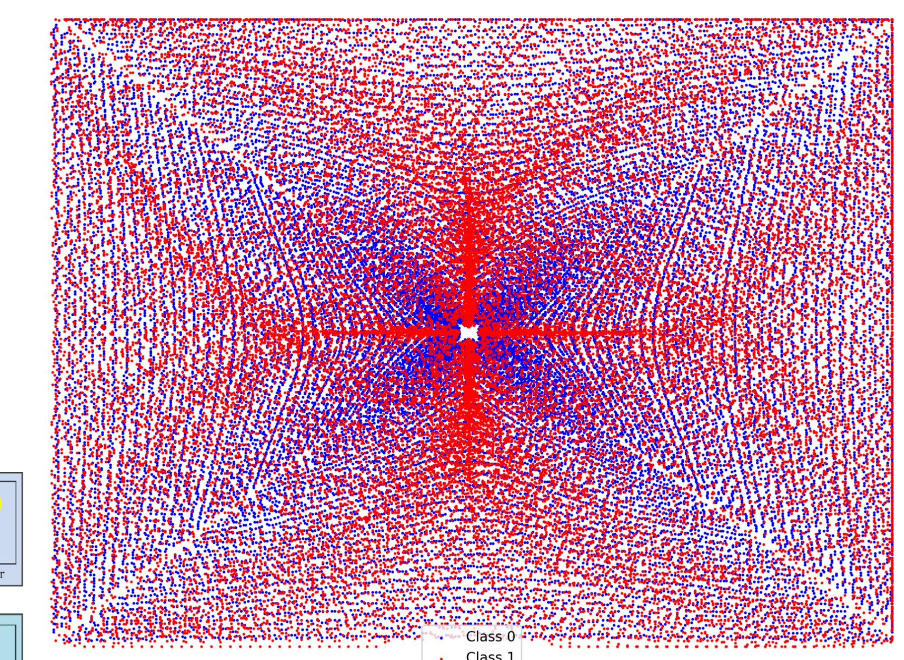
- To enhance accuracy, use background subtraction and cropping
- Real ant data was procured, but training resulted in a high 98% accuracy
  - It is likely that the model is learning from the image background, indicating a flaw in the experimental setup

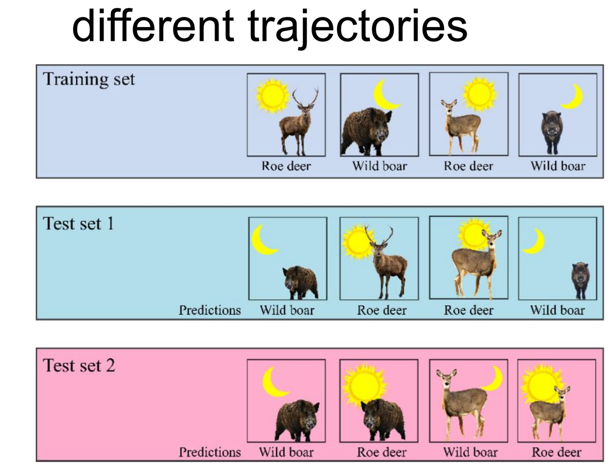
Simulated Data

The objective of simulation data was to identify the best model for our problem using 'ideal' data. Various design considerations encouraged motion to be learned as the primary feature, while minimizing potential shortcut learning:

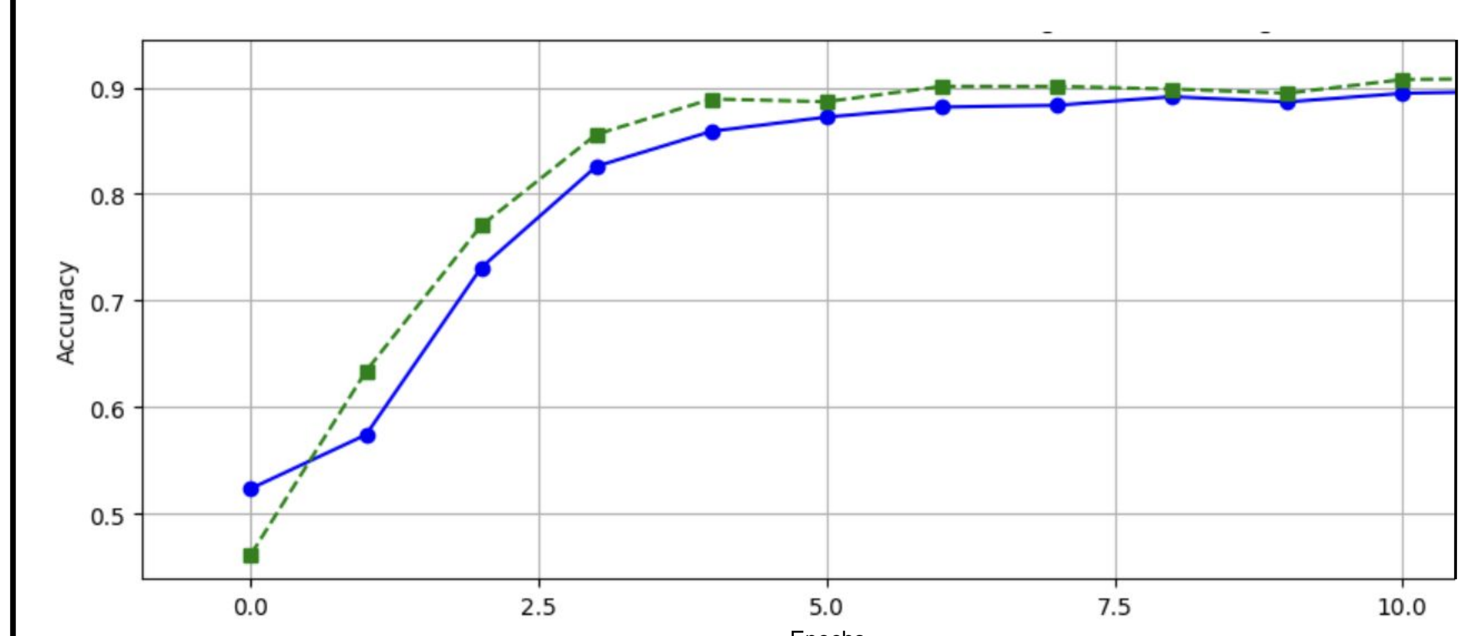
- Fixed animal orientation
- Distortion field causes bee to move nonlinearly
- 2 possible states: field on/off
- Normalized Speed
- Varying field directions
- Continuous frames per sample
- Varying speeds across different trajectories







Frame from simulation video (Top); Trajectory map of a complete dataset, red = field on, blue = field off (Above); Shortcut Learning example (Left)



Training Accuracy Curve, green = testing, blue = training (Above)

Conclusions/Future Work

- The AI model at the moment attempts to shortcut learn by any biasing features in the dataset.
  - Future work will involve further removing any biasing feature such as regional learning or position.
- Experimental setup can be further refined to remove any background factors that are correlated to the electromagnetic field switching.
- Further develop AI model architecture from a pure CNN to other architectures that can model sequential data (i.e. CNN + RNN/LSTM/GRU, ConvLSTM, 3D CNN, etc.)

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