## November 2024



# TibeL Hackathon

#### **Presenter**

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#### **Course Instructor**

Dr. Srijith PK



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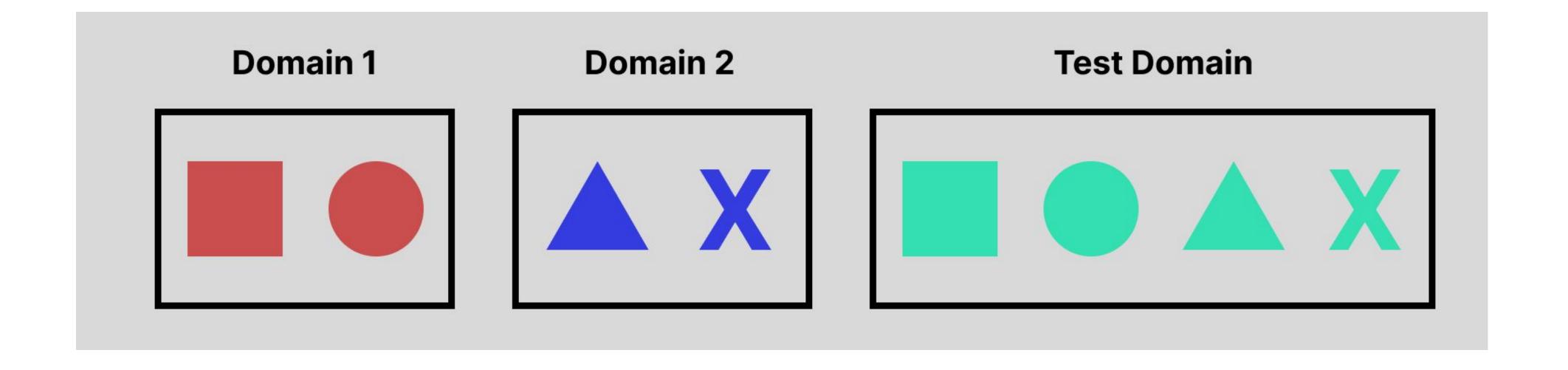
Setup

Observations

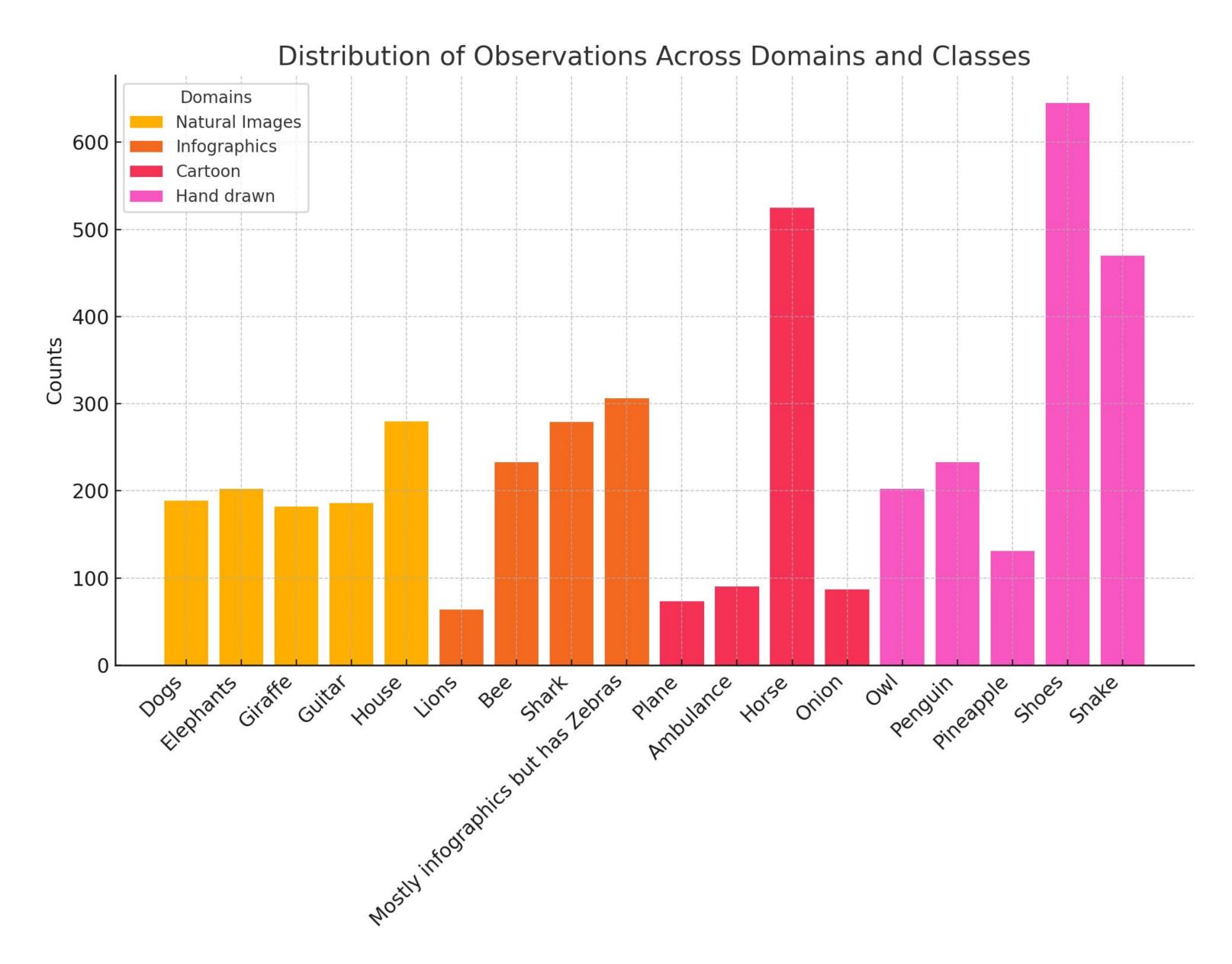
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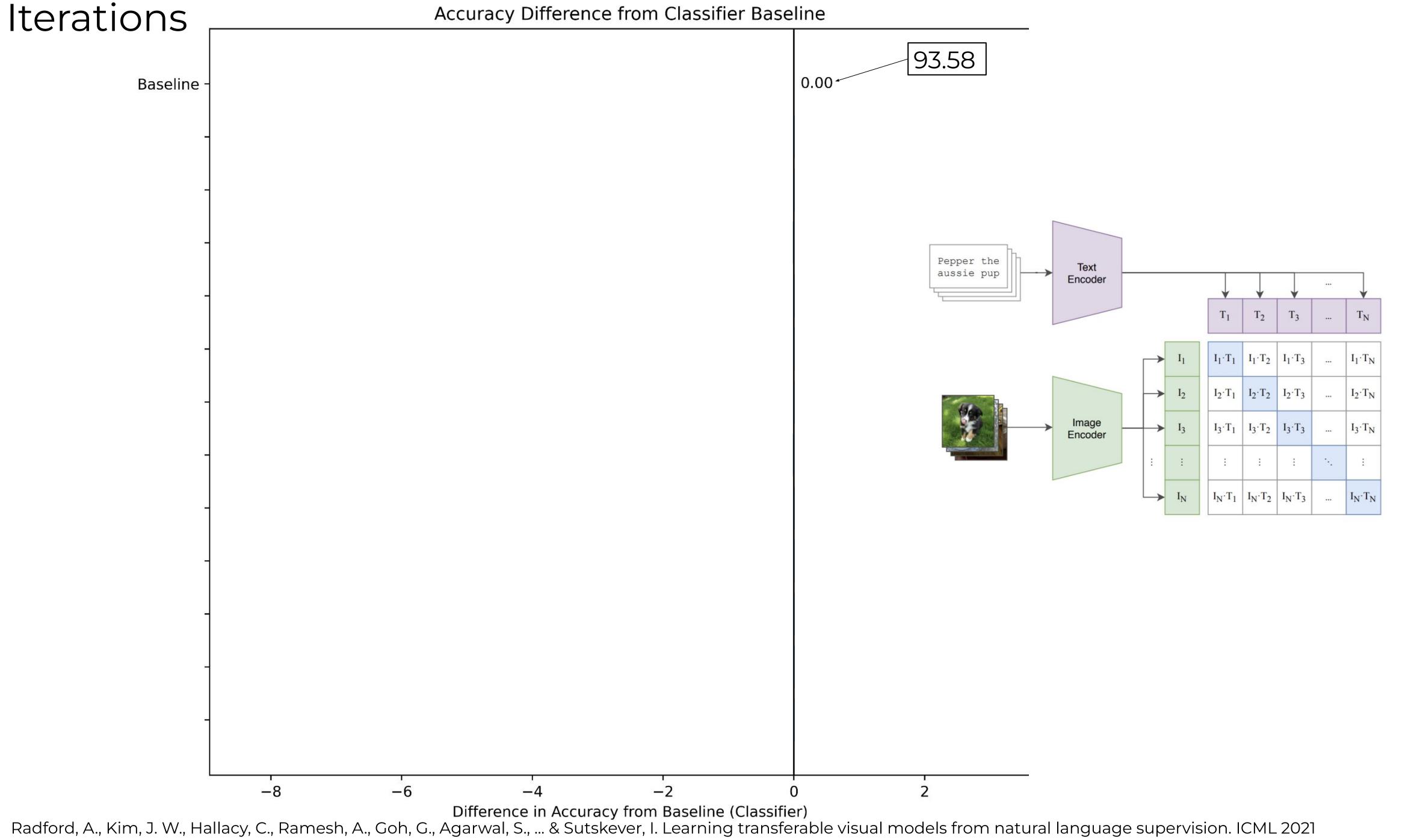
## Setup



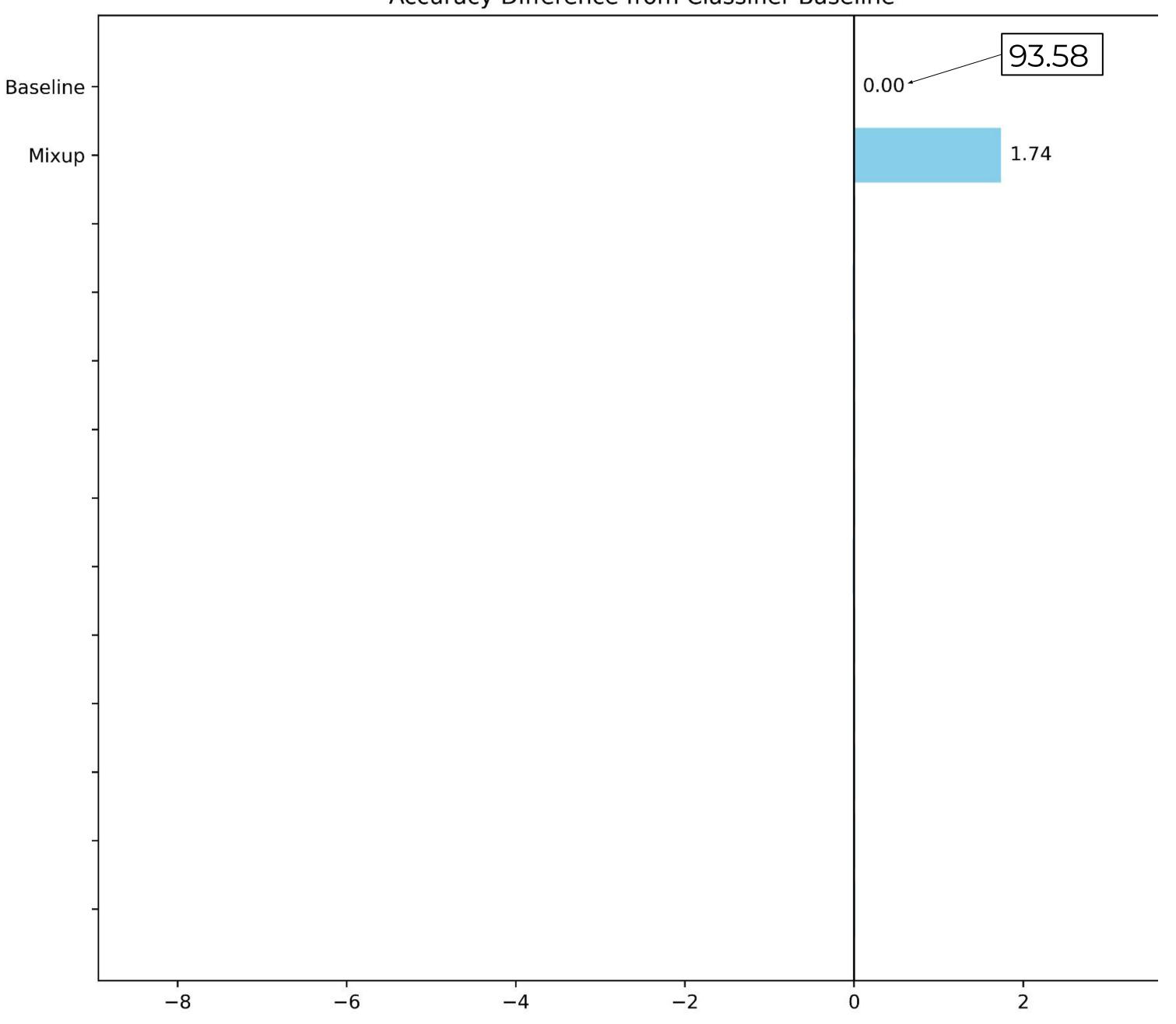
#### Observations



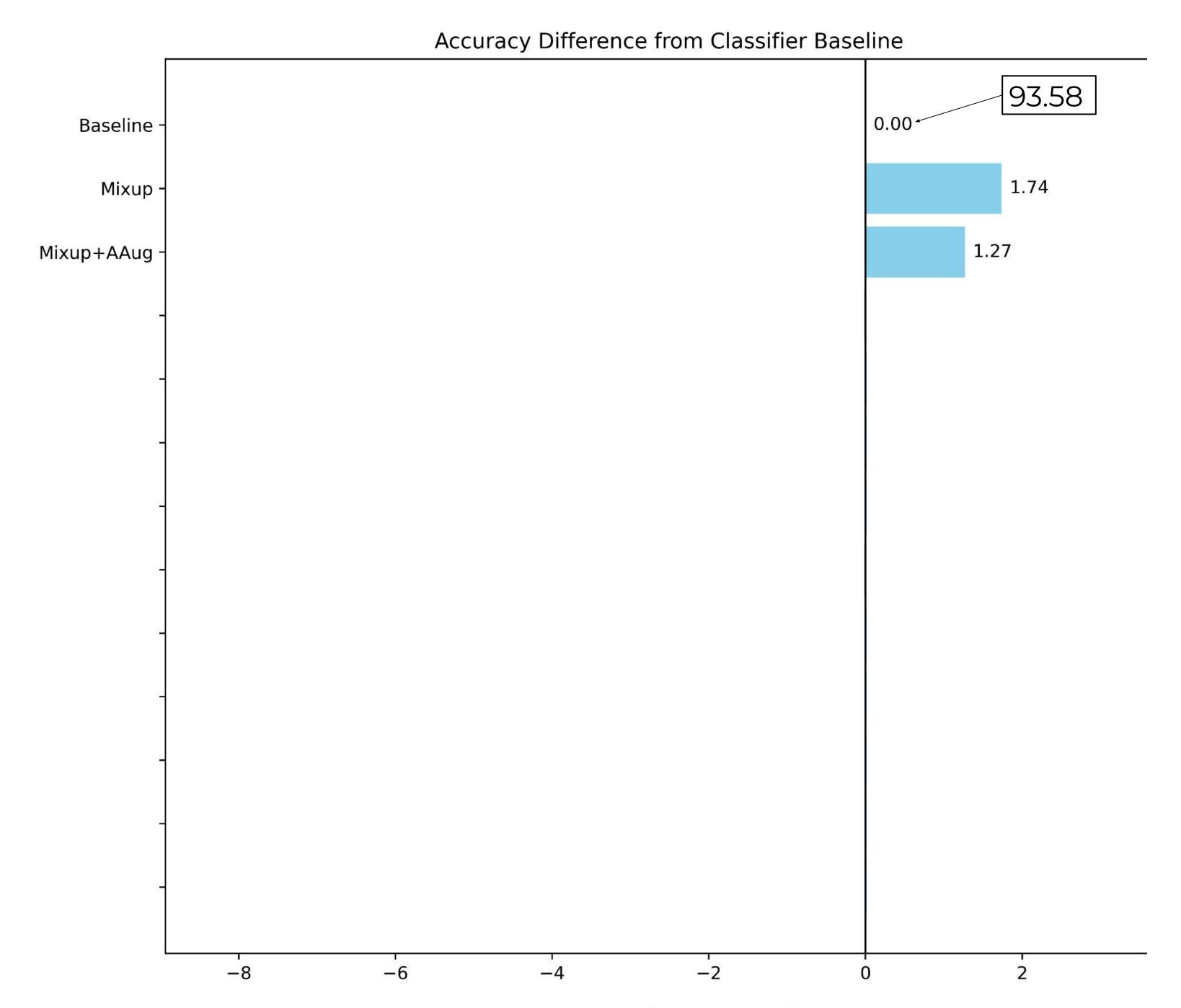
- Imbalance at class level
- Imbalance at domain level
- Disjoint domain
- Out-Of-Distribution classification

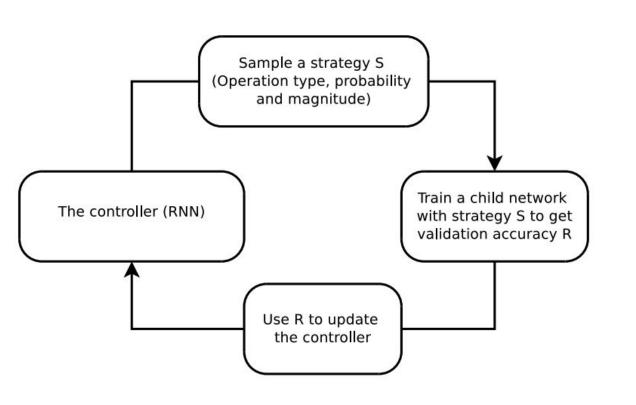


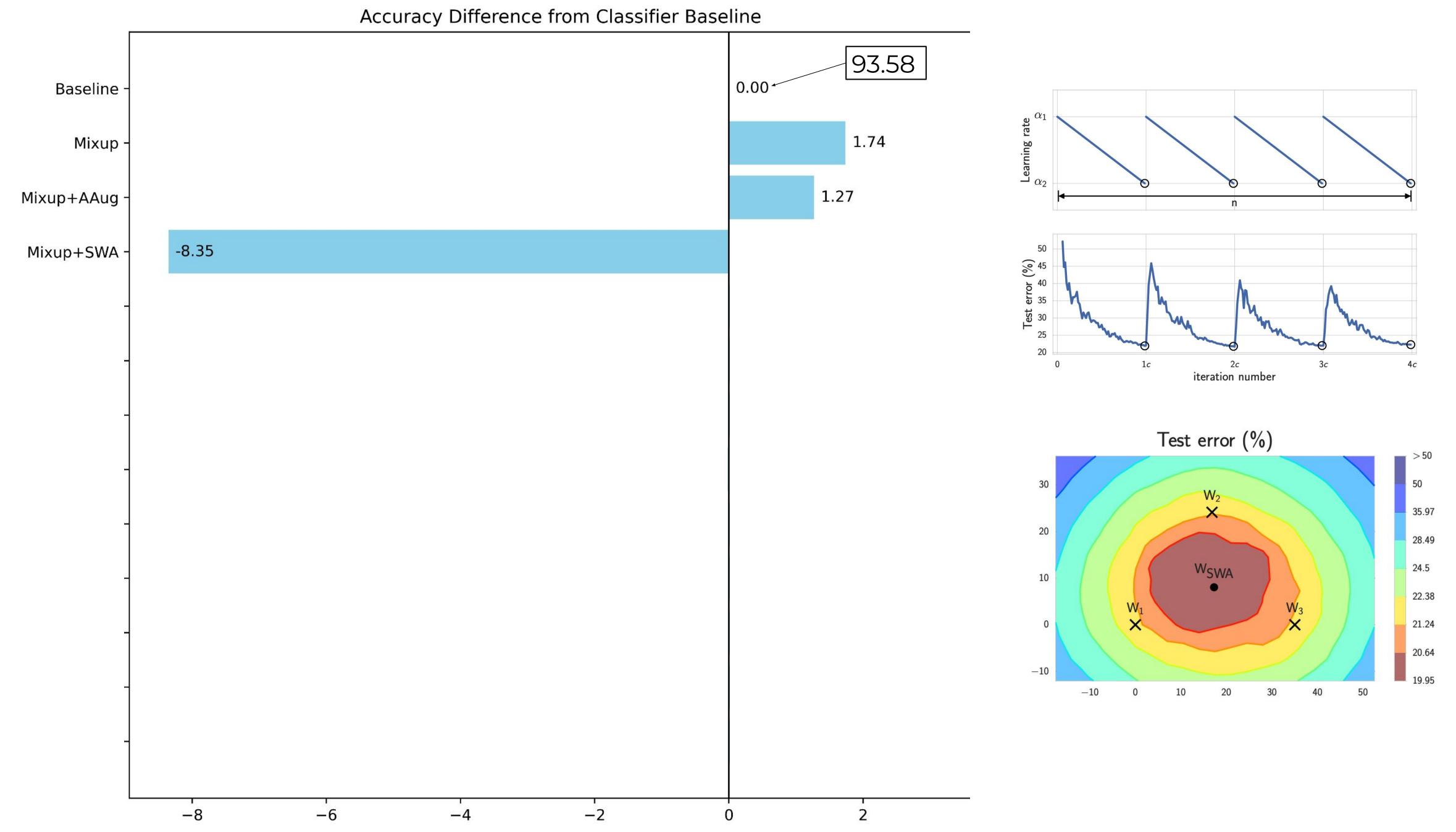


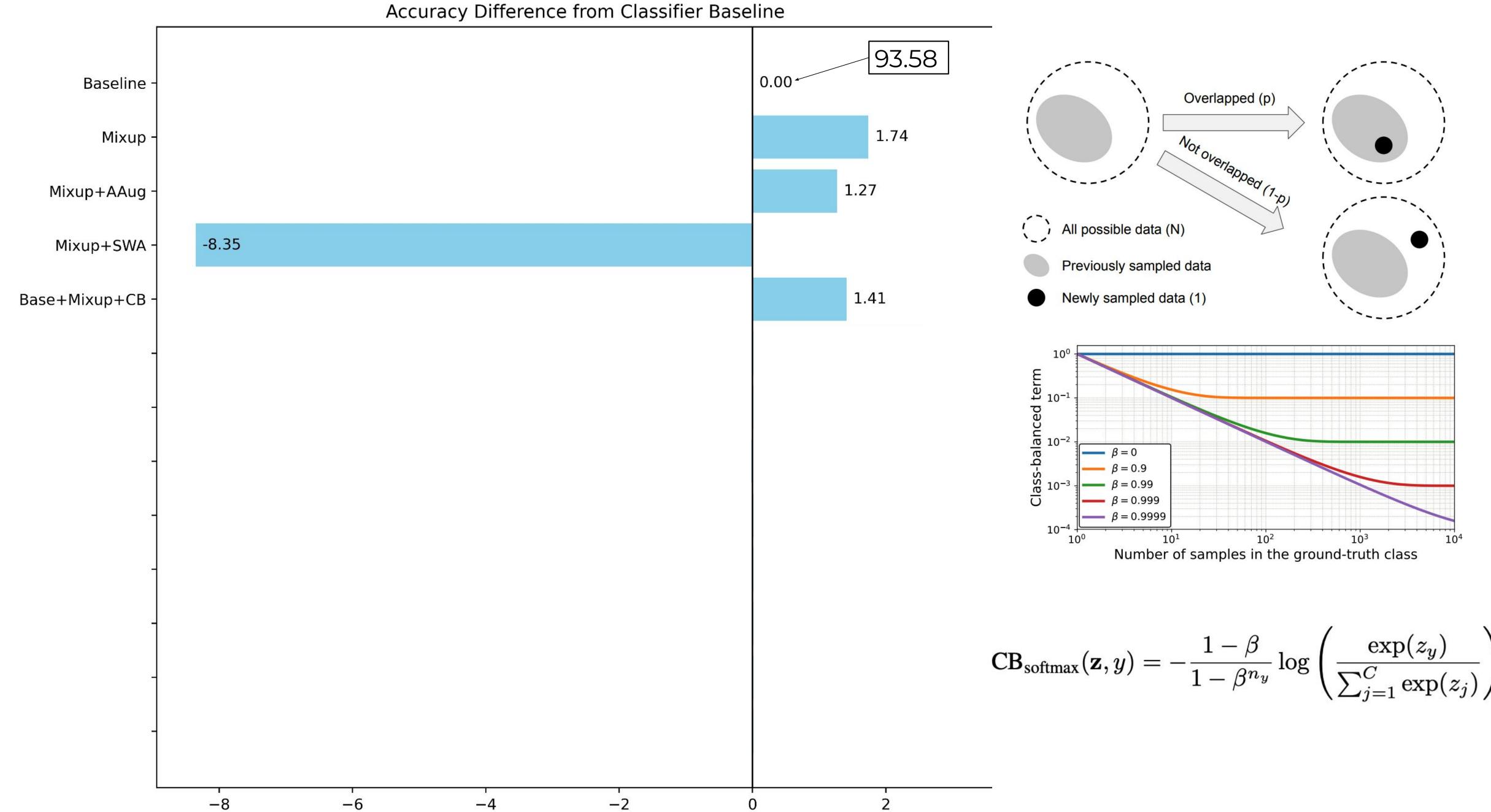


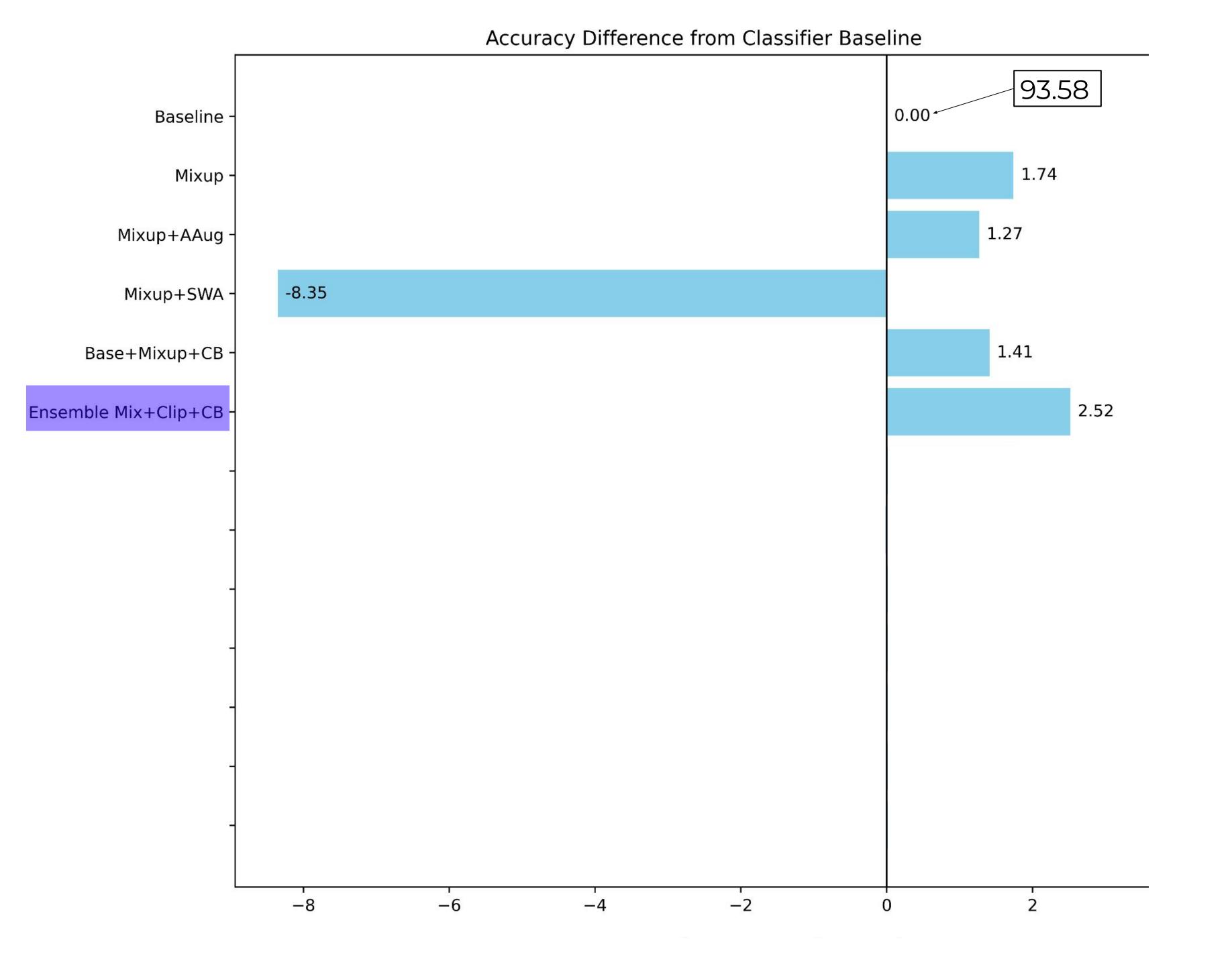
```
# y1, y2 should be one-hot vectors
for (x1, y1), (x2, y2) in zip(loader1, loader2):
    lam = numpy.random.beta(alpha, alpha)
    x = Variable(lam * x1 + (1. - lam) * x2)
    y = Variable(lam * y1 + (1. - lam) * y2)
    optimizer.zero_grad()
    loss(net(x), y).backward()
    optimizer.step()
```

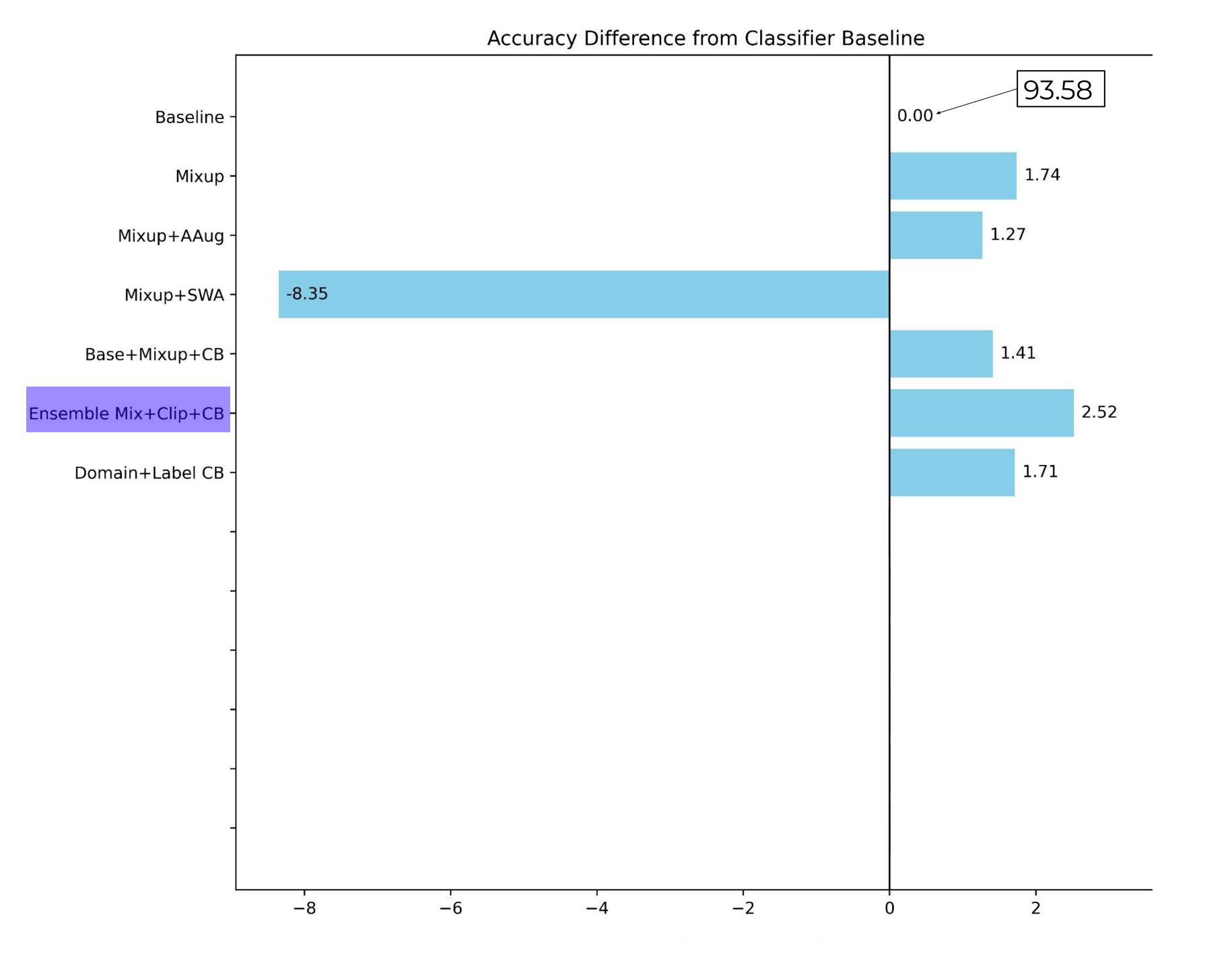


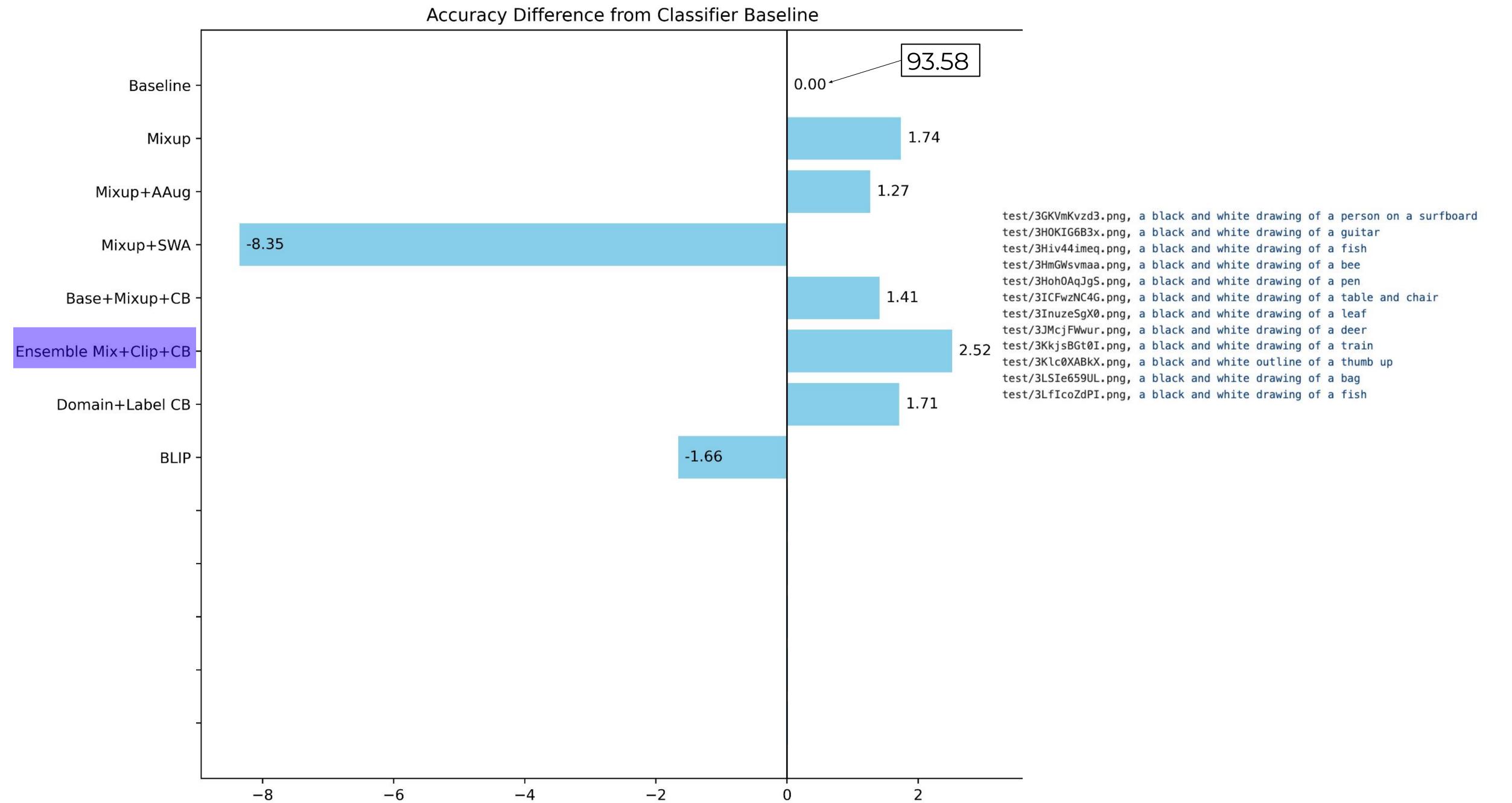




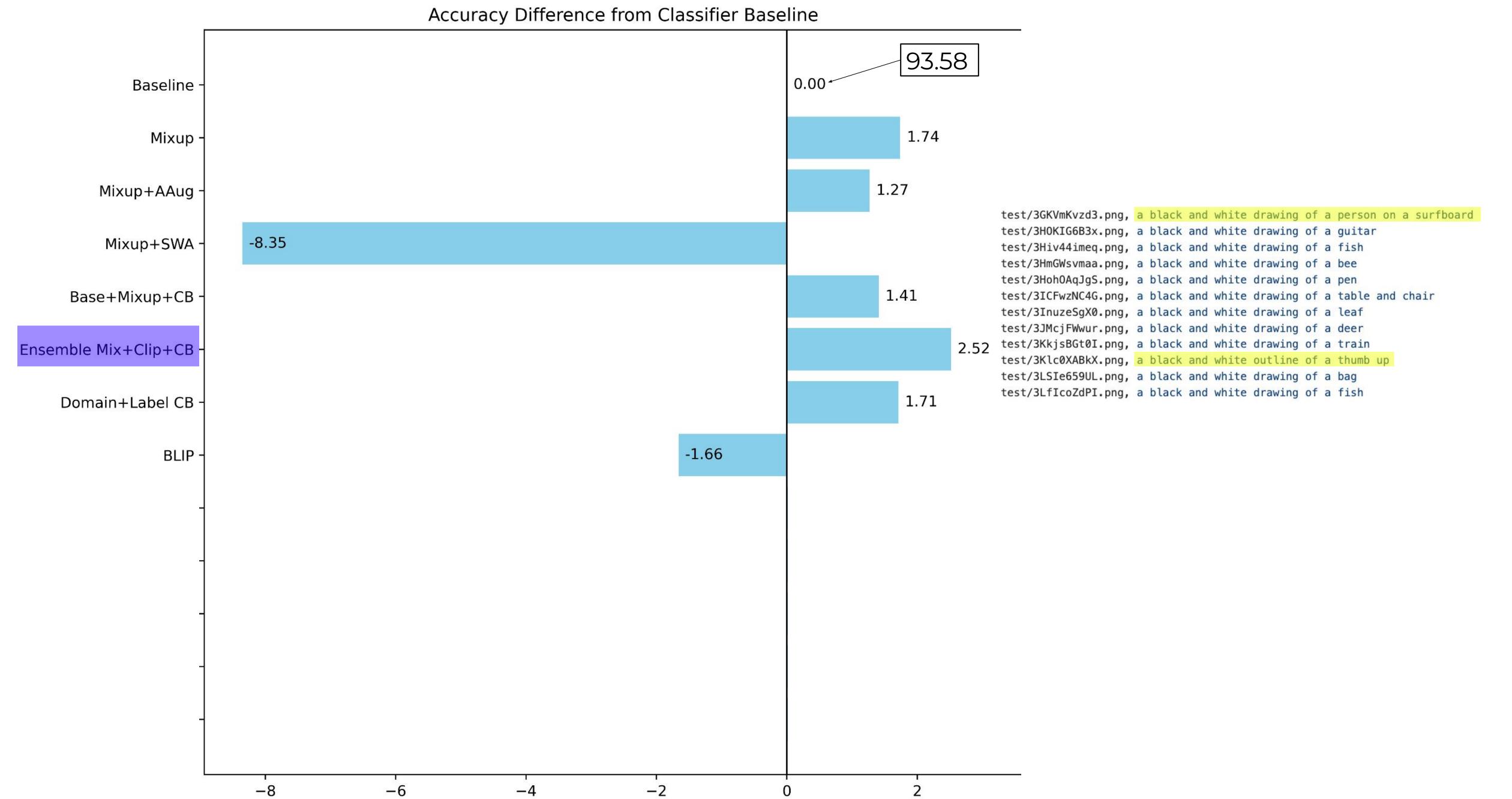




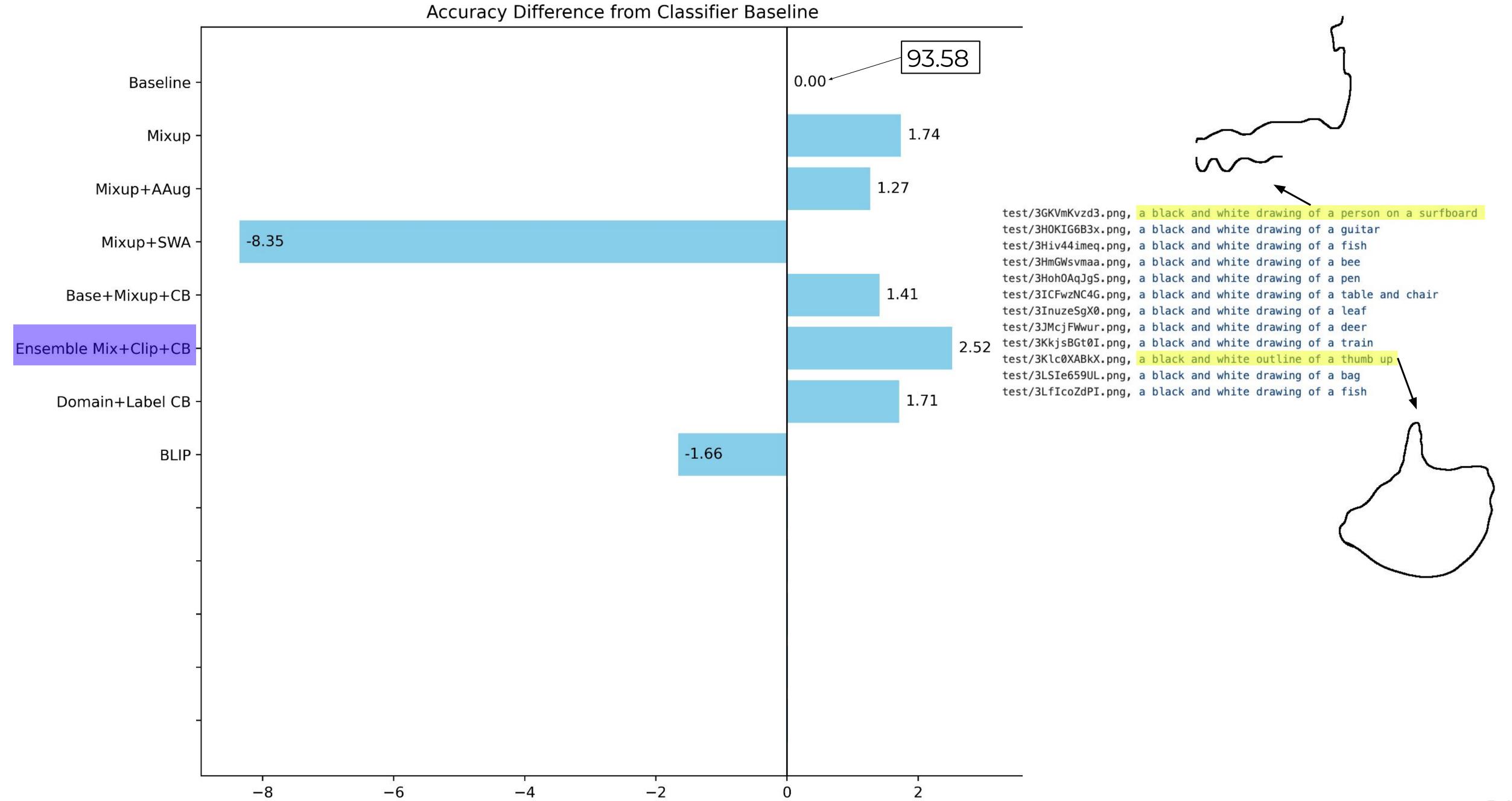




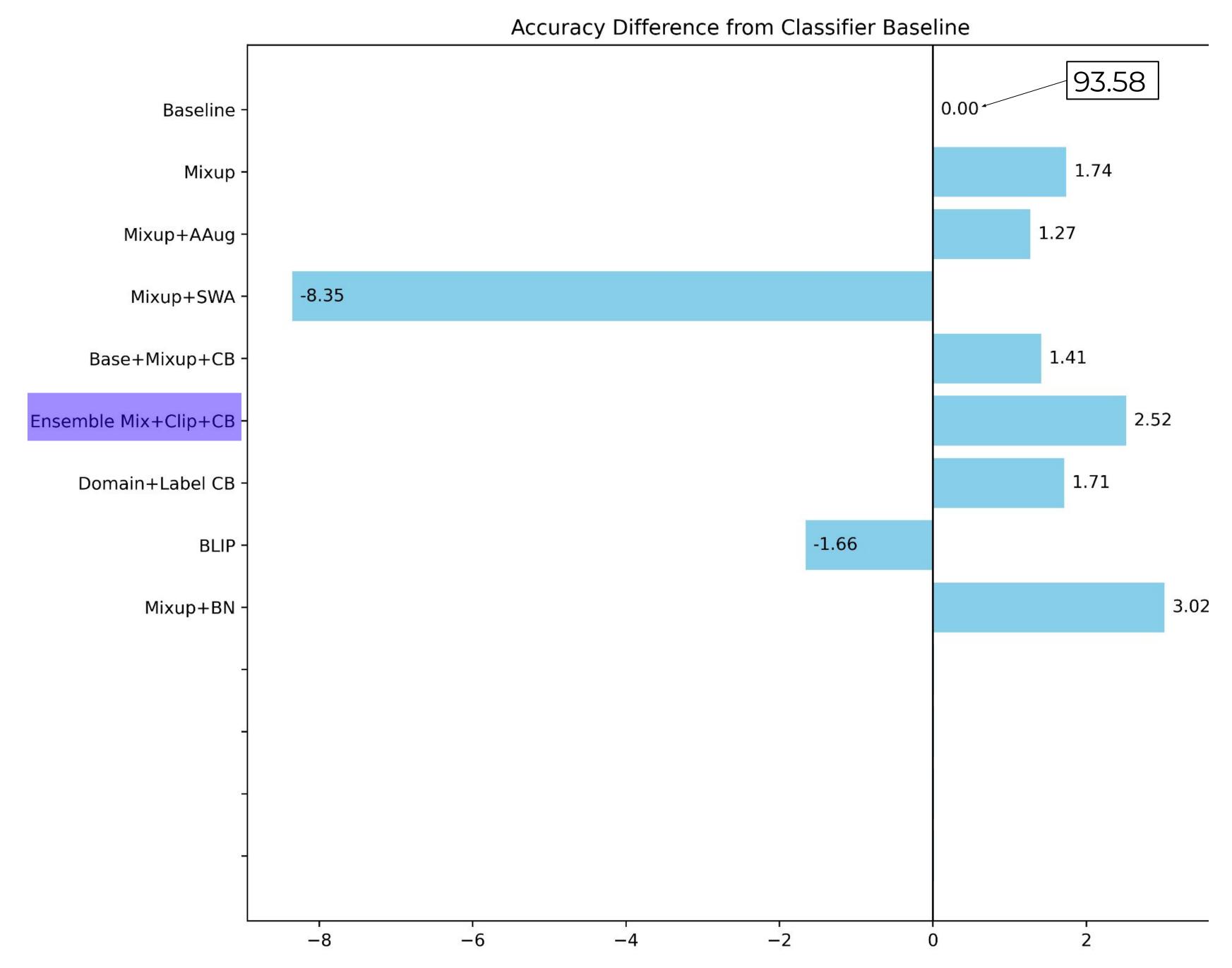
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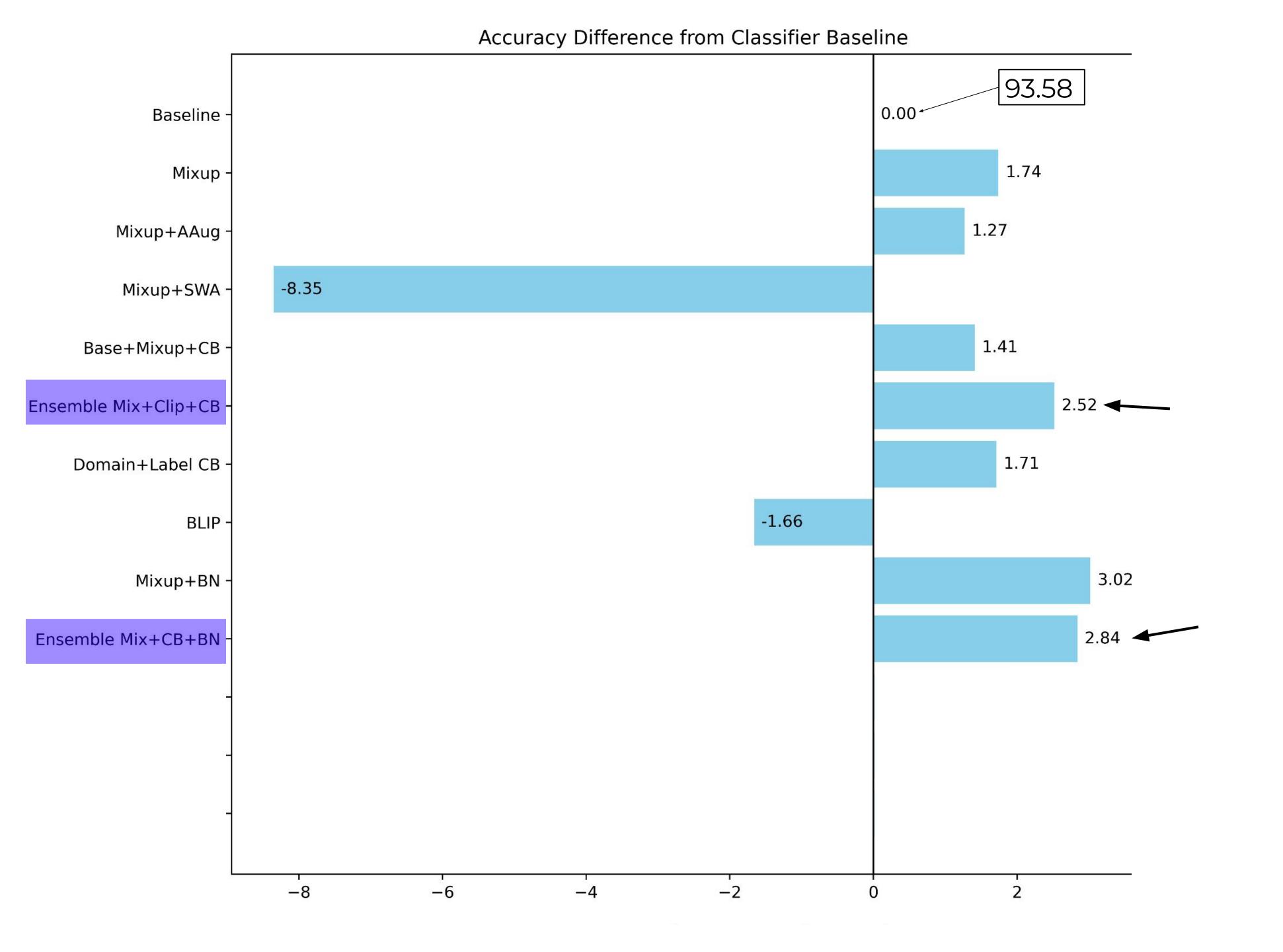
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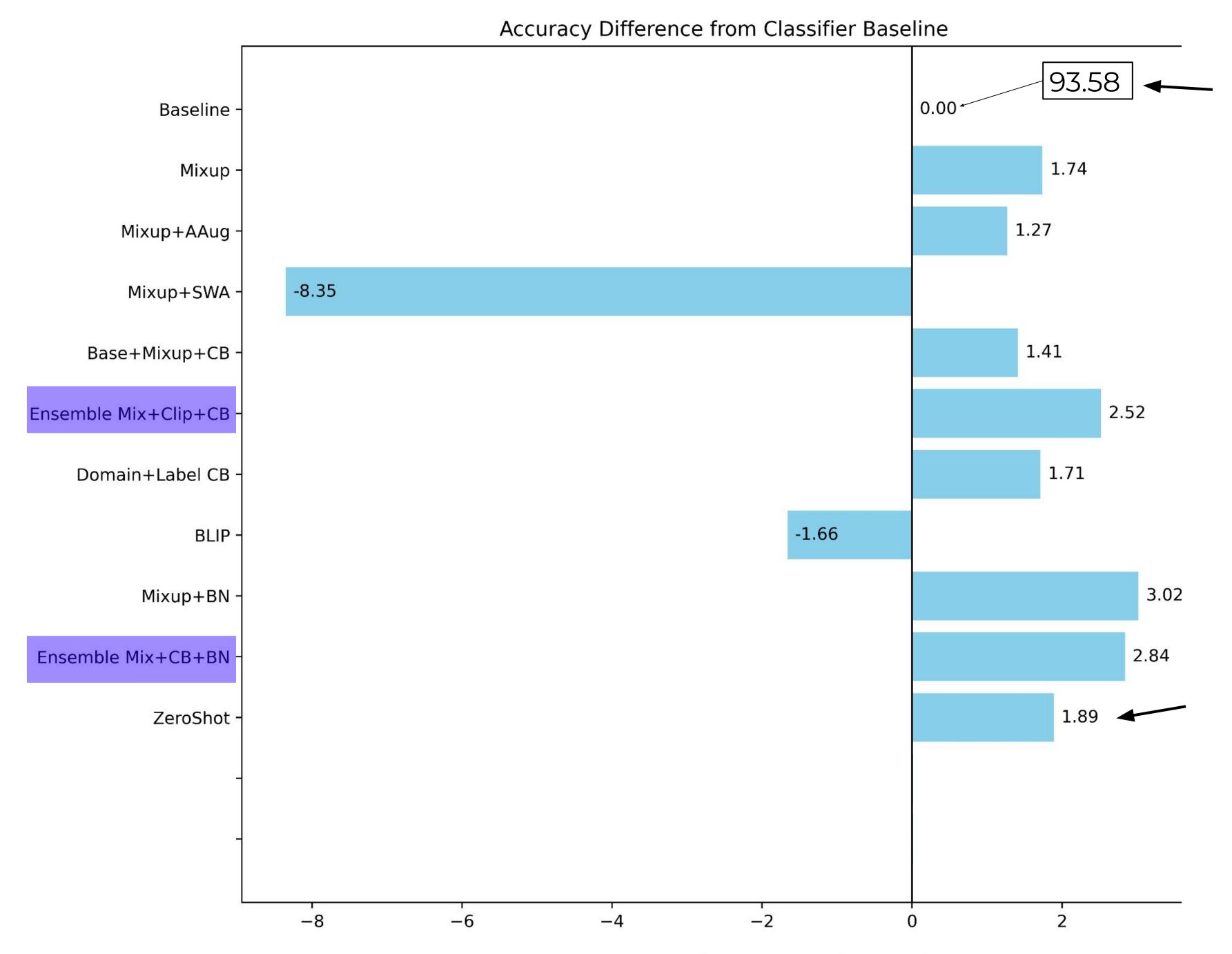


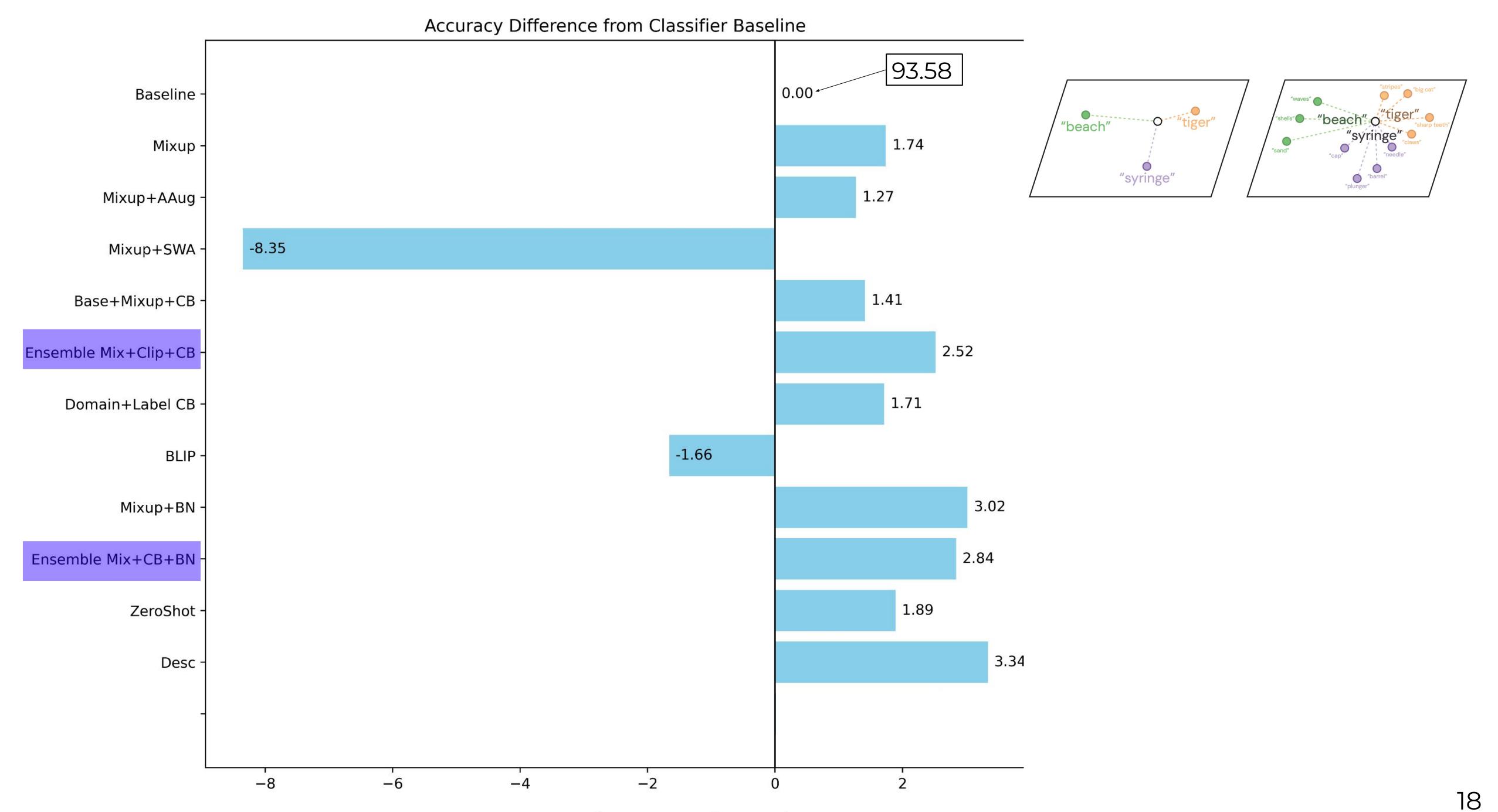
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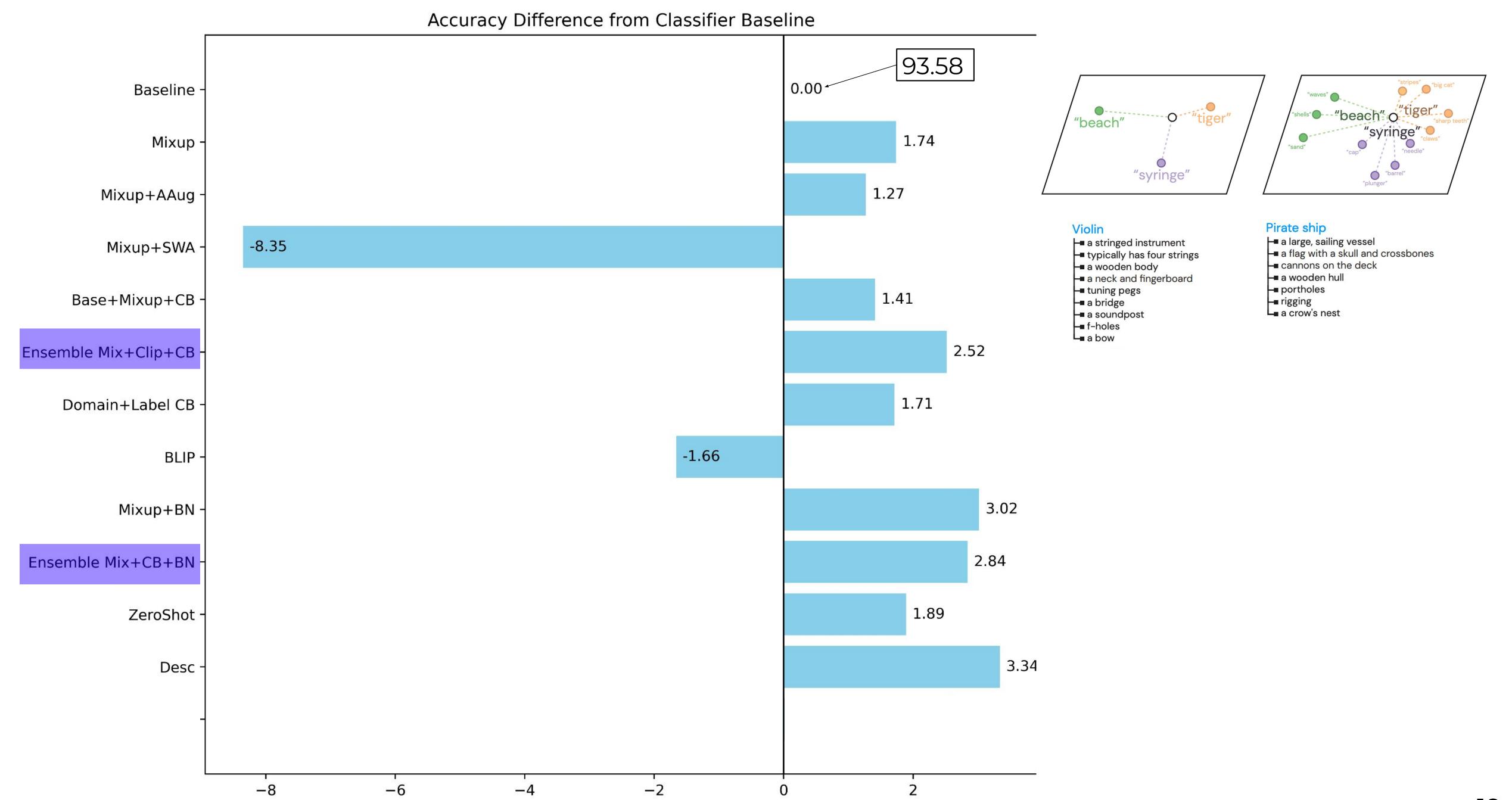


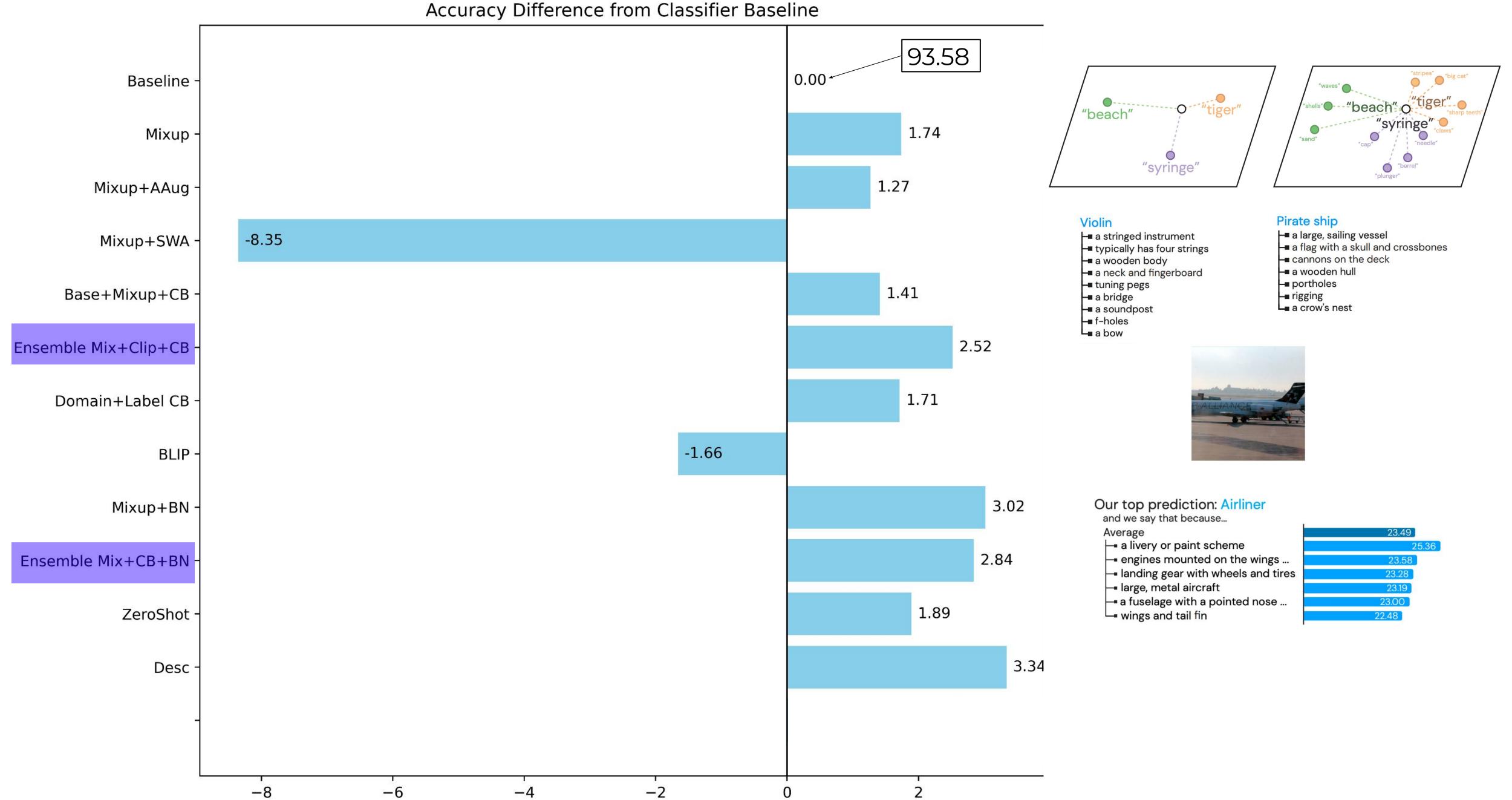
loffe, S. Batch normalization: Accelerating deep network training by reducing internal covariate shift. ICML 2015

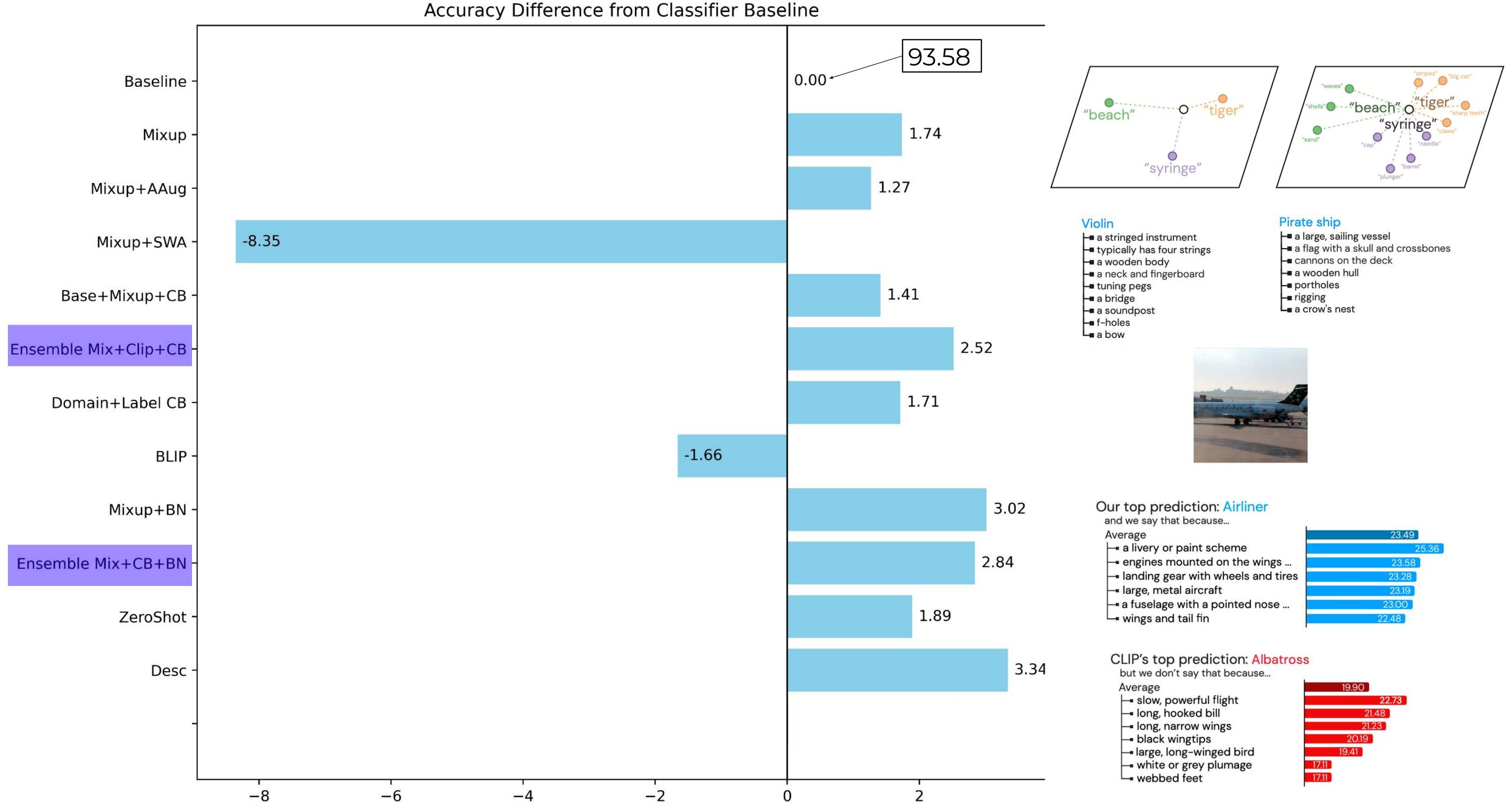


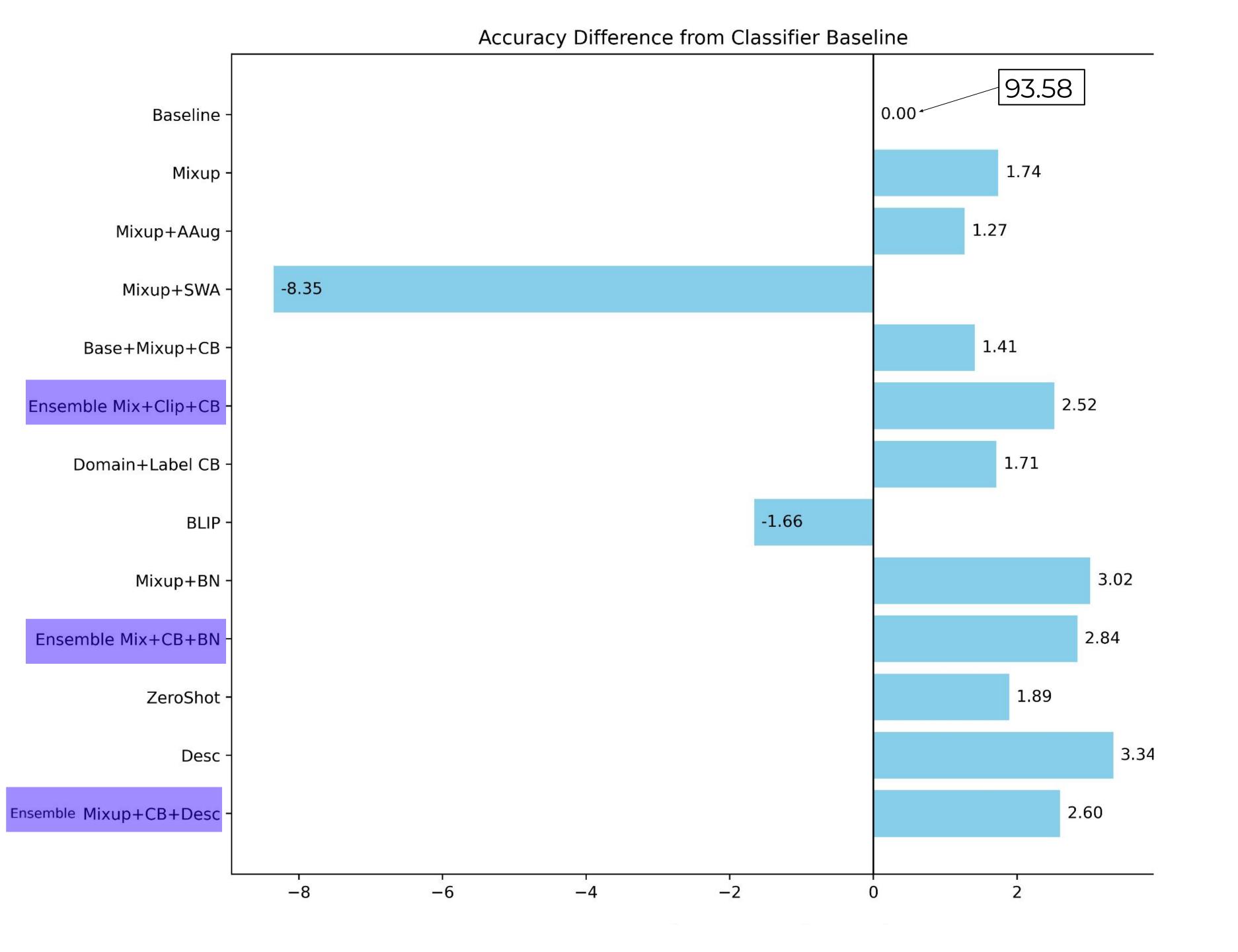


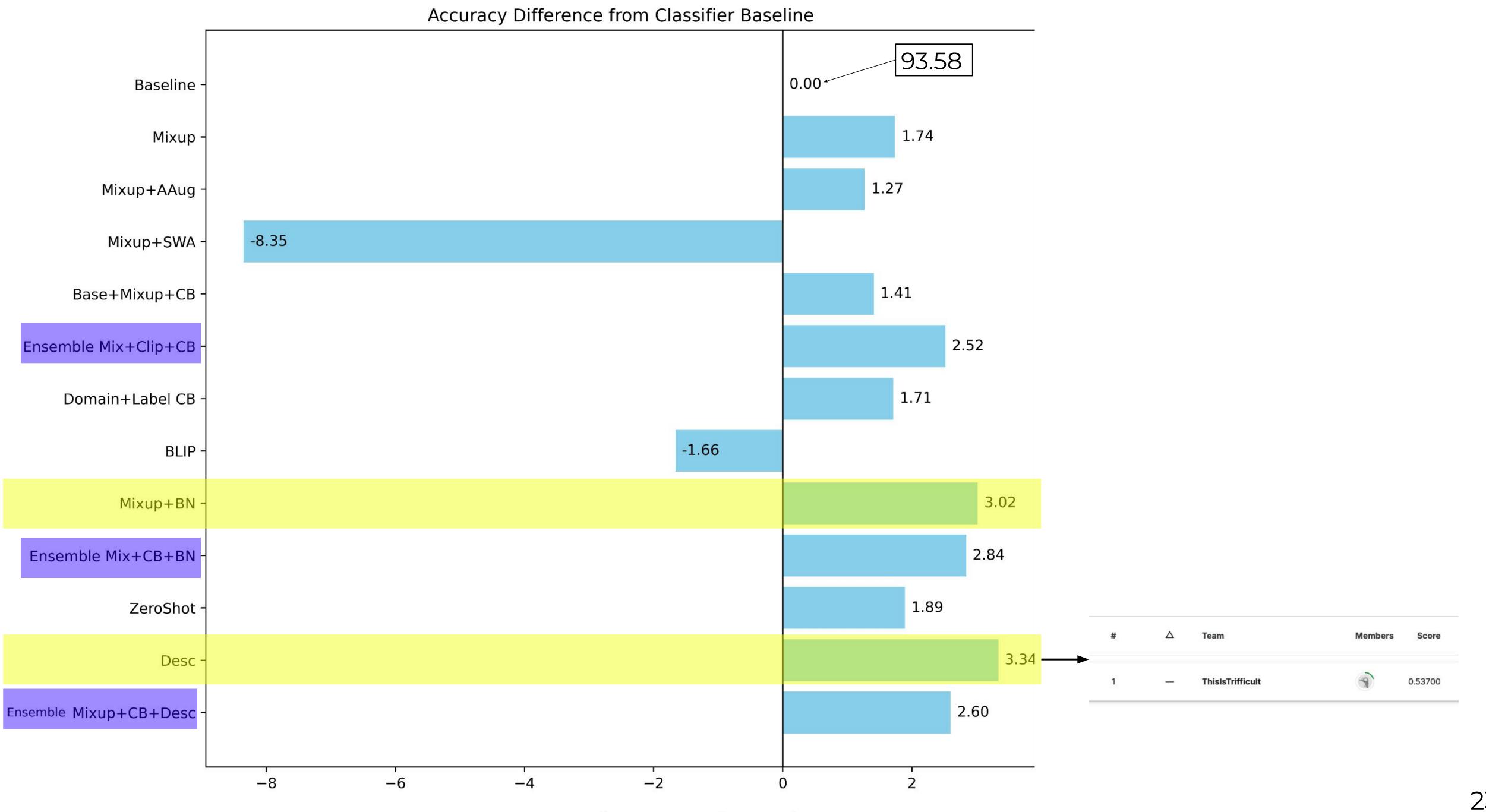












## Takeaways

- Embracing foundational models is essential.
- Foundational models behave differently compared to others.
- There is a gap between what works on paper and what actually works.
- Simple tricks go a long way in improving accuracy.
- If simply adding losses did not help, ensemble them.

#### Citations

- Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., ... & Sutskever, I. Learning transferable visual models from natural language supervision. ICML 2021
- Zhang, Hongyi. mixup: Beyond empirical risk minimization. ICLR 2018
- Cubuk, E. D., Zoph, B., Mane, D., Vasudevan, V., & Le, Q. V. Autoaugment: Learning augmentation policies from data. CVPR 2019.
- Izmailov, P., Podoprikhin, D., Garipov, T., Vetrov, D., & Wilson, A. G. Averaging weights leads to wider optima and better generalization. UAI 2018
- Cui, Y., Jia, M., Lin, T. Y., Song, Y., & Belongie, S. Class-balanced loss based on effective number of samples. CVPR 2019.
- Li, J., Li, D., Xiong, C., & Hoi, S. Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation. ICML 2022
- loffe, S. Batch normalization: Accelerating deep network training by reducing internal covariate shift. ICML 2015
- Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., ... & Sutskever, I. Learning transferable visual models from natural language supervision. ICML 2021
- Menon, S., & Vondrick, C. Visual classification via description from large language models. ICLR 2023.



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Thank you so much to the TAs for tolerating me