AI for Behavioral Discovery

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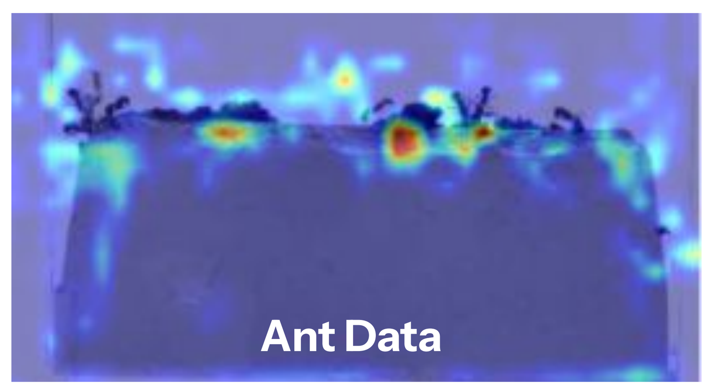
Overview: Unbiased Detection of Insect Behavior

Artificial intelligence (AI) can **revolutionize** the study of insect behavior by analyzing their positioning and movements. For ants, AI can investigate their repsonses to human-generated electromagnetic fields, aiming to **detect** any **biological impacts.** Previous iterations of this project relied on classical conditioning; this study explores whether AI can identify patterns in behavior.

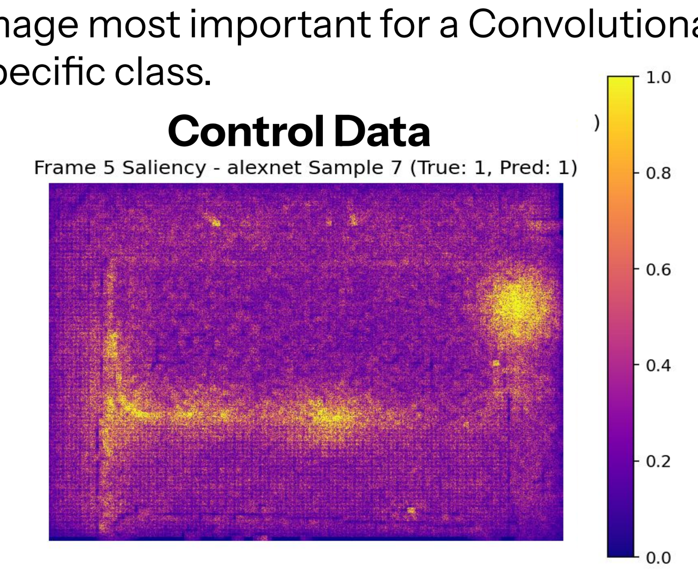
Main Goals:

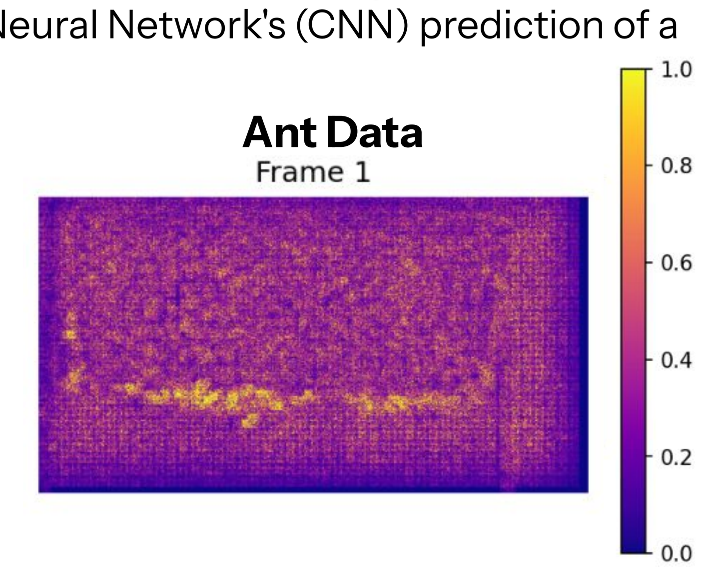
- ➔ **Observe** ants in the presence of an **electromagnetic field** switching between on/off to detect behavioral changes potentially responsible by the radiation.
- ➔ **Train** a deep neural network to detect changes in insect/animal behavior caused by EMF.

Saliency Maps/ Gradcam Plots



The **gradcam plots** above show a heatmap that visualizes the regions of an input image most important for a Convolutional Neural Network's (CNN) prediction of a specific class.





The **saliency maps** show a similar heatmap that computes the gradient of the class score with respect to the input pixels, resulting in a map that indicates how a change in each pixel would affect the prediction.

Results & Discussion

Confusion Matrix

Label 0:	119683	0	0
Label 1:	119683	0	0
Label 2:	119683	0	0

Control Data: The model seems to be guessing, since it has predicted the same label for every single field state, achieving an accuracy of 33% (Up to 60% in some cases).

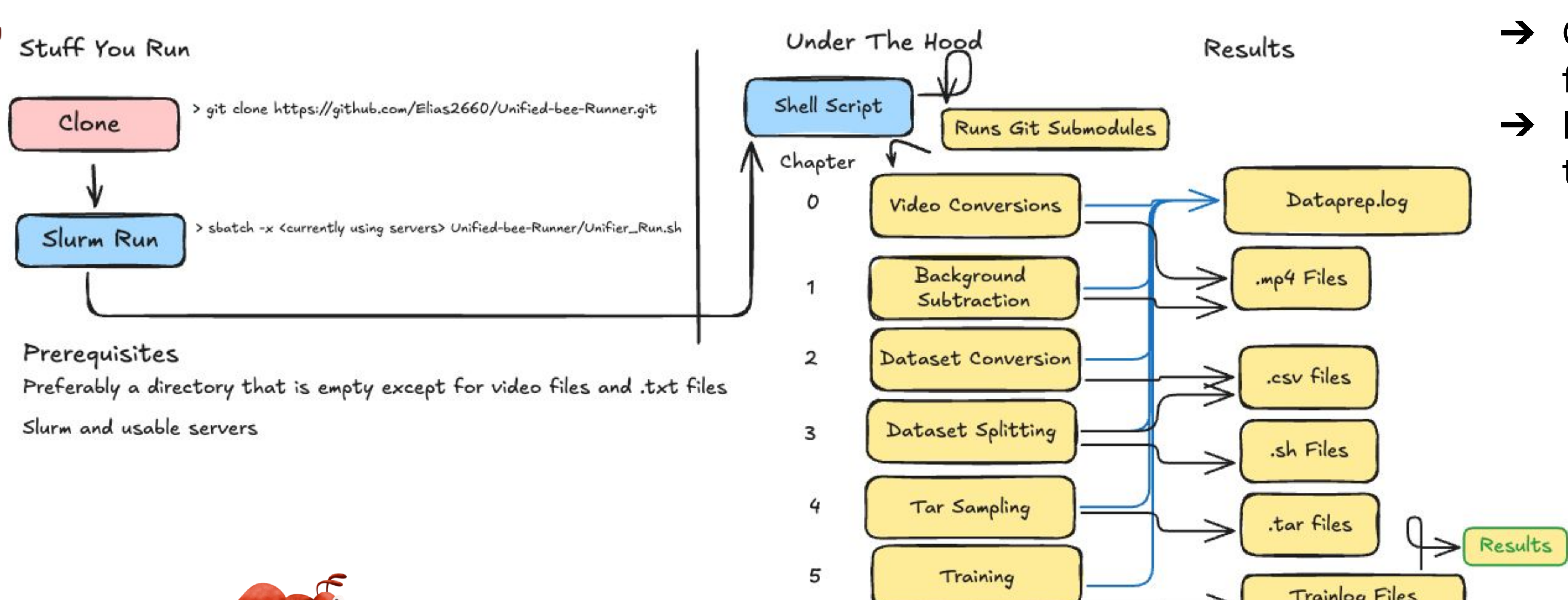
Label 0:	24000	4096	1749
Label 1:	0	29845	0
Label 2:	0	931	28914

Ant Data: The model has achieved an accuracy of 95%, indicating that it is learning some patterns within the ants' behaviour.

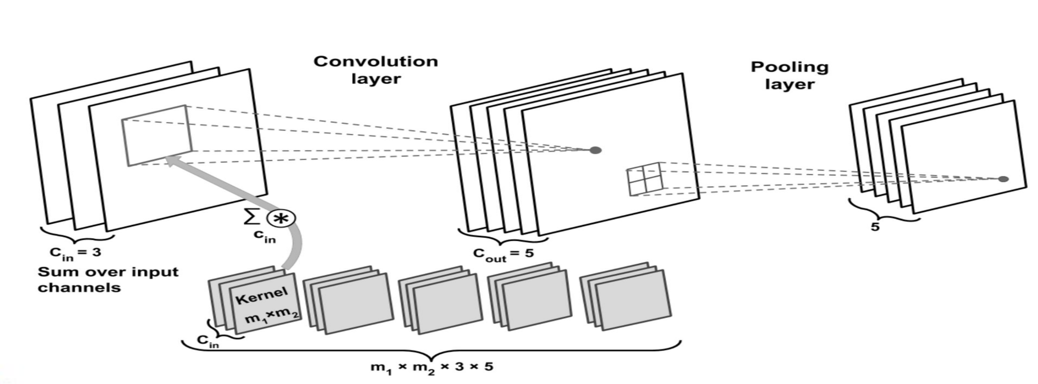
Software Pipeline/ Model Architecture Overview + Progress

The **Model Architecture**, is a Deep Learning **Convulutional Neural Network** (CNN) Model which specializes in image recognition and classification.

- ➔ To model movement, we send multiple contiguous frames by frame stacking the images in the channel dimension for the input tensor.
- ➔ Updated Software Pipeline to become faster and more consistent than the original through changing image conversion from NPZ → PNG conversion. Can now process 1 million+ frames in less than 24 hrs instead of around a week (188 hours)

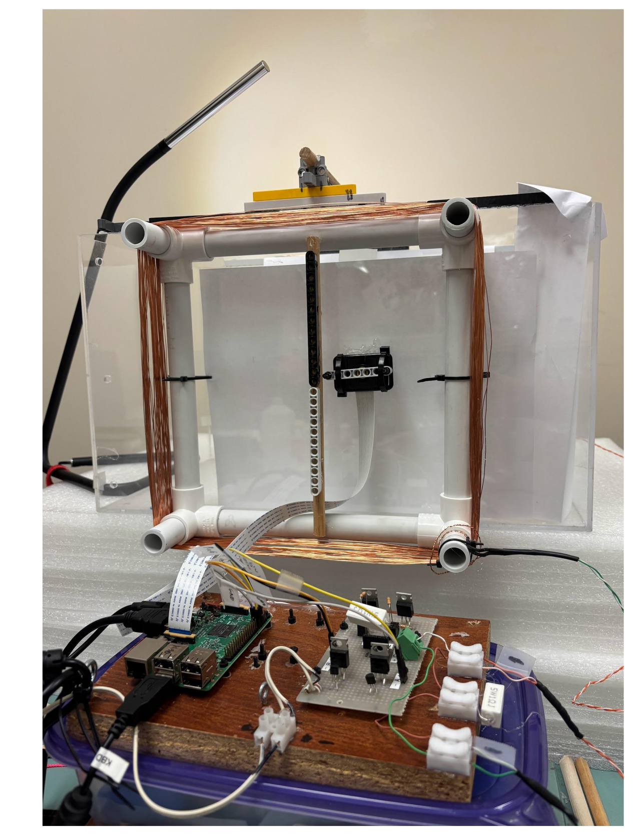


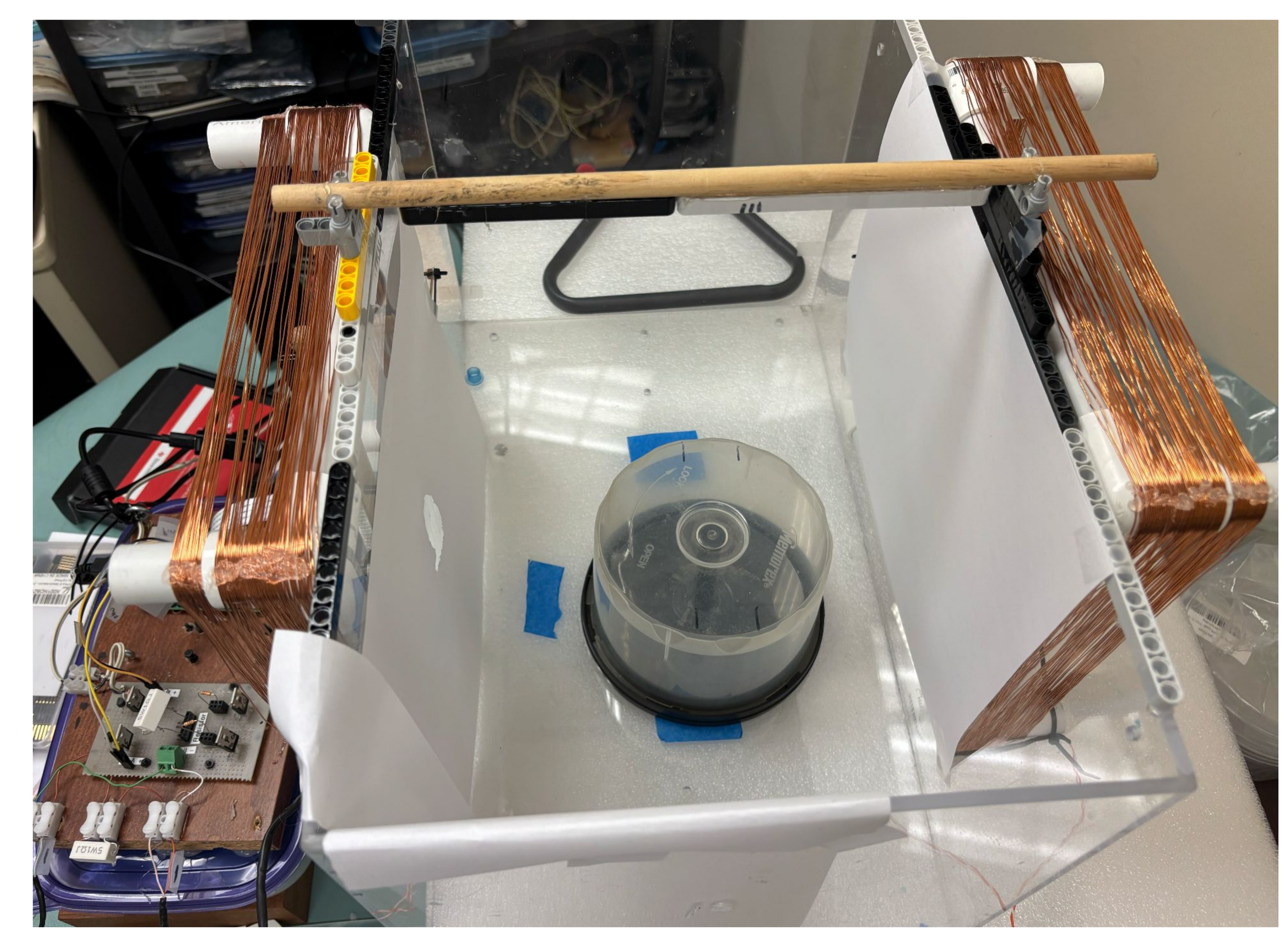
- ➔ Created a Unified Runner which allows for faster testing
- ➔ Multiple frames now allowed; showed through channels



Experiment Setup

- ➔ Copper wire coils in the Helmholtz configuration are utilized to create a static magnetic field.
- ➔ Raspberry Pi captures videos, controls current through the coil, and logs the state.
- ➔ Camera fully adjustable so data can be recorded at various angles.
- ➔ Model could learn from factors from time of day, movement of wires, compasses, lights, etc instead of behavior
- ➔ Examples of preventing confounding variables during the data collection include desynchronizing changes in the field and the time, covering up lights and preventing disturbances and noises in the training setup





Conclusions/Future Work

- ➔ Our findings indicate that models are highly susceptible to shortcut learning and significantly influenced by covariates.
- ➔ In the future, the model and pipeline should be run on more data for ants, bees, and cockroaches to dive deeper into the subject and gain more insights.
- ➔ An automated cropping system could be built that would find the best cropping parameters for each experiment cycle.
- ➔ Collect more data to test on other types of animals (birds next)