Explanation-based Data Augmentation for Image Classification

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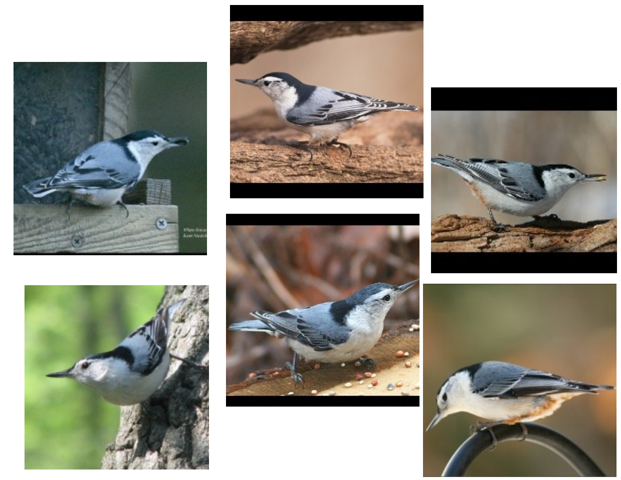
Training Dataset must be Representative.

Black Tern

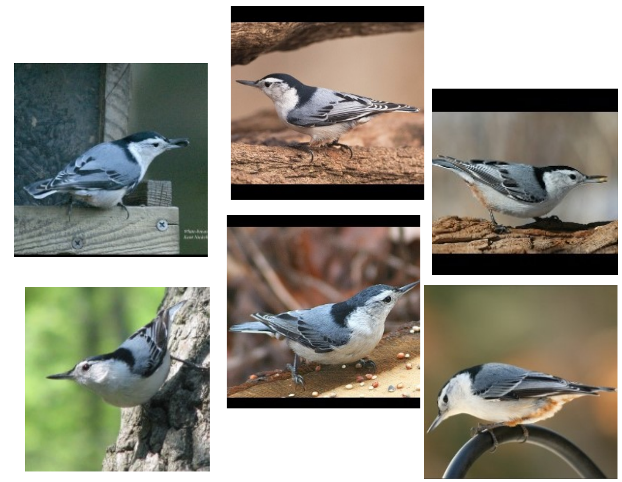


White Breasted Nuthatch

Training Dataset must be Representative.

Juvenile Black Terns

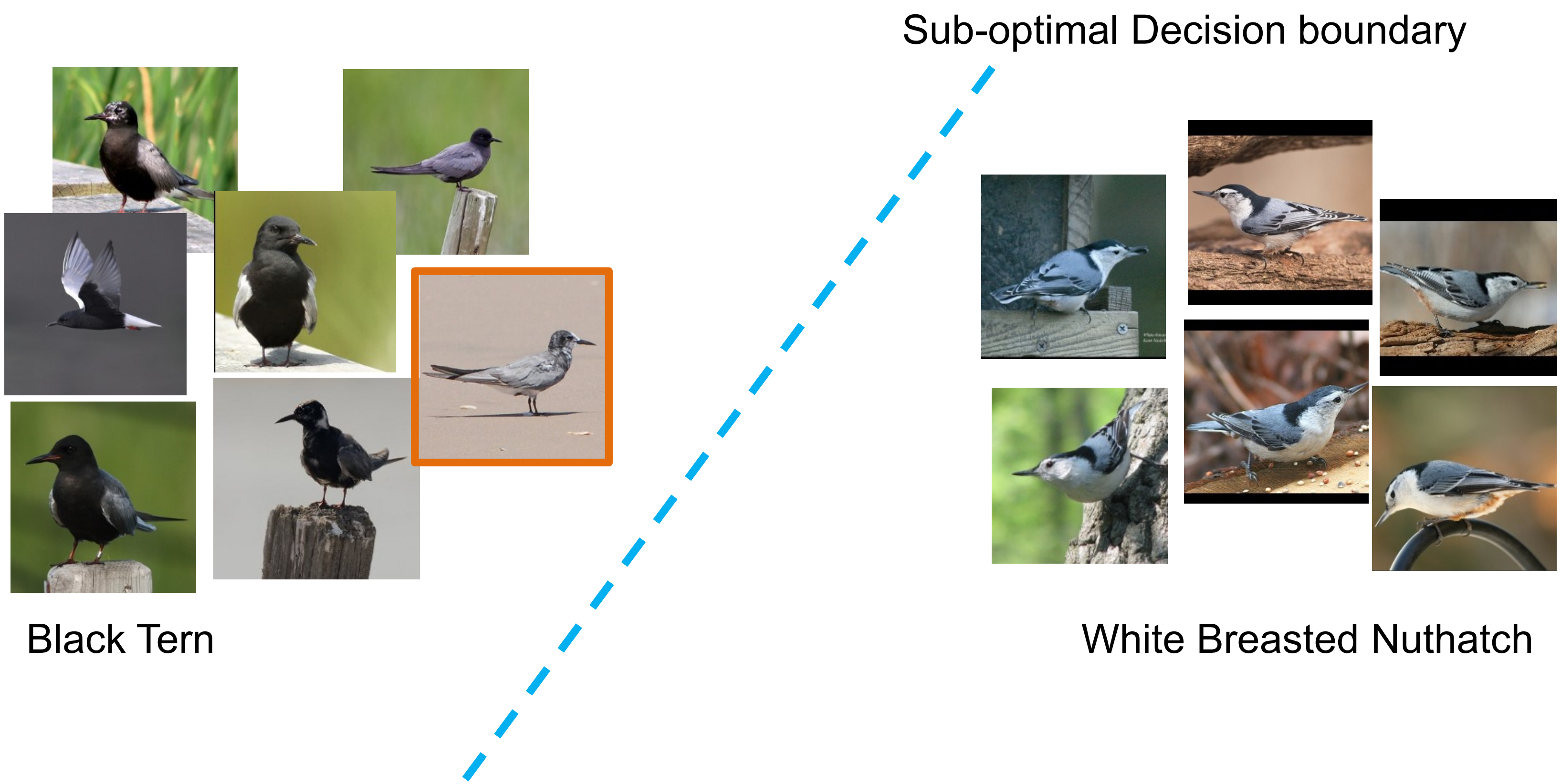
Black Tern



White Breasted Nuthatch

- Train dataset contains very few images of Juvenile Black Terns.
- Juvenile Black Terns are under-represented.

Training Dataset must be Representative.



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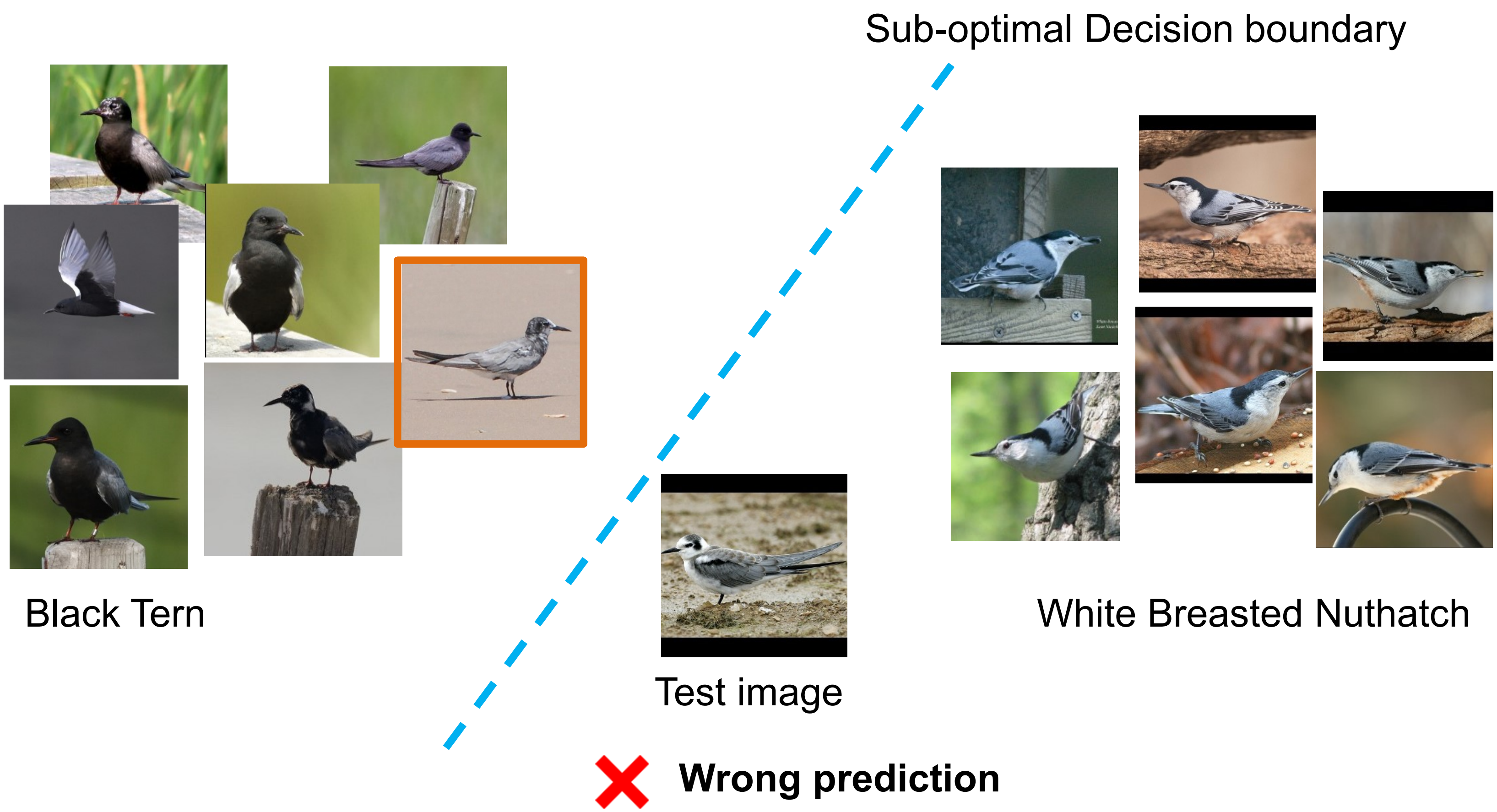
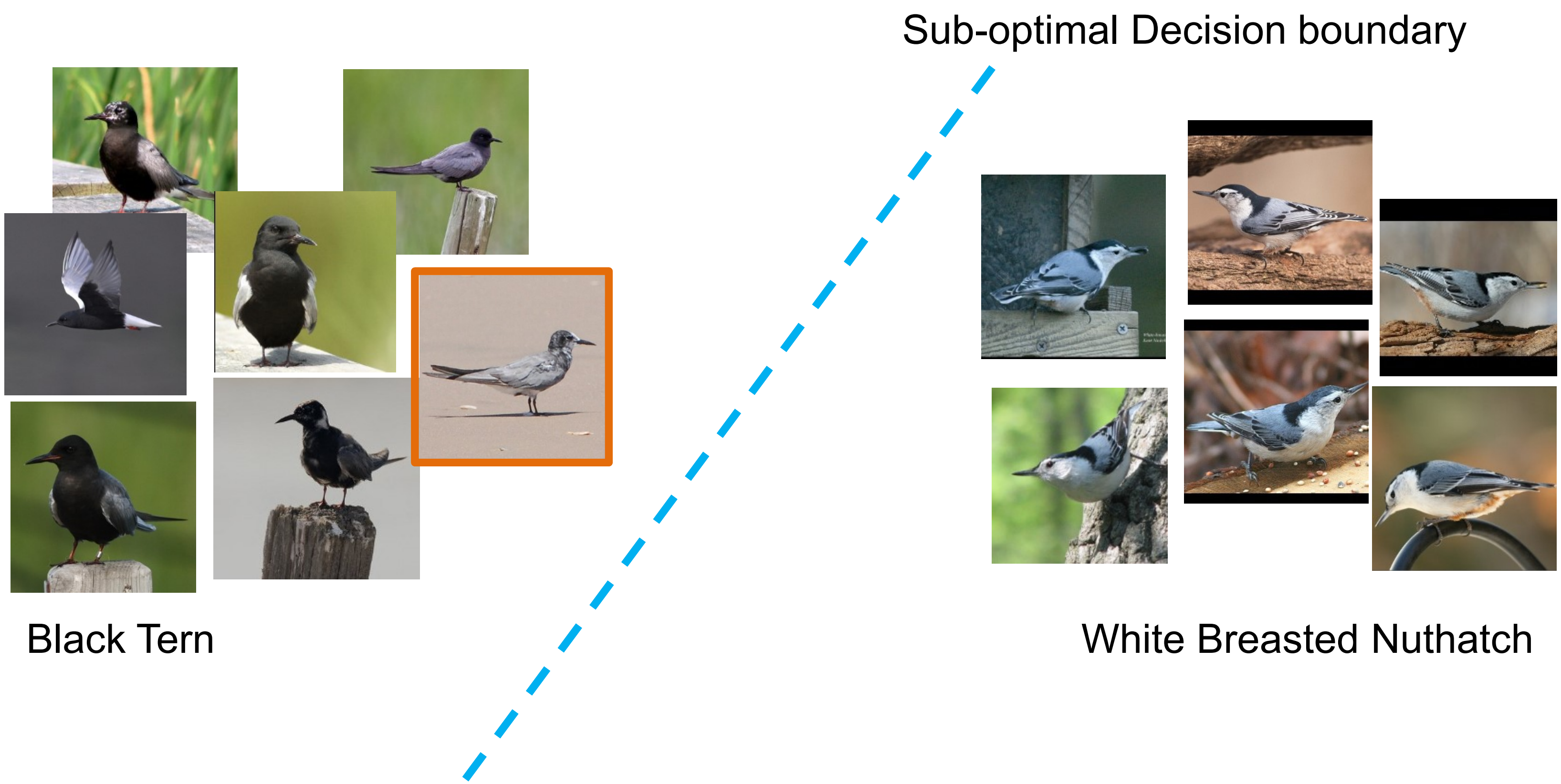


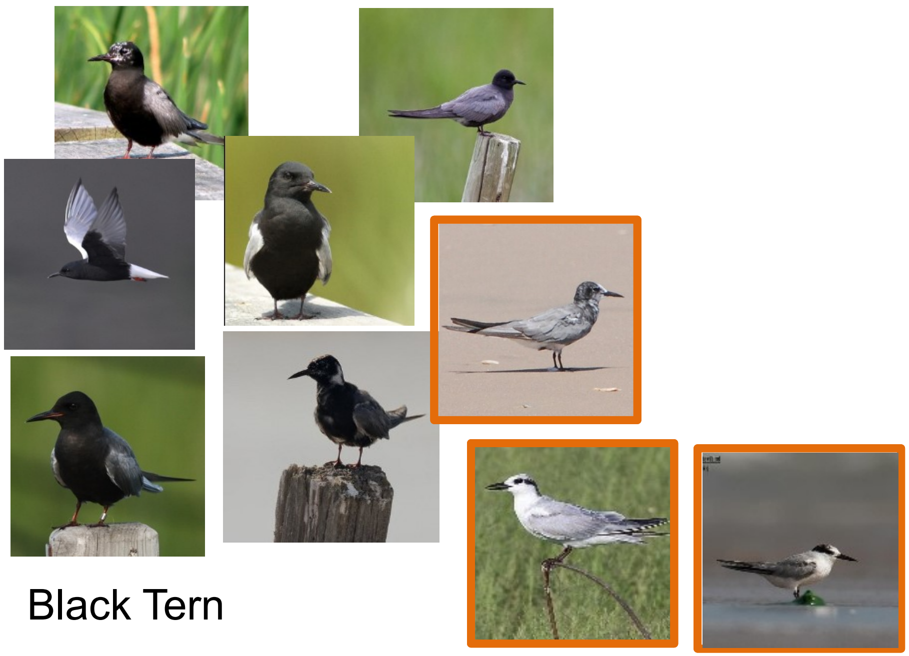
BRACE - BetteR Accuracy from Concept-based Explanation

Transformation-based Data Augmentation?

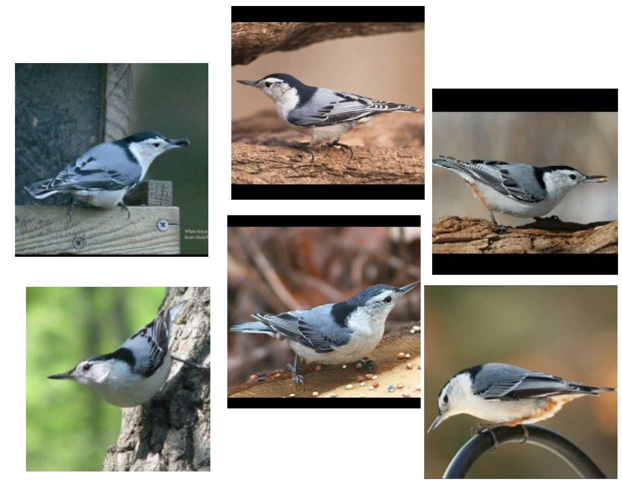


Only explore the neighborhood of existing samples and may not cover the under-represented regions.

Obtain Images from Image Repositories?



Black Tern

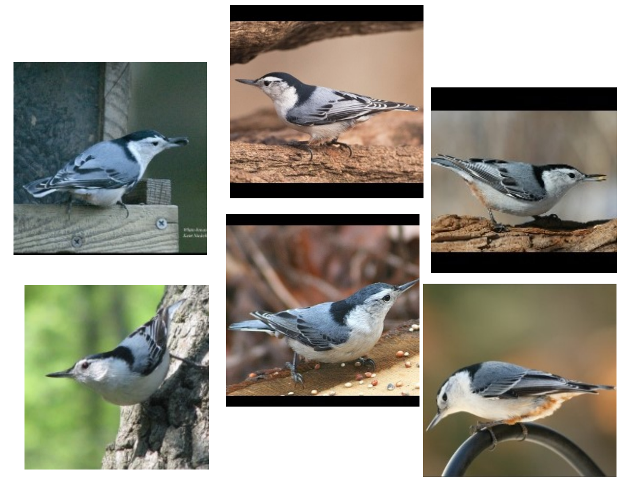


White Breasted Nuthatch

Obtain Images from Image Repositories?

New Decision boundary

Black Tern



White Breasted Nuthatch

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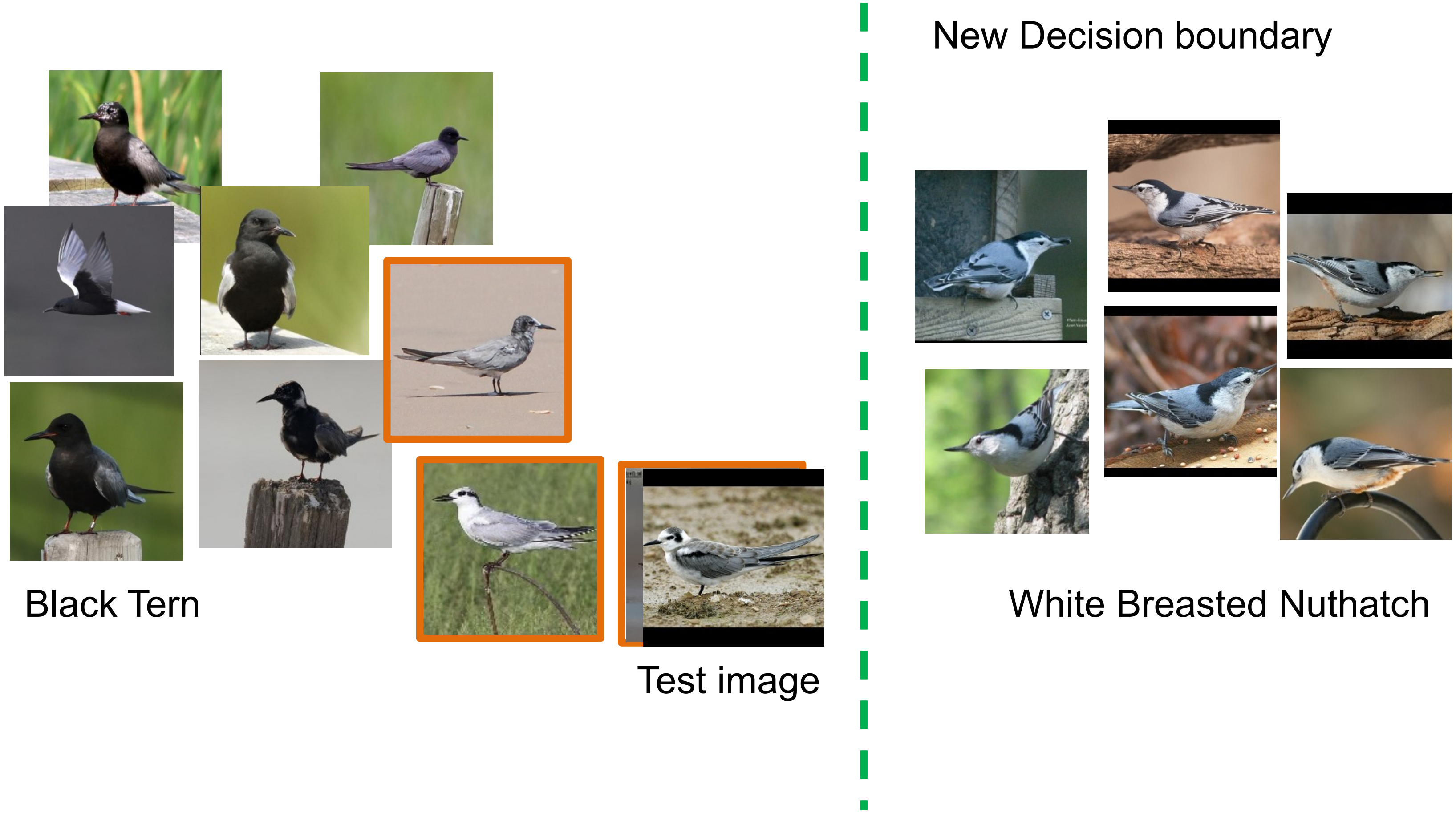

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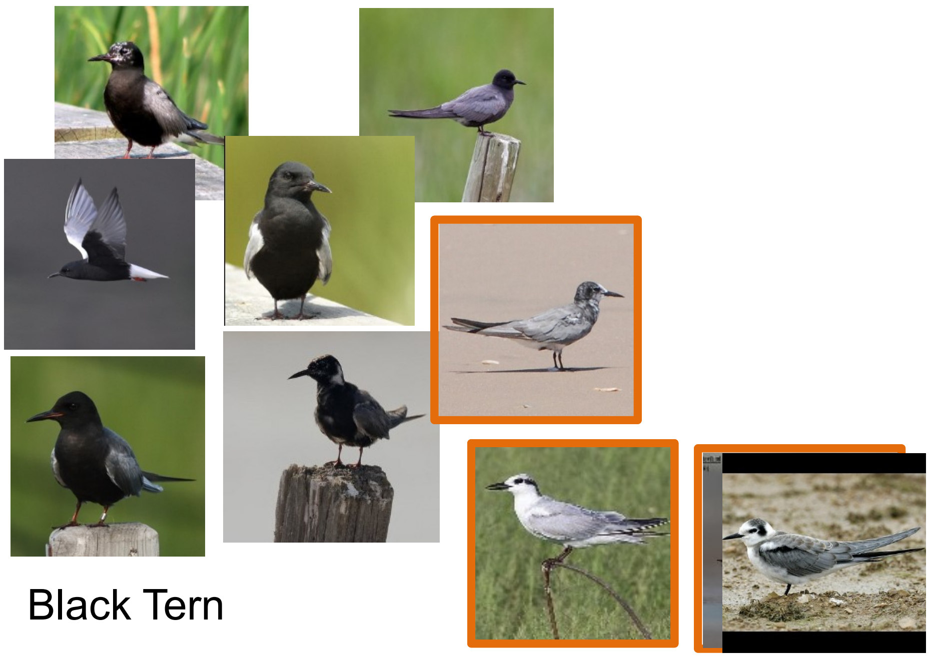
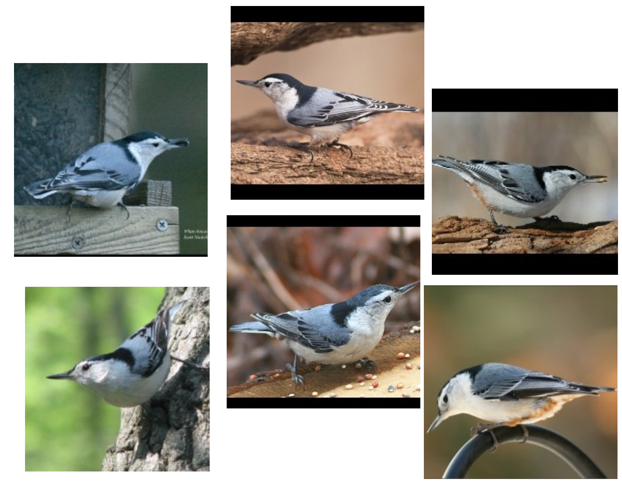


Black Tern

Test image



White Breasted Nuthatch

✓ **Correct prediction**

Obtain Images from Image Repositories?

- Should not introduce noise
  - e.g., out-of-distribution images.

(a) Images obtained for Black Tern class

- Added images should be informative.

Explanations Provide Useful Insights!

- E.g., **CCNN**[1] misclassifies juvenile Black Tern in Fig (a) as White Breasted Nuthatch.
- **Concepts caused misclassification :** *White breast, White belly, Black crown*

(a) Juvenile Black Tern

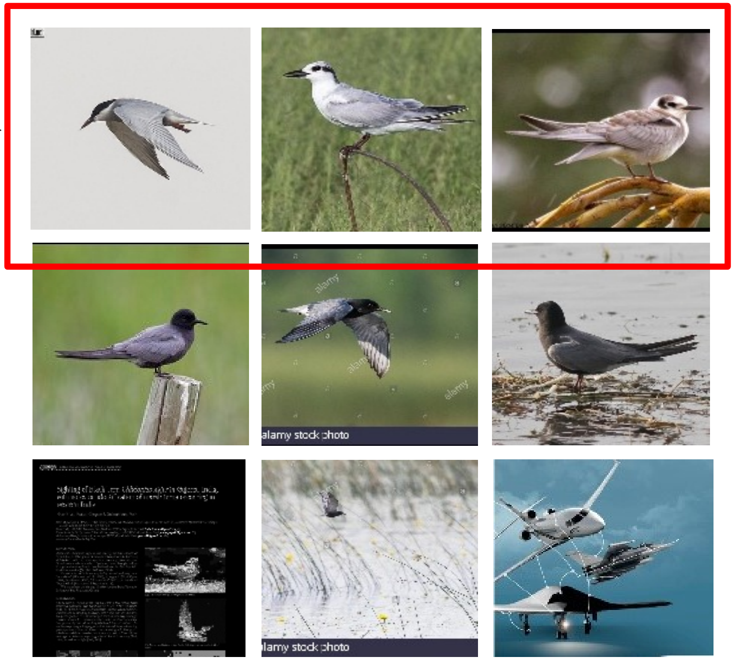
(b) Images of adult Black Tern

(c) Images of White Breasted Nuthatch

[1] Comprehensible Convolutional Neural Networks via Guided Concept Learning, IJCNN, 2021

Use Explanations to Identify Informative Images?

Informative images



(a) Images obtained for Black Tern class

- BRACE - **B**ette**R** **A**ccuracy from **C**oncept-based **E**xplanation

Assess Utility of New Images

- Suppose an image of c is misclassified into $\bar{c}$.
- **Is the new image from the under-represented region?**
  - Similar to the existing images of c.
  - Model's confidence that the new image belongs to a $\bar{c}$ is high.

$$\boldsymbol{\beta(x, c, \bar{c}) = \frac{f_x \cdot f_c}{\|f_x\| \, \|f_c\|} \times e^{P(\bar{c}|x)}}$$

x = new image f_x = visual features of x f_c = avg visual features of class c

Visual features are extracted using the classifier trained with original train dataset.

Assess Utility of New Images

- Does the new image contain concepts caused misclassifications?
  - Derive concepts caused misclassifications - $\boldsymbol{S_{c \rightarrow \bar{c}}}$
  - Computer degree of match between visual features in the new image and $\boldsymbol{S_{c \rightarrow \bar{c}}}$ - $\boldsymbol{\Delta(S_{c \rightarrow \bar{c}}, x)}$

- $\boldsymbol{utility} = \sum_{\bar{c} \in \bar{C}} [\boldsymbol{\beta(x, c, \bar{c})} \times \boldsymbol{\Delta(S_{c \rightarrow \bar{c}}, x)}]$ where $\bar{C} = \cup\, \bar{c}$

Which Explanation Methods?

- Concept-based explanation methods
- Post-hoc explanations or explanations from inherently interpretable models
- Post-hoc methods – GradCAM [1], ACE [2], IBD [3]
- Inherently interpretable models – CCNN [4], ProtoPNet [5]

[1] Grad-cam: Visual explanations from deep networks via gradient-based localization, ICCV, 2017.
[2] Towards automatic concept-based explanations, NeurIPS, 2019.
[3] Interpretable basis decomposition for visual explanation, ECCV, 2018.
[4] Comprehensible Convolutional Neural Networks via Guided Concept Learning, IJCNN, 2021.
[5] This looks like that: deep learning for interpretable image recognition, NeurIPS, 2019.

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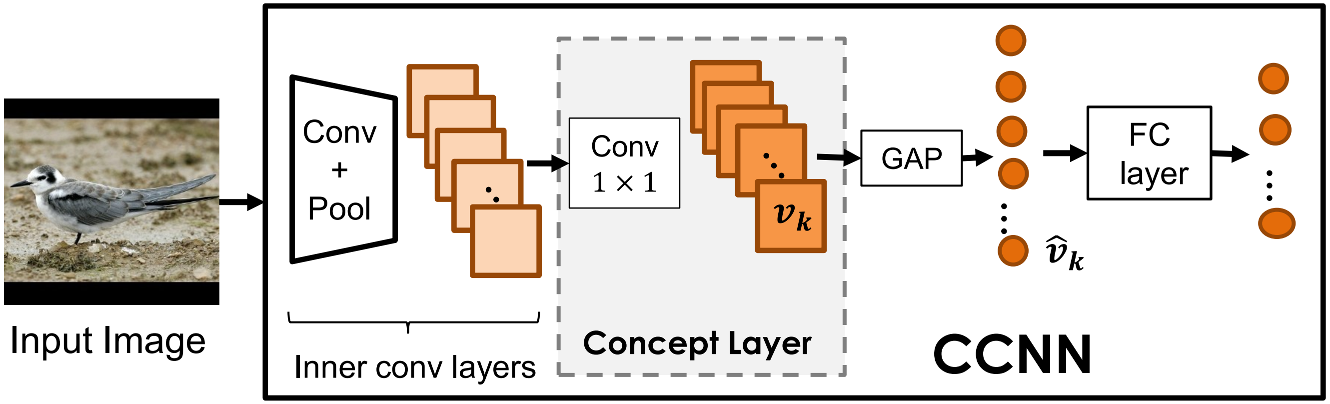
BRACE – CCNN

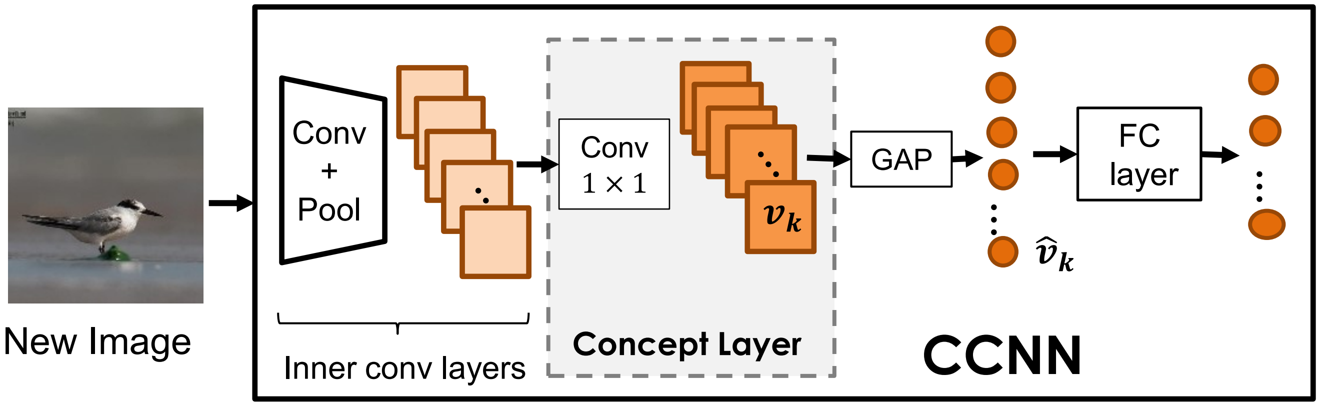


Decision: White Breasted Nuthatch
Contributed concepts:
White breast (0.50)
Black crown (0.30)
White belly (0.20)

- For each misclassified image obtained top-contributed concepts.
- Select top-r concepts that have contributed for highest number of misclassifications of class c - $S_{c \to \bar{c}}$

Comprehensible Convolutional Neural Networks via Guided Concept Learning, IJCNN, 2021.

BRACE – CCNN



- For each concept i in $S_{c \to \bar{c}}$, calculate degree of matching with a new image using the corresponding activation value of GAP layer in CCNN - a_i
- $\Delta(S_{c \to \bar{c}}, x) = \sum_{i=1}^{r} a_i$

Comprehensible Convolutional Neural Networks via Guided Concept Learning, IJCNN, 2021.

Performance Evaluation

- Source code - ***https://github.com/sandareka/BRACE***
- Datasets – CUB, CUB-Families, Tiny Imagenet
- Comparative study
  - Data augmentation methods
    - Cut -mix - Cutmix: Regularization strategy to train strong classifiers with localizable features, ICCV, 2019.
    - Snap-mix - Snapmix: Semantically proportional mixing for augmenting fine-grained data, AAAI, 2021.
    - WS-DAN - See better before looking closer: Weakly supervised data augmentation network for fine-grained visual classification, arXiv, 2019.
    - Metaset-based - Data-driven meta-set based fine-grained visual recognition, ACM-MM, 2020.
  - Sample selection methods
    - Random – samples are selected randomly.
    - Confidence – the most confident samples are selected.
    - Core-set – Active learning for convolutional neural networks: A core-set approach, ICLR, 2018.
    - L-loss - Learning loss for active learning, CVPR, 2019.

Comparison of Data Augmentation Methods

Performance of fully interpretable CCNN classifier based on ResNet-34.

Method	CUB	CUB-Families
Original dataset	84.3	83.8
Cut-mix	80.6	79.0
Snap-mix	82.4	79.9
WS-DAN	81.6	81.8
Metaset-based	85.1	88.1
BRACE	**86.0**	**88.7**

BRACE-augmented datasets achieve the highest accuracy.
The improvement is bigger in CUB-Families, where there are more under-represented regions.

Comparison of Sample Selection Methods

Performance of fully interpretable CCNN classifier based on ResNet-101.

Method	CUB	CUB-Families
Original dataset	86.6	85.7
Core-set	84.6	85.4
L-loss		
Random	87.0	88.0
Confidence	86.7	85.8
BRACE	**88.4**	**92.2**

BRACE-augmented datasets consistently achieves the highest accuracy.

Comparison of Samples Selected by Different Methods

Sample original images | Sample images of removed sub-categories | BRACE | Random | Confidence

Icteridae class of Cub-Families

- **BRACE selects images similar to those are in the removed subcategories.**
- **Random may select out-of-distribution images.**
- **Confidence selects images similar to those are in the original dataset.**

Performance Evaluation – Generalizability with BRACE

Comparison on generalizability of ResNet-34 trained with different data augmentation methods.

Method	NAbirds-Sub	ImageNet-V2-Sub
Original dataset	81.5	54.4
Cut-mix	72.1	37.2
Snap-mix	76.0	42.6
WS-DAN	67.0	56.1
Metaset-based	83.5	42.4
BRACE	**84.9**	**70.0**

BRACE enables the classifier to learn features that are generalizable to handle more diverse images.

Thank You