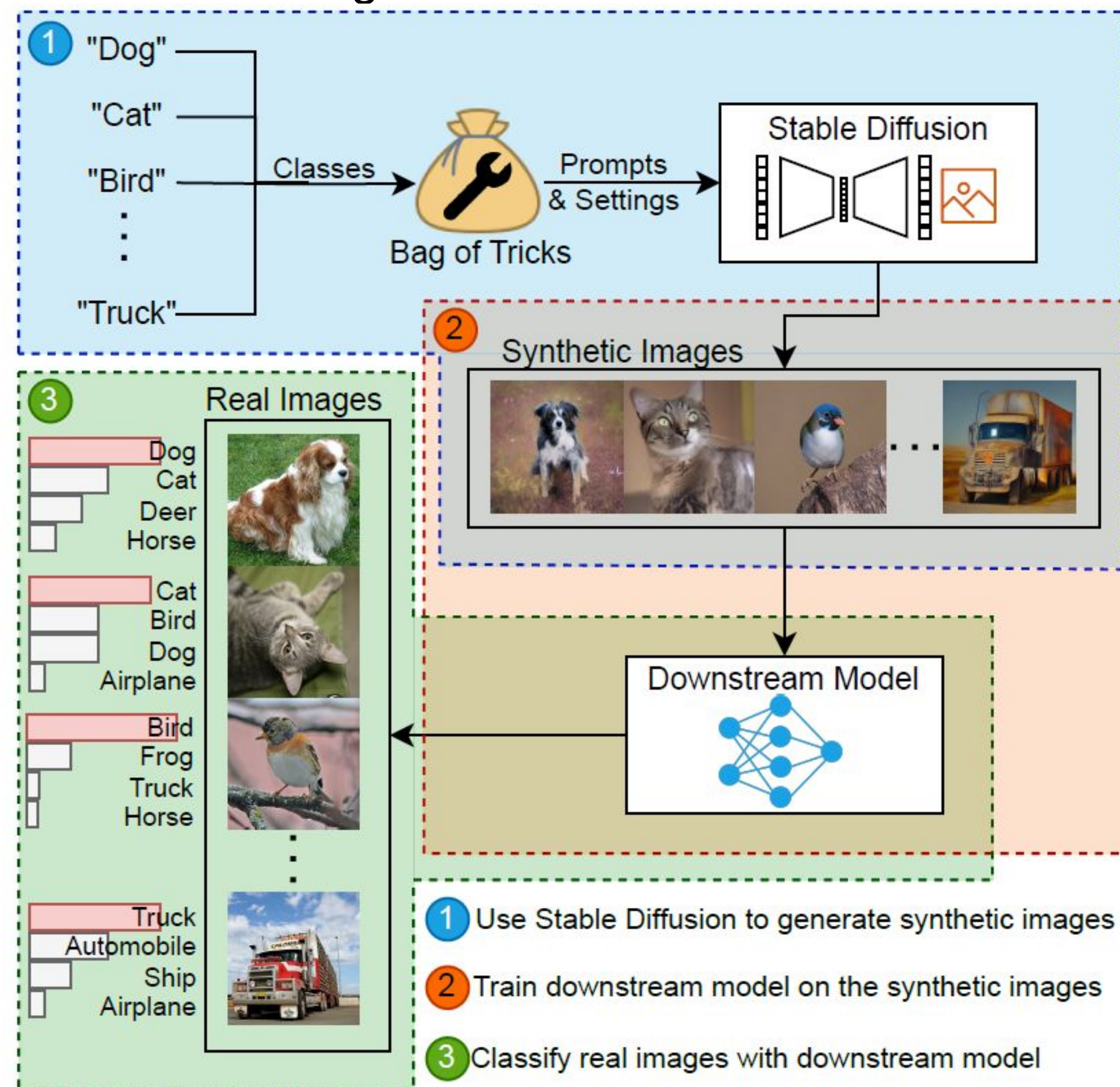


Overview of Method

- How do we solve **Model Agnostic Zero-Shot Classification**?
- Use **stable diffusion** to generate **synthetic training data** to train **downstream models**.
- The performance of real data is dependent on the **diversity** of the synthetic images used for training.

- Enhance the diversity** of the synthetic training data with **adjustments to the prompts and generation settings** used.

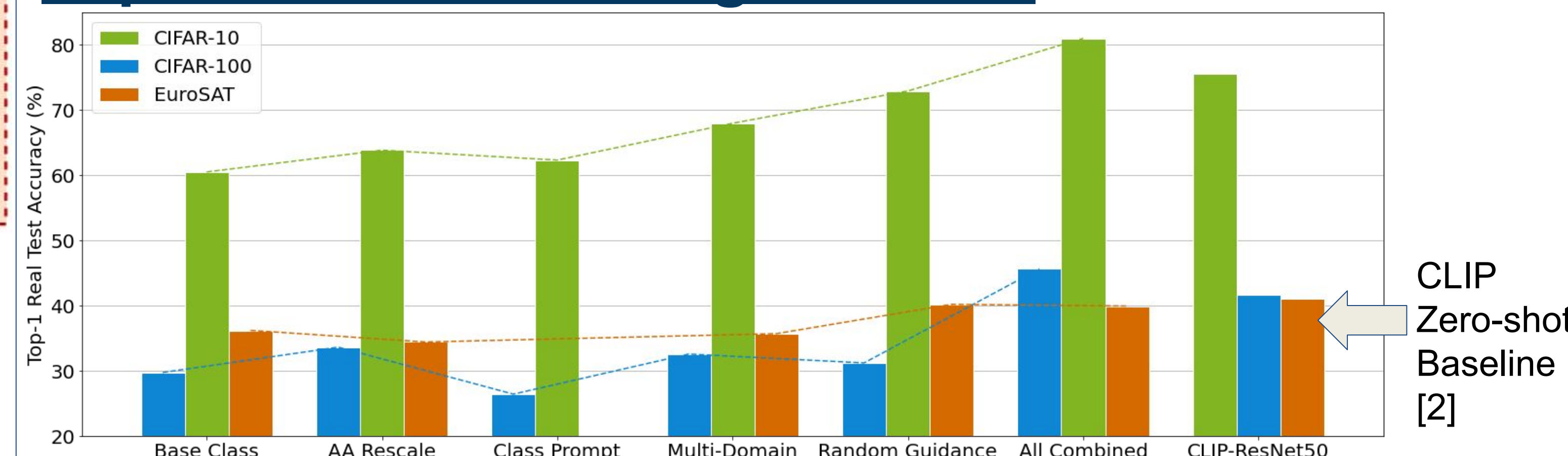


GitHub Code

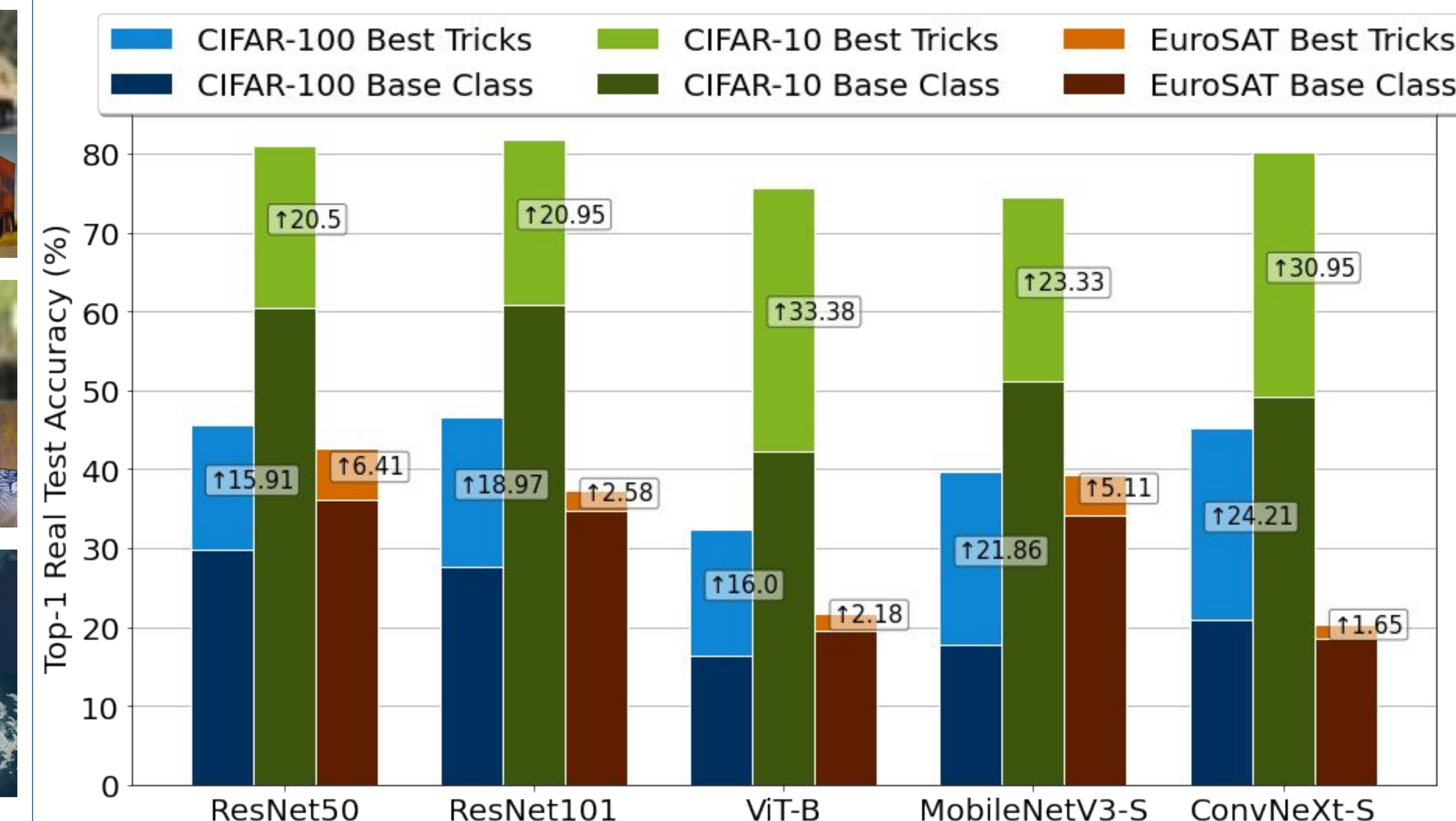
Real (top) vs Synthetic (bottom) Datasets



Improvement from Bag of Tricks



Improvement with Different Models



Future Work

- More datasets, such as ImageNet and domain specific datasets, such as additional remote sensing datasets/medical datasets.
- Making the method more efficient through reducing the number of training images needed.
- Expanding to other computer vision tasks, such as semantic segmentation and object detection.

Questions?

Join our Zoom call during the poster session or email us a question.

Meeting ID: 926 453 9384

Email: jordan.shipard@hdr.qut.edu.au

Acknowledgement

This work has been supported by the SmartSat CRC, whose activities are funded by the Australian Government's CRC Program; and partly supported by Sentient Vision Systems. Sentient Vision Systems is one of the leading Australian developers of computer vision and artificial intelligence software solutions for defence and civilian applications.

Citations

- [1] "Classifier-free diffusion guidance", Jonathan Ho and Tim Salimans, NIPS 2021
 [2] "Learning Transferable Visual Models From Natural Language Supervision", Radford et al., ICML 2021

Bag of Tricks

Base Class: "An image of a {class}"

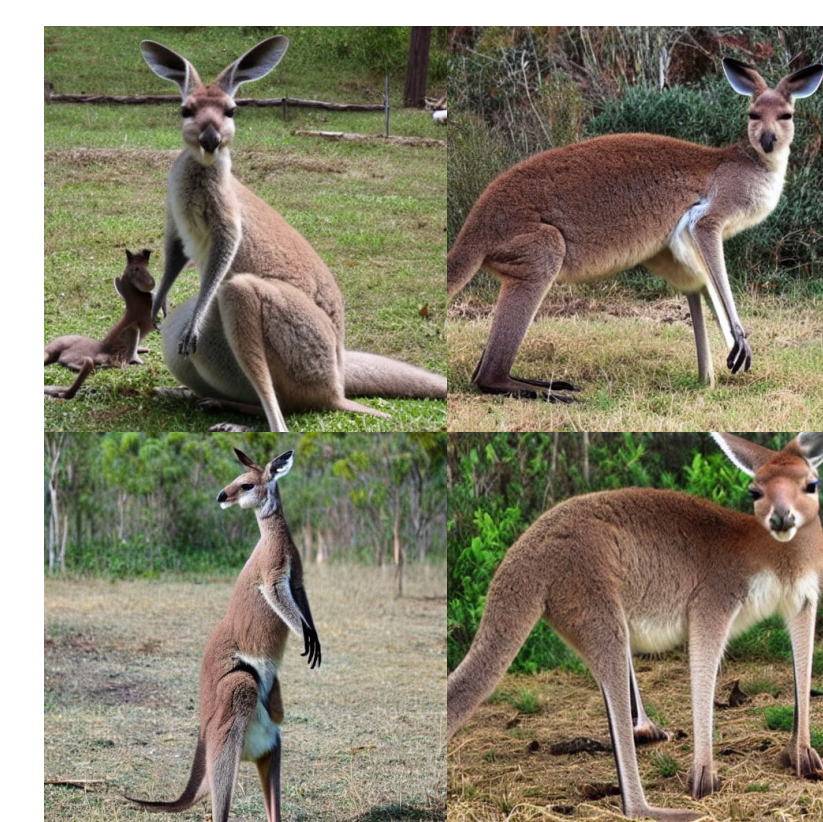
Class Prompt: "{class}"

Multi-Domain: "a {domain} of a {class}"

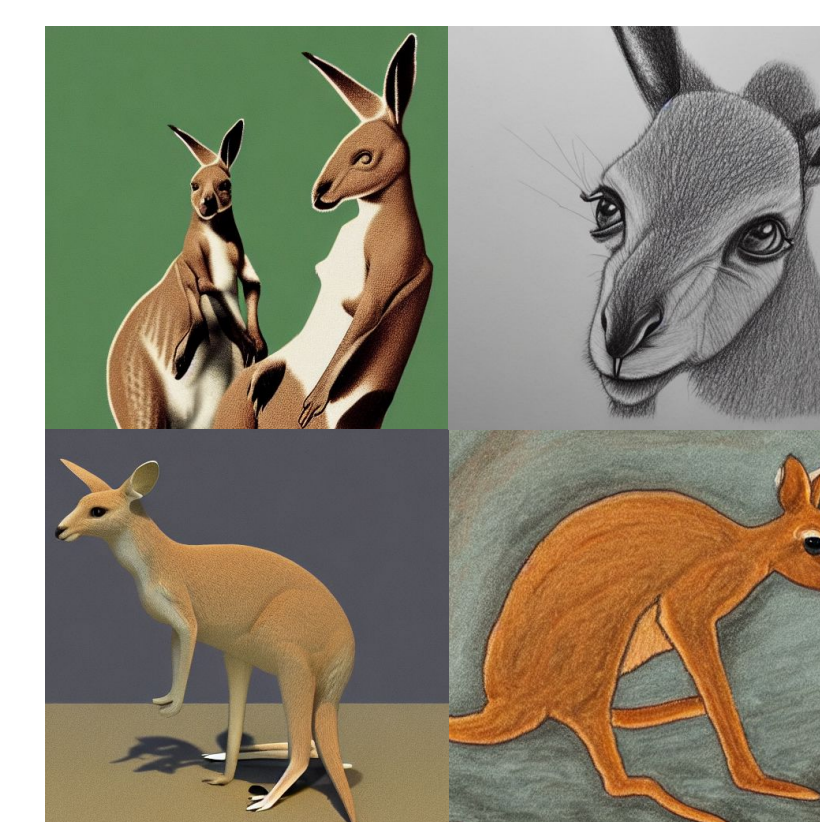
Random Guidance: "An image of a {class}" + random unconditional guidance [1] value set between 1-5



Base Class



Class Prompt



Multi-Domain



Random Guidance